A Theoretical Analysis of Federated Learning for Coverage and Capacity Improvement in 5G HetNets

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***Abstract*—This paper investigates the application of federated learning (FL) for enhancing coverage and capacity in fifth-generation heterogeneous networks (5G HetNets). The increasing densification of networks with macro cells, small cells, and diverse user equipment introduces significant challenges in resource allocation, interference management, and user association. Traditional centralized machine learning approaches require extensive data sharing, which raises privacy concerns and increases communication overhead. To address these limitations, this work proposes a federated learning-based framework that enables distributed model training across multiple base stations without sharing raw user data. The proposed method leverages local observations such as signal strength, interference levels, and traffic demand to collaboratively optimize network performance.The proposed framework incorporates efficient aggregation mechanisms to ensure convergence while minimizing communication costs. Simulation results demonstrate that the proposed approach significantly improves signal-to-interference-plus-noise ratio (SINR) and overall network capacity compared to conventional techniques. Furthermore, the system shows robustness under high user density and mobility scenarios, which are critical in practical 5G deployments.**

***Index Terms*—Federated Learning, HetNet, Coverage, Capacity**

I. INTRODUCTION

Fifth-generation (5G) wireless communication systems are evolving rapidly, driving the widespread adoption of heterogeneous networks (HetNets). These networks combine macro cells, small cells, and various user equipment to address the increasing need for high data speeds and uninterrupted connectivity. Although densifying networks enhances spectral efficiency and coverage, it creates major challenges including heightened inter-cell interference, fluctuating traffic patterns, and complicated user association choices. Traditional optimization methods typically depend on static or heuristic-based approaches, which fall short when managing the highly dynamic and complex characteristics of today's wireless environments. As a result, there's an increasing demand for intelligent, data-driven solutions capable of adaptively optimizing network performance.

Machine learning (ML) techniques have recently become popular for tackling these challenges by enabling data-driven optimization of network parameters. However, centralized ML approaches demand gathering large amounts of data at a central server, which creates significant communication overhead, latency issues, and potential privacy risks. In 5G HetNets, where user data is spread across multiple base stations and edge devices, centralized training proves impractical and inefficient. Additionally, regulatory and privacy concerns limit the sharing of sensitive user information, which restricts how traditional ML frameworks can be used in real-world deployments.

Federated learning (FL) has emerged as an promising approach that enables collaborative model training without needing to exchange raw data. In FL, multiple distributed entities—such as base stations or edge nodes—train local models using their own data and periodically share only model updates with a central aggregator. This method significantly reduces communication overhead and maintains data privacy while still taking advantage of collective learning. FL's inherent distributed nature makes it especially well-suited for 5G HetNets, where network elements function in a decentralized manner and have localized information about channel conditions, interference patterns, and traffic demands.

In this paper, we propose a federated learning-based framework for improving coverage and capacity in 5G HetNets through intelligent user association and resource allocation. The proposed approach leverages local observations at each base station to train a global model that adapts to dynamic network conditions. We design efficient aggregation and update mechanisms to ensure fast convergence and scalability in large-scale deployments. Extensive simulations demonstrate that the proposed method outperforms conventional approaches in terms of signal-to-interference-plus-noise ratio (SINR), throughput, and overall network efficiency. The contributions of this work highlight the potential of integrating federated learning into next-generation wireless systems for achieving intelligent and privacy-preserving network optimization.

II. RELATED WORK

The work in [1] provides a comprehensive overview of the role of federated learning (FL) in transforming wireless communication systems. The author emphasizes that the rapid expansion of data-driven applications and the widespread increase of connected devices require intelligent and privacy-preserving learning frameworks. Traditional centralized machine learning approaches face limitations due to high communication overhead, latency, and privacy concerns, making

FL a promising alternative for distributed learning in wireless environments.

The authors of [2] position FL as a key enabler for distributed intelligence in wireless systems, facilitating collaborative training across edge devices while preserving data privacy.The authors emphasize that foundation models typically demand substantial computational resources, memory, and communication bandwidth, which are often unavailable on edge devices participating in wireless networks. These constraints create bottlenecks in model training, parameter exchange, and real-time deployment. Furthermore, issues such as system heterogeneity, communication efficiency, and scalability become more pronounced when handling large-scale models.

