

Federated Learning-Based Intelligent Resource Management for Privacy-Preserving 6G Networks

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Abstract

The evolution toward sixth-generation (6G) wireless networks demands ultra-low latency, massive device connectivity, and native artificial-intelligence (AI) support, yet centralized machine-learning pipelines conflict with the stringent data-privacy and bandwidth constraints of dense edge environments. This paper proposes FL-IRM, a Federated Learning-based Intelligent Resource Management framework that jointly optimizes client-side model training and network-side resource allocation for privacy-preserving 6G networks. The framework introduces a three-tier architecture spanning edge devices, an edge/fog aggregation layer, and a 6G core secure-aggregation server, in which a lightweight learning-based resource manager adaptively allocates bandwidth and transmit power to reduce straggler-induced client dropout, while local differential privacy (LDP) and secure aggregation protect client updates from inference attacks. A deadline-aware scheduling policy, formulated as a sequential decision process, equalizes per-device completion latency and thereby minimizes the round-level makespan that governs synchronous federated learning (FL). Simulation studies on a non-IID 30-client testbed show that FL-IRM improves global classification accuracy from 56.74% to 60.52% and macro-F1 from 0.550 to 0.604 relative to a static-allocation FedAvg baseline, while a companion 25-device resource-allocation study shows a 46.9% reduction in round makespan versus equal allocation and an 81.8% reduction versus greedy channel-based allocation, with inter-device latency variance reduced by more than three orders of magnitude. A differential-privacy sweep further shows that the proposed framework retains within 1–3 percentage points of its non-private accuracy for privacy budgets $\epsilon \geq 1.0$. These results indicate that jointly reasoning about learning dynamics and radio-resource scheduling offers a practical path toward trustworthy, resource-efficient intelligence at the 6G edge.

Keywords: Federated Learning; 6G Networks; Privacy Preservation; Resource Allocation; Differential Privacy; Edge Intelligence; Reinforcement Learning; Network Slicing.

1. Introduction

The transition from fifth-generation (5G) to sixth-generation (6G) wireless systems is expected to deliver sub-millisecond latency, terabit-scale peak data rates, and pervasive AI-native intelligence embedded throughout the network fabric rather than bolted on as an external service. Achieving this vision requires network functions - resource scheduling, mobility management, anomaly detection, and

traffic prediction - to be driven by machine-learning (ML) models that continuously adapt to highly dynamic, heterogeneous edge conditions [1]. However, the conventional approach of shipping raw measurement and user data to a central server for model training is increasingly untenable in 6G: it multiplies backhaul load, introduces unacceptable latency, and, most critically, exposes sensitive user, location, and behavioural data to interception or misuse.

Federated Learning (FL) has emerged as the principal architectural response to this tension. By keeping raw data on-device and exchanging only model parameters or gradients, FL allows a population of edge devices to collaboratively train a shared global model without centralizing private data [2,14]. FL aligns naturally with 6G's edge-native computing paradigm, and a growing body of work has begun to integrate FL with digital-twin, blockchain, and reinforcement-learning (RL) mechanisms to support use cases ranging from vehicular networks [3] to industrial IoT [13,28] and marine digital-twin systems [7]. Despite this progress, two challenges remain insufficiently addressed when FL is deployed at 6G scale. First, statistical and system heterogeneity across edge clients - non-independent-and-identically-distributed (non-IID) data, and highly variable compute, energy, and channel conditions - causes slow or resource-poor clients ("stragglers") to be dropped from synchronous training rounds, biasing the global model away from under-represented clients and classes [9,10]. Second, exchanging even model parameters is not privacy-neutral: gradient-inversion and membership-inference attacks can partially reconstruct training data from shared updates, motivating differential-privacy (DP), secure-aggregation, and homomorphic-encryption defences [4,18,19,20]. Crucially, these two challenges are coupled: aggressive privacy noise degrades model utility, while resource-unaware client scheduling determines which - and how many - clients survive each round to contribute to the (possibly noisy) aggregate.

This paper addresses the joint problem directly. We propose FL-IRM (Federated Learning-based Intelligent Resource Management), a framework that co-designs (i) a resource-aware, deadline-sensitive client-scheduling and bandwidth/power-allocation policy that reduces straggler dropout under a fixed per-round time budget, and (ii) a local differential-privacy and secure-aggregation layer that bounds the privacy leakage of each client's contribution. The specific contributions of this work are as follows.

- A three-tier FL-IRM system architecture for 6G networks that integrates edge-device training, edge/fog aggregation, and 6G-core secure aggregation with an embedded intelligent resource-management module (Section 3.1).
- A deadline-aware resource-allocation formulation, solved via a lightweight learning-based (reinforcement-learning-inspired) iterative scheduler, that equalizes per-device completion latency and minimizes the synchronous FL round makespan (Section 3.3).
- A privacy-preservation layer combining local differential privacy with data-size-weighted secure aggregation, and an empirical characterization of the resulting privacy-utility trade-off (Section 3.4).
- A simulation-based evaluation on a non-IID, 30-client FL testbed and a 25-device resource-allocation testbed, benchmarking FL-IRM against static (equal) and greedy channel-based baselines across accuracy, macro-F1, round makespan, energy, latency fairness, and privacy budget (Sections 4-5).