The work in [3] investigates the impact of wireless channel impairments on the performance of federated learning (FL) systems. Unlike conventional FL studies that assume ideal communication links, this paper considers a more practical scenario where model updates are transmitted over wireless fading channels, introducing noise, interference, and bandwidth limitations.Instead of transmitting digital updates separately from each device, local gradients are transmitted simultaneously in an analog manner, significantly reducing communication latency and bandwidth usage. This approach is particularly beneficial in large-scale networks with many participating devices.However, the performance is sensitive to channel noise and synchronization errors, which may degrade aggregation accuracy in highly dynamic wireless scenarios.

The work in [4] outlines key research directions for advancing FL-enabled security in 6G networks. These include developing lightweight and adaptive FL models, integrating with edge intelligence and zero-trust architectures, and designing resilient frameworks capable of operating under dynamic and adversarial conditions. Overall, this survey offers a comprehensive roadmap for leveraging federated learning to address emerging security challenges in next-generation wireless systems.

In [5], the authors explore the integration of distributed learning paradigms, including federated learning (FL), into emerging 6G wireless networks from both communication and computing perspectives. The authors emphasize that 6G systems are expected to support AI-native functionalities, requiring tight coupling between communication, computation, and intelligence across distributed network entities. In this context, distributed learning is identified as a key enabler for scalable and privacy-preserving intelligence at the network edge.

The work in [6] presents a detailed performance analysis of FL under varying network conditions, examining key metrics such as convergence speed, communication overhead, and model accuracy. The study emphasizes how factors such as the number of participating devices, data distribution patterns, and communication frequency influence the overall efficiency of the learning process. Specifically, increasing the number of devices enhances learning diversity while simultaneously introducing higher communication costs and potential delays.

The work in [7] presents a distributed AI-native architecture designed to support intelligent services in emerging 6G wireless networks. Unlike traditional network designs where AI is integrated as an add-on component, the proposed architecture embeds AI capabilities natively into the network infrastructure, enabling seamless interaction between communication, computation, and intelligence. By leveraging edge intelligence, the architecture reduces communication overhead and latency while improving responsiveness to dynamic network conditions.

The work in [8] investigates the design of communication- and computation-efficient federated learning (FL) frameworks for wireless networks through the integration of split learning and federated learning paradigms. The authors emphasize that traditional FL approaches place significant communication and computational burdens on edge devices, limiting their use in resource-constrained wireless environments. To address this challenge, the neural network is split into two parts: the initial layers run on edge devices while the remaining layers are processed at the server. This split learning approach reduces computational load on edge devices while preserving data privacy, since raw data never leaves local devices. Meanwhile, federated aggregation combines model updates across multiple devices, enabling collaborative learning without centralized data collection.

The work in [9] investigates the performance of federated learning (FL) in cellular wireless networks characterized by unreliable communication links and limited device resources. The authors emphasize that practical wireless environments introduce significant challenges to FL deployment, including intermittent connectivity, packet losses, limited bandwidth, and energy constraints at user devices. These factors can severely degrade the convergence and reliability of distributed learning systems.To address these challenges, the paper develops a comprehensive analytical framework that captures the impact of communication unreliability and resource limitations on FL performance. The authors model the effects of random device participation, transmission failures, and constrained computational capabilities, and analyze their influence on the convergence behavior of the global model. The work in [10] explores the integration of federated learning (FL) with over-the-air computation (AirComp) to improve communication efficiency in wireless networks. The authors highlight that conventional FL approaches rely on orthogonal communication schemes for transmitting local model updates, which results in significant communication latency and bandwidth consumption, especially in large-scale distributed systems.To overcome these limitations, the paper proposes an AirComp-based aggregation framework that exploits the superposition property of wireless channels to enable simultaneous transmission of local updates from multiple devices. This approach allows the receiver to directly compute the aggregated global model update, thereby significantly reducing communication overhead and latency compared to traditional digital communication methods.Simulation results show that the AirComp-based FL framework significantly reduces communication latency while maintaining competitive model accuracy compared to conventional approaches. However, the performance is sensitive to synchronization errors and channel noise, which remain important challenges for practical deployment.