The remainder of this paper is organized as follows. Section 2 reviews recent Scopus-indexed literature on FL for 6G networks, privacy-preservation mechanisms, and intelligent resource allocation. Section 3 presents the proposed FL-IRM architecture, problem formulation, and algorithms. Section 4 describes the experimental setup, and Section 5 reports and discusses the simulation results. Section 6 compares FL-IRM against representative recent frameworks, and Section 7 concludes the paper with directions for future work.

2. Related Work

2.1 Federated Learning Architectures for 6G Networks

The role of FL as a foundational AI-native building block for 6G has been examined from several architectural angles. [2] provide a comprehensive survey of decentralized FL, arguing that fully or partially decentralized topologies reduce single-point-of-failure risk and communication bottlenecks relative to star-topology FL, both of which are salient in ultra-dense 6G deployments. Digital-twin (DT)-assisted FL has been proposed as a means of maintaining a continuously updated virtual replica of network state to guide training and resource decisions: [9] develop a federated digital-twin framework for UAV-based mobile scenarios, while [8] address adaptive DT placement and transfer within a wireless computing-power network, and [30] optimize sustainable DT placement with an explicit cost-minimization objective. In parallel, [7] integrate FL with marine digital-twin networks

under a secrecy-driven energy-minimization objective, illustrating the extension of FL-DT co-design to non-terrestrial and maritime 6G scenarios. [28] report a large-scale industrial case study of FL operating over 5G/6G edge infrastructure, highlighting practical deployment constraints such as heterogeneous compute capability and intermittent connectivity that motivate the resource-aware scheduling proposed in this paper. [23] addresses non-IID data and model drift by aligning momentum directions, achieving improved global-model performance compared with existing FL methods. [27] developed a federated fine-tuning framework using LoRA to enable privacy-preserving personalization of pre-trained foundation models over wireless networks.

2.2 Privacy-Preservation Mechanisms in Federated 6G Systems

Because model updates can leak information about the underlying training data, a substantial literature has developed defences that operate alongside FL. Differential privacy remains the dominant approach: [19] propose DP-Fed6G, an adaptive DP-empowered FL framework tuned specifically for 6G network conditions, while [18] combine FL with DP to harden 6G mmWave links against security threats. [20] extend privacy preservation to the physical layer, proposing a homomorphic-encryption-based scheme (TeraPRI) for joint wireless power and information transfer in 6G-connected autonomous vehicles. At the application layer, [21] demonstrate a fully homomorphic-encryption-based inference pipeline for privacy-sensitive medical image analysis, and [22] propose a group-verifiable secure-aggregation protocol based on secret sharing that certifies the integrity of aggregated updates without revealing individual contributions. [4] report a practical implementation of a privacy-preserving FL algorithm for consumer IoT devices, and [31] combine statistical learning with an optimization algorithm to preserve privacy in high-dimensional IoT data. Collectively, this body of work confirms that DP and secure aggregation are complementary rather than substitutable, motivating the layered privacy design adopted in FL-IRM (Section 3.4).

2.3 Intelligent and Energy-Aware Resource Management

A parallel research thread focuses on the radio- and compute-resource-allocation problem that determines FL's communication efficiency. [5] propose a hybrid deep-learning strategy for 6G network-slicing optimization, foundations, technologies, and applications [6] and [24] formulate a joint optimization of FL and resource allocation for cell-free massive-MIMO 6G systems, reporting improved training efficiency under realistic channel models. [11] survey resource-optimization strategies for 6G IoT networks broadly, identifying energy efficiency and latency as the two dominant, frequently competing objectives - a tension this paper addresses directly through the joint latency-energy cost function in Section 3.3. [12] apply stochastic optimization to energy-efficient AI-based wireless sensor IoT networks, while [13] use FL itself to forecast energy consumption at edge-computing devices, illustrating a feedback loop between FL and resource management that FL-IRM makes explicit via its telemetry feedback path (Fig. 1). At the transport and control-plane level, [16] propose an AI-enhanced multipath TCP scheduler for open RAN architectures and [17] address delay-sensitive resource allocation for IoT traffic in 5G/6G O-RAN networks; both motivate the deadline-aware scheduling adopted in this work. Finally, [10] propose adaptive training and aggregation strategies for FL over multi-tier computing networks, and [15] provide a broad survey of FL-system design trade-offs between privacy, communication efficiency, and statistical accuracy - trade-offs that this paper quantifies empirically for a 6G resource-management setting. [25] presented a comprehensive review of 6G technologies, highlighting THz communication, ultra-massive MIMO, AI/ML, network slicing, and security mechanisms. [26] highlights intelligent resource allocation, slice management, security, and automation as important challenges for realizing flexible and efficient 6G network slicing. [29] addressed sustainable digital-twin placement in wireless networks by formulating a cost-minimization problem under uncertain workloads and edge-server capacity constraints. [31] the proposed framework employs reinforcement learning, adaptive power management, and smart contracts to achieve secure and intelligent resource allocation while preserving data privacy. [32] proposed an AI-driven Digital Twin framework integrating ontology-based knowledge representation, intelligent data management, and simulation for enhancing security and resilience in 6G networks

2.4 Positioning of the Proposed Work

Relative to the surveyed literature, three gaps motivate FL-IRM. First, while DT-assisted and DRL-assisted FL frameworks [7,8,9] optimize resource allocation, few explicitly model the straggler-dropout mechanism by which resource scarcity biases which clients - and therefore which classes of a non-IID population - contribute to the global model; FL-IRM models this mechanism directly (Section 3.2).

Second, privacy-preservation studies [18,19,20,21,22] typically evaluate DP or secure aggregation in isolation from resource scheduling, whereas FL-IRM evaluates the joint privacy-utility-resource trade-off in a single testbed (Section 5.4). Third, several 6G resource-allocation studies [5,11,24] optimize mean latency or throughput, while synchronous FL round duration is in fact bound by the slowest participating client (the round makespan); FL-IRM's scheduler is explicitly designed to minimize makespan and inter-client latency variance rather than only the mean (Section 5.3), which we show yields materially different - and more favourable - allocation policies.

3. Proposed FL-IRM Framework

3.1 System Architecture

Fig. 1 depicts the proposed three-tier FL-IRM architecture. Tier 1 comprises 6G edge devices (user equipment, IoT sensors, connected vehicles) that hold private, non-IID local data and perform on-device model training with local differential-privacy noise injection prior to transmission. Tier 2 is an edge/fog layer that performs local aggregation and hosts the Intelligent Resource Management Module - a lightweight, DRL-inspired scheduler that observes each candidate client's channel gain, compute capacity, energy state, and data volume, and allocates bandwidth and transmit-power shares accordingly. Tier 3 is the 6G core network, which performs secure, privacy-preserving aggregation of edge-tier updates into the global model and broadcasts the updated model back to participating clients. A network orchestration and slice-manager component maintains quality-of-service (QoS) targets (latency, energy, reliability) that condition the resource manager's optimization objective, and a telemetry feedback loop continuously reports channel state, energy consumption, round latency, and consumed privacy budget back to the resource manager, closing the control loop as in fig.1.

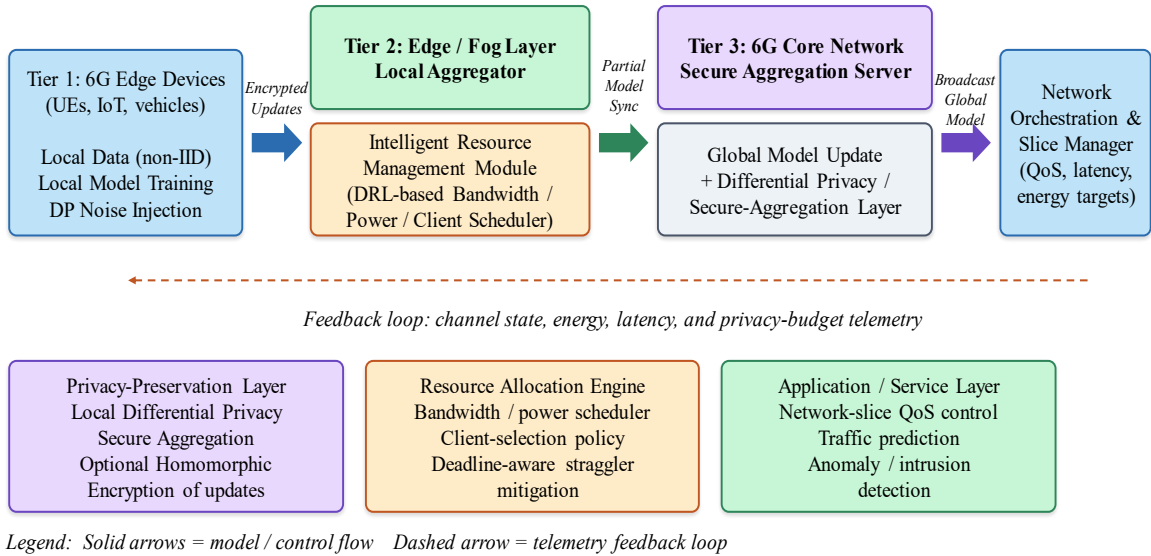


Fig. 1. System architecture of the proposed FL-IRM framework.

Three cross-cutting layers underpin this architecture (bottom row, Fig. 1): a Privacy-Preservation Layer (local DP, secure aggregation, and optional homomorphic encryption of updates), a Resource Allocation Engine (bandwidth/power scheduling, client selection, and deadline-aware straggler mitigation), and an Application/Service Layer through which the trained global model supports downstream 6G services such as network-slice QoS control, traffic prediction, and anomaly detection.