The work in [11] studies the implementation of federated learning (FL) over wireless fading channels, focusing on the impact of communication impairments on distributed learning performance. The authors point out that most existing FL frameworks assume ideal communication links, which is unrealistic in practical wireless environments characterized by channel fading, noise, and limited bandwidth. These factors significantly affect the reliability and efficiency of model update transmission.Simulation results demonstrate that the AirComp-based FL framework significantly reduces communication overhead and accelerates convergence compared to traditional digital FL approaches, particularly in bandwidth-limited scenarios. Nevertheless, the performance is sensitive to synchronization errors and channel noise, which remain key challenges for real-world deployment. The work in [12] investigates the integration of reconfigurable intelligent surfaces (RIS) with over-the-air computation (AirComp) to enhance federated learning (FL) performance in wireless networks. The authors highlight that conventional AirComp-based FL frameworks suffer from channel fading, signal misalignment, and noise, which degrade aggregation accuracy and slow down convergence. To address these limitations, the paper proposes the use of active RIS to improve wireless channel conditions during model aggregation. This enables better alignment of simultaneously transmitted local model updates from distributed devices, thereby improving the reliability and accuracy of over-the-air aggregation. The integration of RIS with AirComp enhances signal strength and mitigates the adverse effects of channel fading and interference. However, the deployment of active RIS introduces additional system complexity and energy consumption, which must be carefully managed in practical implementations.

The work in [13] investigates the challenges of applying federated learning (FL) in wireless networks with non-independent and identically distributed (non-IID) data across devices. The authors highlight that, in practical scenarios, user data is inherently heterogeneous due to differences in user behavior, channel conditions, and local environments. This statistical heterogeneity leads to divergence in local model updates, resulting in slower convergence and degraded global model performance.Simulation results show that the proposed methods significantly improve convergence speed and model accuracy compared to standard FL approaches under non-IID settings. However, the introduction of data sharing mechanisms may increase communication overhead, highlighting a trade-off between learning performance and resource utilization.

The work in [14] presents a comprehensive overview of federated reinforcement learning (FRL) for wireless networks, combining the strengths of federated learning (FL) and reinforcement learning (RL) to enable distributed and adaptive decision-making. The authors highlight that traditional RL approaches often rely on centralized training and data collection, which raises scalability, privacy, and communication overhead issues in wireless environments. FRL is introduced as a promising paradigm that allows distributed agents to collaboratively learn optimal policies while keeping local interaction data private.

The paper discusses the fundamental architecture of FRL, where multiple agents independently interact with their local environments and periodically share model parameters or policy updates with a central server or in a decentralized manner. This approach is particularly suitable for dynamic wireless networks, where parameters such as channel conditions, interference levels, and traffic patterns vary over time. By leveraging distributed learning, FRL improves adaptability and reduces reliance on centralized data aggregation.

The work in [15] investigates federated learning (FL) in heterogeneous wireless environments by leveraging over-the-air computation (AirComp) for efficient model aggregation. The authors highlight that practical wireless networks exhibit significant heterogeneity in terms of device capabilities, channel conditions, and data distributions, which poses challenges for conventional FL frameworks that assume uniform participation and ideal communication links.To address these challenges, the paper proposes a heterogeneous FL framework that integrates AirComp to enable simultaneous transmission and aggregation of local model updates. By exploiting the superposition property of wireless channels, the proposed approach reduces communication latency and bandwidth consumption while accommodating diverse device characteristics. The framework is designed to handle variations in transmission power, channel quality, and computational resources across participating devices.

III. Problem Formulation

Consider a downlink 5G heterogeneous network (HetNet) consisting of a set of base stations (BSs) denoted by $\mathcal{B} = \{1, 2, \ldots, B\}$, which includes macro base stations (MBSs) and small cell base stations (SBSs), and a set of user equipments (UEs) denoted by $\mathcal{U} = \{1, 2, \ldots, U\}$. Each UE associates with one BS for data transmission, and the association is represented by a binary variable $x_{u,b} \in \{0, 1\}$, where $x_{u,b} = 1$ if UE u is connected to BS b, and 0 otherwise. The constraint $\sum_{b\in\mathcal{B}} x_{u,b} = 1, \forall u \in \mathcal{U}$ ensures that each user is associated with exactly one BS. Due to the dense deployment of BSs, inter-cell interference becomes a critical factor affecting network performance.