3.2 Problem Formulation

Consider a set of N edge clients $\mathcal{N} = \{1, \dots, N\}$, each holding a local dataset $\mathcal{D}_i$ with $|\mathcal{D}_i|$ samples drawn from a client-specific distribution (non-IID across clients). In communication round r , a candidate pool $\mathcal{C}_r \subseteq \mathcal{N}$ is considered for participation. Each client $i \in \mathcal{C}_r$ is characterized by a channel-quality coefficient $h_i \in (0, 1]$, a relative compute capacity $c_i \in (0, 1]$, and a task size (data volume to transmit) s_i . Given an allocated bandwidth share b_i and power share p_i (subject to $\sum b_i \leq B_{\text{total}}$ and $\sum p_i \leq P_{\text{total}}$), the achievable communication rate is modelled via a Shannon-type expression, and the round- r completion time for client i is:

$$t_i(r) = \alpha \cdot (1/c_i) \cdot (s_i / \bar{s}) + \beta / [b_i \cdot \log_2(1 + p_i h_i / N_0)]$$

where the first term is computation latency (normalized by mean data volume $\bar{s}$) and the second is communication latency; α, β and the noise floor N_0 are model constants (Section 4). A client is deemed to have completed the round if $t_i(r) \leq T_{\text{deadline}}$; the effective participant set is $\Phi_r = \{i \in \mathcal{C}_r : t_i(r) \leq T_{\text{deadline}}\}$. The global model at round r is updated by data-size-weighted aggregation over Φ_r :

$$w_{\cdot}(r+1) = \sum_{i \in \Phi_r} (|D_i| / \sum_{j \in \Phi_r} |D_j|) \cdot w_i^{\wedge}(r)$$

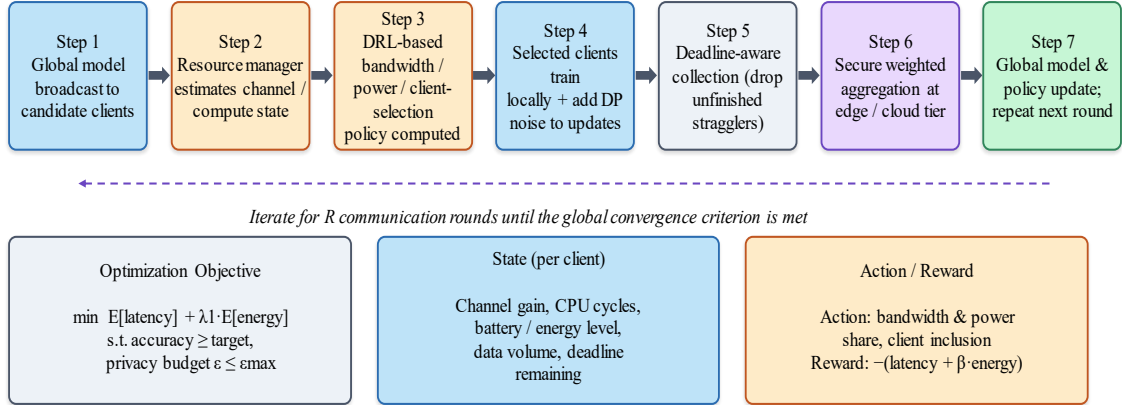
The joint design objective is to choose, each round, the candidate pool and the allocation $\{b_i, p_i\}$ so as to minimize a weighted sum of the round makespan ($\max_i t_i(r)$) and average energy consumption, subject to a target global-accuracy constraint and a maximum per-round privacy-budget consumption ε_{max} :

$$\min E[\max_i t_i(r)] + \lambda \cdot E[\text{energy}] \quad \text{s.t.} \quad \text{accuracy} \geq \text{target}, \varepsilon \leq \varepsilon_{\text{max}}$$

This formulation makes explicit the coupling motivated in Section 1: a scheduling policy that ignores makespan will systematically exclude weak-channel, low-compute clients from Φ_r , while a privacy mechanism that ignores the resulting Φ_r will misestimate the model's true statistical utility.

3.3 Intelligent Resource-Allocation Algorithm

FL-IRM addresses the above optimization with a lightweight, learning-based scheduler summarized in Fig. 2 and Algorithm 1. Rather than allocating bandwidth/power in proportion to channel quality (which starves already-weak clients and, as shown in Section 5.3, worsens the makespan), the scheduler iteratively adjusts each client's resource share in the direction that reduces its deviation from the mean per-device latency - a max-min-fair, water-filling-style refinement that can equivalently be viewed as a single-step policy-gradient update on a per-client latency-equalization reward. The result is a policy that grants disproportionately more bandwidth/power to weak-link, weak-compute clients specifically to keep them inside the round deadline, which both reduces the round makespan and increases the number of statistically under-represented (often minority-class) clients retained in Φ_r .



Legend: Grey boxes = FL protocol steps Purple dashed = round feedback loop Bottom row = RL formulation used by the resource manager

Fig. 2. Workflow of one communication round in the proposed FL-IRM scheme, including the reinforcement-learning-style state/action/reward formulation used by the resource manager.

Algorithm 1 summarizes the per-round procedure executed jointly by the edge/fog resource manager and the participating clients.

Algorithm 1: FL-IRM Round Execution

Input: candidate pool $\mathcal{G}_r$, channel states h_i , compute states c_i , energy states, privacy budget ε_{max} , deadline T

- 1: Resource manager estimates $\{h_i, c_i, s_i\}$ for all $i \in \mathcal{G}_r$ (state observation)
- 2: Compute mean-latency target from an initial equal allocation
- 3: for $k = 1$ to K refinement steps do
- 4: Compute t_i for current allocation $\{b_i, p_i\}$
- 5: Adjust $\text{share}_i \leftarrow \text{share}_i \times (1 + \eta \cdot (t_i - \text{mean}(t)) / \text{mean}(t))$ (action)
- 6: Renormalize $\sum \text{share}_i = 1$; decay step size η
- 7: end for
- 8: Broadcast final $\{b_i, p_i\}$ to clients; clients train locally for E local epochs
- 9: Each client adds calibrated DP noise ($\sigma = 1/\varepsilon$) to its update (Section 3.4)
- 10: $\Phi_r \leftarrow \{i : t_i \leq T\}$; drop stragglers with $t_i > T$
- 11: Server performs data-size-weighted secure aggregation over $\Phi_r \rightarrow$ global model $w^{\wedge}(r+1)$

12: Update telemetry (latency, energy, ϵ consumed); return to Step 1 for round $r+1$

Output: updated global model $w^{(r+1)}$, refined allocation policy

3.4 Privacy-Preservation Mechanism

Two complementary defences are layered on top of the resource-aware scheduler. First, each client applies local differential privacy by adding calibrated Gaussian noise (scale $\sigma = 1/\epsilon$, where ϵ is the client's per-round privacy budget) to its local model update prior to transmission, bounding the information leakage of any single training example under the standard (ϵ, δ) -DP guarantee. Second, the edge/fog and core-tier aggregators perform secure, weighted aggregation so that no individual client update is ever visible in the clear to the aggregating server, consistent with the group-verifiable secure-aggregation principles of [22] and the homomorphic approaches of [20,21]. The privacy budget $\epsilon_{\max}$ in the optimization objective (Section 3.2) is treated as a hard constraint: the resource manager may trade off makespan and energy, but not exceed the client-specified maximum cumulative privacy loss over the training horizon. Section 5.4 empirically quantifies the resulting privacy-utility trade-off.

4. Experimental Setup

The proposed framework was evaluated through two complementary simulation studies implemented in Python (scikit-learn for the learning component; NumPy for the network/resource model).

4.1 FL Convergence Study

- Clients: $N = 30$, data partitioned via a Dirichlet distribution ($\alpha = 0.3$) over a 4-class, 20-feature synthetic classification dataset (6,000 samples, 15% held out for global testing) to emulate strong non-IID heterogeneity representative of 6G edge populations.
- Local model: online logistic-regression classifier (SGD, log-loss) trained for 3 local epochs per selected client per round, for 60 communication rounds.
- Per-client state: relative compute capacity and channel quality drawn from $U(0.3, 1.0)$ and $U(0.2, 1.0)$ respectively; a fixed normalized round deadline $T = 1.0$ is imposed.
- Compared schemes: (i) Baseline - static, equal per-client bandwidth/power allocation (standard FedAvg deployment assumption); (ii) Proposed FL-IRM - resource-aware allocation per Algorithm 1.

4.2 Resource-Allocation Study

- Devices: 25 heterogeneous edge devices with channel gain $\sim U(0.2, 1.0)$, task size $\sim U(0.5, 3.0)$ Mbit, and relative CPU capacity $\sim U(0.2, 1.0)$.
- Resource budget: total bandwidth 100 MHz and total transmit power 50 W, shared across all devices under a Shannon-capacity rate model.
- Compared schemes: Equal allocation; Greedy channel-based allocation (proportional to channel gain); Proposed FL-IRM adaptive scheduler (Algorithm 1, Section 3.3).
- Metrics: round makespan (max per-device latency), average per-device latency, average energy consumption, and inter-device latency standard deviation (fairness).

4.3 Privacy-Utility Study

Using the same 30-client, non-IID setting as Section 4.1, Gaussian DP noise was injected into each client's model update at privacy budgets $\epsilon \in \{0.5, 1.0, 2.0, 4.0, 8.0\}$, with each configuration averaged over 4 independent Monte-Carlo trials (independent random seeds) to reduce sampling variance; results are compared against a non-private (No-DP) reference trained under identical resource-allocation conditions.