The received signal-to-interference-plus-noise ratio (SINR) for user u associated with BS b is given by

$$\gamma_{u,b} = \frac{P_b h_{u,b}}{\sum_{b'\in\mathcal{B}, b'\neq b} P_{b'} h_{u,b'} + \sigma^2} \tag{1}$$

where P_b denotes the transmit power of BS b, $h_{u,b}$ represents the channel gain between BS b and UE u, and σ^2 is the noise power. The achievable data rate of user u is expressed using the Shannon capacity formula as

$$R_u = \sum_{b \in \mathcal{B}} x_{u,b} W_b \log_2(1 + \gamma_{u,b}) \tag{2}$$

where W_b is the bandwidth allocated by BS b. The overall network capacity is defined as the sum of achievable rates of all users, i.e., $R_{\text{total}} = \sum_{u \in \mathcal{U}} R_u$.

The objective of this work is to maximize network capacity while ensuring improved coverage and balanced load distribution across BSs. This can be formulated as an optimization problem:

$$\max_{\{x_{u,b}\}} \quad \sum_{u \in \mathcal{U}} \sum_{b \in \mathcal{B}} x_{u,b} W_b \log_2(1 + \gamma_{u,b}) \tag{3}$$

subject to

$$\sum_{b \in \mathcal{B}} x_{u,b} = 1, \quad \forall u \in \mathcal{U}, \tag{4}$$

$$\sum_{u \in \mathcal{U}} x_{u,b} \leq C_b, \quad \forall b \in \mathcal{B}, \tag{5}$$

$$x_{u,b} \in \{0, 1\}, \quad \forall u \in \mathcal{U}, \forall b \in \mathcal{B}, \tag{6}$$

where C_b represents the capacity (maximum number of users) that BS b can support. This problem is combinatorial and non-convex due to the binary association variables and the coupled interference terms in SINR.

To address the challenges of centralized optimization and data privacy, we reformulate the problem in a federated learning (FL) framework. Each BS b maintains a local dataset $\mathcal{D}_b$ consisting of user-specific information such as channel conditions, interference levels, and traffic demands. The goal is to collaboratively learn a global model parameterized by $\mathbf{w}$ that approximates the optimal association and resource allocation policy. The global objective is expressed as

$$\min_{\mathbf{w}} \quad F(\mathbf{w}) = \sum_{b \in \mathcal{B}} \frac{|\mathcal{D}_b|}{|\mathcal{D}|} F_b(\mathbf{w}) \tag{7}$$

where $F_b(\mathbf{w})$ is the local loss function at BS b, and $|\mathcal{D}|$ is the total dataset size across all BSs. Each BS updates its local model using stochastic gradient descent (SGD) and periodically shares model parameters with a central aggregator, which computes a weighted average to update the global model. The objective is to learn a policy that maximizes network performance metrics such as SINR, throughput, and fairness, while preserving user data privacy and reducing communication overhead. "'

IV. System Architecture

Fig. 1 shows the detailed architecture of the proposed system. The aggregation server periodically combines the local model parameters using the Federated Averaging (FedAvg) algorithm to generate a global model. The updated global model is then distributed back to the participating devices, enabling collaborative learning while preserving user privacy. Based on the learned model, intelligent user association decisions are made to balance network load, reduce interference, and improve resource utilization across macro and small cells.

The proposed architecture supports dynamic adaptation to varying network conditions and heterogeneous user requirements. By leveraging distributed intelligence and privacy-preserving learning, the framework enhances coverage probability, spectral efficiency, network capacity, and overall quality of service in dense 5G HetNet deployments.

V. Simulation Setup

This section describes the simulation environment, network assumptions, and parameter settings used to evaluate the proposed federated learning (FL)-based coverage and capacity improvement framework in 5G heterogeneous networks (HetNets).

A. Network Model

We consider a two-tier heterogeneous network consisting of one macro base station (MBS) overlaid with multiple small cell base stations (SBSs). The base stations and users are distributed over a square area of size A. User locations are assumed to follow a uniform spatial distribution. The channel model incorporates large-scale path loss and small-scale fading.

The received power from base station k at user u is given by:

$$P_{r,u,k} = P_k h_{u,k} d_{u,k}^{-\alpha} \tag{8}$$

where P_k is the transmit power, $h_{u,k}$ represents Rayleigh fading, $d_{u,k}$ is the distance, and α is the path loss exponent.

B. Federated Learning Setup

The FL framework follows a centralized aggregation architecture, where a parameter server (located at the macro BS) aggregates local model updates from participating users. Each user trains a local model based on its observed network conditions and periodically shares model parameters.