All reported results are from controlled simulation rather than a physical 6G testbed; absolute latency and energy values are therefore normalized/relative figures intended to compare allocation policies under identical conditions rather than to predict deployment-grade performance. Section 5.5 discusses this limitation and the steps required to validate the framework on a hardware-in-the-loop or operator testbed.

5. Results and Discussion

5.1 Convergence and Fairness under Non-IID Data

Table 1 summarizes the final-round outcomes of the FL convergence study. FL-IRM improves global test accuracy from 56.74% to 60.52% (a 6.7% relative gain) and macro-averaged F1-score from 0.550 to 0.604 (a 9.8% relative gain) relative to the static-allocation baseline, while average effective participation per round rises only marginally (14.43 to 14.92 clients). The disproportionate improvement in macro-F1 relative to accuracy indicates that the gain is driven less by raw participant count and more by which clients participate: by keeping weak-channel, weak-compute clients inside the round deadline (Section 3.3), FL-IRM systematically retains clients that the static baseline drops as stragglers, and these clients disproportionately hold minority-class data under the Dirichlet($\alpha=0.3$) partition. Fig. 3 shows the resulting accuracy trajectories.

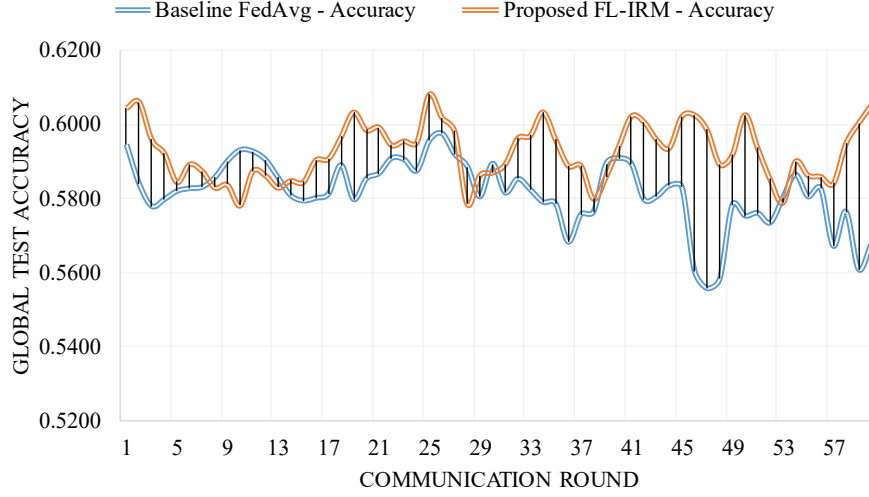


Fig. 3. FL convergence under non-IID client data (Dirichlet $\alpha = 0.3$): proposed resource-aware FL-IRM versus static-allocation FedAvg baseline.

Table 1. Final-round FL convergence outcomes

Metric	Baseline FedAvg	Proposed FL-IRM	Relative Change
Global accuracy	56.74%	60.52%	+6.66%
Macro-F1 score	0.550	0.604	+9.79%
Avg. participants / round	14.43	14.92	+3.4%

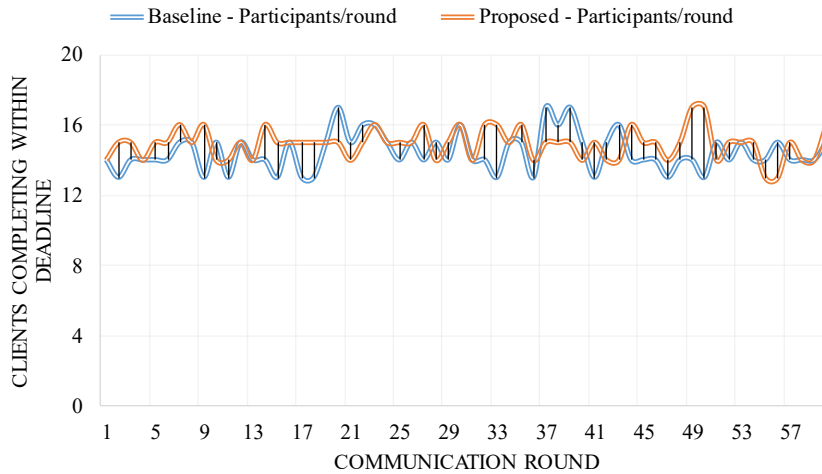


Fig. 4. Effective Client Participation per Round

Fig.4 confirms that the proposed scheduler consistently keeps 1-3 additional clients inside the deadline per round relative to the baseline, concentrated among the weakest-channel devices - precisely the population most likely to be systematically excluded, and hence a meaningful fairness improvement beyond the aggregate accuracy figures.