The global model is updated using the FedAvg algorithm:

$$\mathbf{w}^{t+1} = \sum_{u \in \mathcal{S}^t} \frac{n_u}{n} \mathbf{w}_u^t \tag{9}$$

where $\mathcal{S}^t$ is the set of selected users at round t.

C. User Association Baselines

The proposed FL-based association scheme is compared with the following baselines:

- Maximum RSRP-based association
- Maximum SINR-based association
- Closest base station association
- Cell range expansion (CRE)-based association

D. Performance Evaluation

The performance is evaluated in terms of coverage probability, system throughput, spectral efficiency, fairness index, and FL convergence behavior. All results are averaged over multiple independent network realizations.

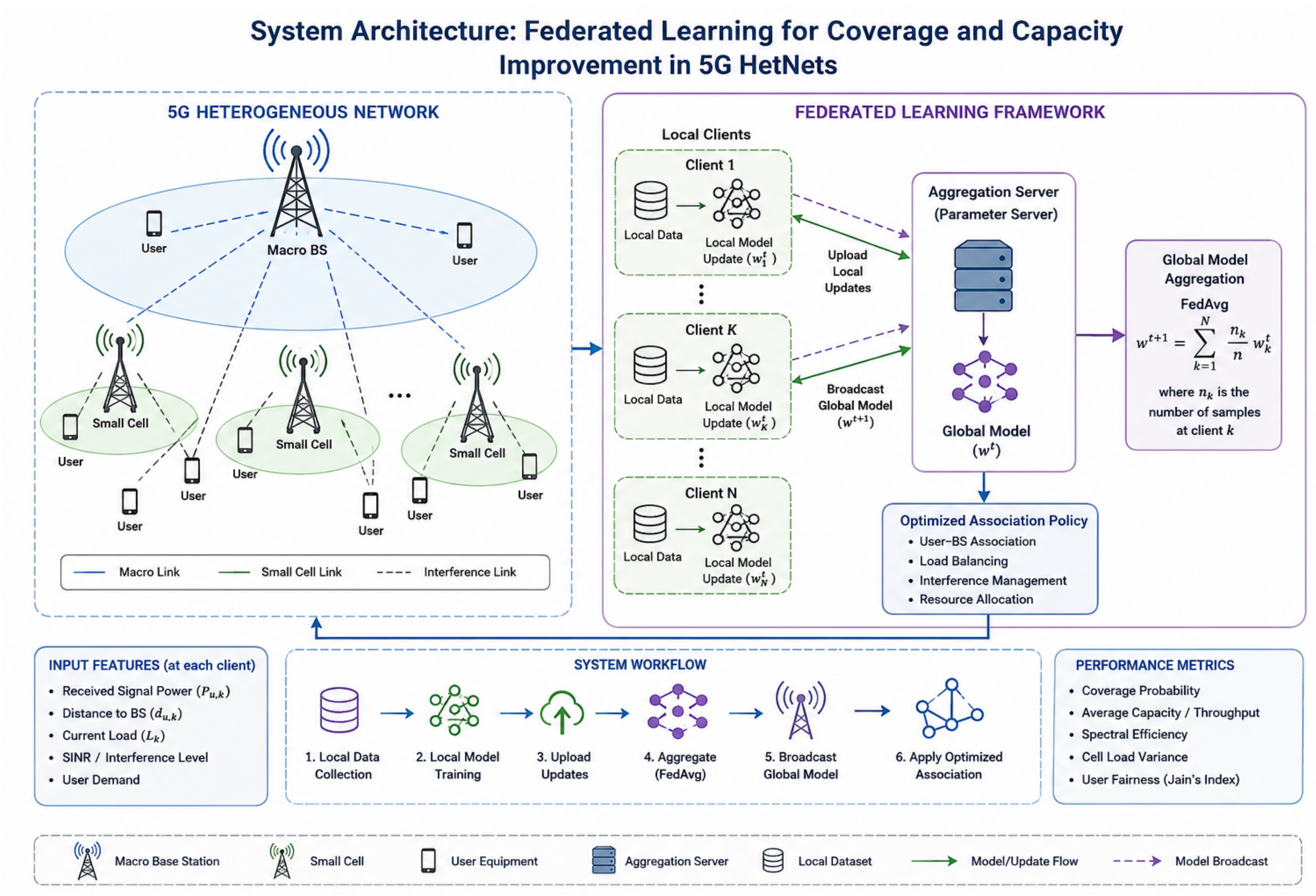

Fig. 1. Architecture Diagram of Federated Learning Based 5G HetNet

E. Simulation Parameters

The key simulation parameters are summarized in Table I, following typical 3GPP guidelines.