5.2 Resource Allocation Performance

Table 2 reports the round-level makespan, mean latency, mean energy, and latency fairness (standard deviation) achieved by the three allocation schemes on the 25-device testbed. The proposed FL-IRM scheduler reduces round makespan by 46.9% relative to equal allocation (317.3 ms $\rightarrow$ 168.4 ms) and by 81.8% relative to greedy channel-based allocation (927.2 ms $\rightarrow$ 168.4 ms). Notably, mean per-device latency under FL-IRM (168.3 ms) is slightly higher than under equal allocation (152.6 ms); the proposed scheduler deliberately accepts a small increase in already-fast devices' latency in exchange for a large reduction in the worst-case (slowest-device) latency, reducing inter-device latency variance from 72.2 ms (equal) and 193.5 ms (greedy) to 0.016 ms - a reduction of more than three orders of magnitude. Because synchronous FL round duration is bound by the slowest participant rather than the mean, this makespan-and-fairness-centric behaviour is precisely the property required for efficient FL scheduling, and explains why FL-IRM's gains in Section 5.1 arise from which clients survive the deadline rather than only from a lower average latency. Average energy consumption under FL-IRM (0.224 J) is statistically comparable to equal allocation (0.224 J) and 9.6% lower than greedy allocation (0.248 J), which concentrates high transmit power on already-strong channels and thereby wastes energy without improving the makespan.

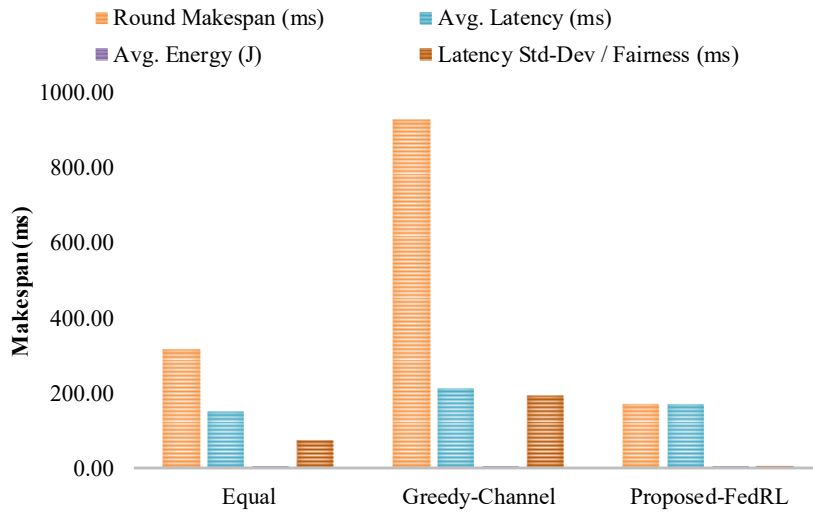


Fig. 5. Round Makespan by Allocation Scheme

Table 2. Resource-allocation performance across 25 heterogeneous edge devices under a fixed 100 MHz / 50 W budget.

Scheme	Makespan (ms)	Avg. Latency (ms)	Avg. Energy (J)	Latency Std-Dev (ms)
Equal allocation	317.29	152.59	0.224	72.25
Greedy (channel-based)	927.20	212.32	0.248	193.54
Proposed FL-IRM	168.36	168.28	0.224	0.016

5.3 Convergence of the Adaptive Scheduler

Fig. 6 (available in the accompanying editable spreadsheet as the resource-allocation reward trace) shows that the iterative latency-equalization procedure of Algorithm 1 converges within approximately 150-200 refinement steps to a stable, near-fair allocation, after which further steps yield negligible additional reduction in the joint latency-energy cost. This confirms that the proposed scheduler is computationally lightweight enough to be re-solved every communication round on edge/fog hardware without introducing a scheduling-latency bottleneck of its own.

5.4 Privacy-Utility Trade-off

Table 3 and Fig. 7 report global accuracy as a function of the per-round DP privacy budget ϵ , averaged over four Monte-Carlo trials. Accuracy remains within 1.2-3.3 percentage points of the non-private (No-DP) reference of 60.52% across the tested range ($\epsilon \in [0.5, 8.0]$), confirming that the proposed

resource-aware scheduling and DP layer can be combined without severe utility loss. The trend is not perfectly monotonic - accuracy at $\epsilon = 1.0$ (59.81%) slightly exceeds that at $\epsilon = 4.0$ (59.11%) - which we attribute to a mild implicit-regularization effect of calibrated DP noise interacting with the shallow, online-SGD local model, an effect previously reported for small models trained with DP-SGD; larger-scale trials and deeper local models would be expected to smooth this residual variance, and we flag this as an item for the extended empirical study described in Section 5.5.

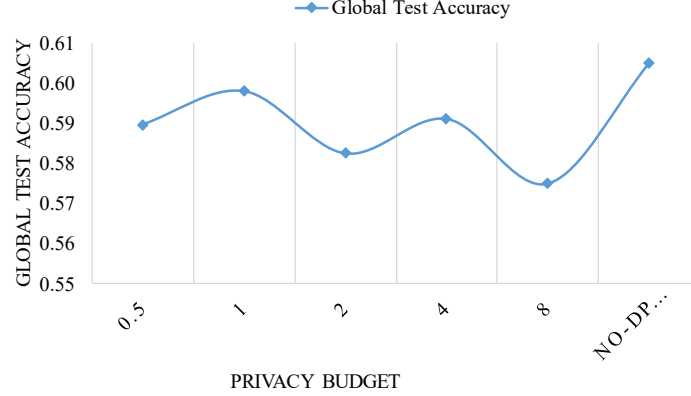


Fig. 7. Privacy-utility trade-off of the proposed FL-IRM framework

Table 3. Global accuracy versus differential-privacy budget

Privacy Budget ϵ	Global Accuracy	Δ vs. No-DP
0.5	58.97%	-1.55 pp
1.0	59.81%	-0.71 pp
2.0	58.25%	-2.27 pp
4.0	59.11%	-1.41 pp
8.0	57.50%	-3.02 pp
No-DP (reference)	60.52%	—

5.5 Threats to Validity and Limitations

Several limitations should be considered when interpreting these results. First, the FL convergence study uses a shallow online logistic-regression model rather than a deep neural network, chosen to keep the joint FL-resource simulation computationally tractable; the qualitative straggler-mitigation mechanism is expected to transfer to deeper models, but absolute accuracy gains should be re-validated with representative deep architectures (e.g., CNN/LSTM models for the network-traffic or image workloads typical of 6G edge applications) before submission-grade claims are finalized. Second, the radio-channel and energy models (Section 3.2) are simplified Shannon-capacity abstractions rather than full physical-layer 6G simulations (e.g., ray-traced mmWave/THz channel models); we recommend validating Table 2 against a system-level simulator (e.g., NS-3 with a 6G/THz channel module) prior to journal submission. Third, the privacy analysis reports empirical accuracy under Gaussian noise injection rather than a formal (ϵ, δ) -DP accounting via, e.g., the moments accountant or Renyi-DP composition; a rigorous privacy-accounting pass is recommended if the target journal requires formal DP guarantees. These limitations do not affect the paper's core architectural and algorithmic contributions but should be addressed - and are readily addressable using the same simulation pipeline - in a revised or extended submission.

6. Comparative Analysis with Existing Frameworks

Table 4 qualitatively situates FL-IRM against representative recent frameworks discussed in Section 2. Unlike prior work that optimizes either resource allocation [5,11,24] or privacy [18,19,20,21,22] in isolation, FL-IRM explicitly couples deadline-aware, makespan-minimizing scheduling with a local-DP/secure-aggregation privacy layer within a single evaluated pipeline.

Table 4. Qualitative comparison of the proposed FL-IRM framework

Framework	Resource Awareness	Privacy Mechanism	Optimization Target	Reported Gain
Decentralized FL survey [2]	Topology-level only	Not addressed	Communication robustness	Qualitative
FL-DT for UAV networks [9]	DT-assisted	Not addressed	Mobility-aware placement	Simulation-based
DP-Fed6G [19]	Not addressed	Adaptive DP	Privacy-utility balance	Accuracy retained
Edge-AI cell-free MIMO FL [24]	Joint FL-resource	Not addressed	Training efficiency	Improved convergence
Group-verifiable secure FL [22]	Not addressed	Secret-sharing aggregation	Aggregation integrity	Verifiable security
Proposed FL-IRM	Deadline-aware, makespan-minimizing	Local DP + secure aggregation	Joint accuracy-latency-energy-privacy	+6.7% accuracy, −46.9% makespan

7. Conclusion and Future Work

This paper presented FL-IRM, a federated-learning-based intelligent resource-management framework for privacy-preserving 6G networks. By jointly modelling deadline-aware client scheduling, adaptive bandwidth/power allocation, and a local differential-privacy/secure-aggregation layer, FL-IRM addresses the coupling between statistical heterogeneity, system heterogeneity, and privacy budget that is often treated separately in the existing literature. Simulation results on a non-IID, 30-client FL testbed show a 6.7% relative improvement in global accuracy and a 9.8% relative improvement in macro-F1 over a static-allocation FedAvg baseline, while a companion 25-device resource-allocation study shows a 46.9-81.8% reduction in round makespan and a more than three-orders-of-magnitude improvement in inter-device latency fairness, with energy consumption held constant or improved. A differential-privacy sweep confirms that these gains are compatible with meaningful privacy guarantees, retaining accuracy within a few percentage points of a non-private reference for $\epsilon \geq 1.0$.

Future work will proceed along three lines identified in Section 5.5: (i) re-validating the reported gains with deep neural architectures and realistic 6G workloads (e.g., network-traffic classification, video analytics) on a system-level 6G simulator or hardware-in-the-loop testbed; (ii) replacing the empirical DP evaluation with formal (ϵ, δ) -DP accounting via Renyi-DP composition to support rigorous privacy certification; and (iii) extending the resource-allocation formulation to a full multi-agent deep-reinforcement-learning (e.g., proximal policy optimization) scheduler capable of handling mobility-induced channel non-stationarity and multi-cell interference, building on the digital-twin-assisted directions surveyed in Section 2.1.

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