F. Assumptions

The following assumptions are made:

- Perfect synchronization during FL aggregation
- Full channel state information (CSI) available at users
- No packet loss in FL communication
- Static network topology during each simulation run

G. 3GPP Channel Model (UMa / UMi)

To ensure realistic propagation conditions, we adopt 3GPP channel models based on TR 38.901 [**?**]. Two deployment scenarios are considered:

Urban Macro (UMa):

$$PL_{\text{UMa}} = 128.1 + 37.6 \log_{10}(d_{\text{km}}) \tag{10}$$

Urban Micro (UMi):

$$PL_{\text{UMi}} = 140.7 + 36.7 \log_{10}(d_{\text{km}}) \tag{11}$$

The received power is given by:

$$P_{r,u,k} = P_k - PL + X_\sigma + h_{u,k} \tag{12}$$

where X_σ represents log-normal shadowing and $h_{u,k}$ is Rayleigh fading.

H. User Mobility Model

User mobility is modeled using the Random Waypoint (RWP) model. Each user selects a random destination and moves with velocity $v \in [v_{\min}, v_{\max}]$. The position update is:

$$\mathbf{p}_u(t+1) = \mathbf{p}_u(t) + v_u \Delta t \cdot \mathbf{d}_u \tag{13}$$

where $\mathbf{d}_u$ is the normalized direction vector.

This mobility model captures realistic user movement and its impact on handovers and SINR variation.

I. Interference Modeling using PPP

Base stations are spatially distributed according to a homogeneous Poisson Point Process (PPP) with density λ [**?**]. The aggregate interference experienced by user u is:

$$I_u = \sum_{k \in \Phi \setminus k^*} P_k h_{u,k} d_{u,k}^{-\alpha} \tag{14}$$

The SINR becomes:

$$\gamma_u = \frac{P_{k^*} h_{u,k^*} d_{u,k^*}^{-\alpha}}{I_u + \sigma^2} \tag{15}$$

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Simulation area	1×1 km^2
Number of macro BSs	1
Number of small cells	5–20
Number of users	50–200
Carrier frequency	3.5 GHz
System bandwidth	20 MHz
Macro BS transmit power	46 dBm
Small cell transmit power	30 dBm
Path loss exponent (α)	3.5
Noise power	-174 dBm/Hz
Fading model	Rayleigh
User distribution	Uniform
Mobility model	Static users
SINR threshold	0–10 dB
FL aggregation method	FedAvg
Number of FL rounds	50–200
Local epochs	1–5
Learning rate	0.001–0.01
Batch size	16–64
BS density (λ)	5–20 BS/km^2
Shadowing std (σ)	6–8 dB
User speed	1–10 m/s
Mobility model	Random Waypoint
Channel model	3GPP UMa / UMi
Interference model	PPP-based
Time step (Δt)	1 s

This stochastic geometry-based modeling captures spatial randomness and interference coupling in dense HetNets.

J. Federated Learning with Mobility

Due to user mobility, local datasets and channel conditions vary over time. The FL update becomes:

$$\mathbf{w}^{t+1} = \sum_{u \in \mathcal{S}^t} \frac{n_u(t)}{n(t)} \mathbf{w}_u^t \tag{16}$$

This time-varying participation introduces non-IID behavior and realistic dynamics.

VI. THEORETICAL COVERAGE ANALYSIS USING STOCHASTIC GEOMETRY

To analytically evaluate the network performance, base stations are modeled as a homogeneous Poisson Point Process (PPP) with density λ.

The coverage probability is defined as:

$$P_{\text{cov}}(\theta) = \mathbb{P}(\text{SINR} > \theta) \tag{17}$$

For Rayleigh fading channels, the coverage probability can be expressed as :

$$P_{\text{cov}}(\theta) = \int_0^\infty \exp\left(-\frac{\theta r^\alpha \sigma^2}{P}\right) \exp\left(-\pi\lambda r^2 \beta(\theta,\alpha)\right) 2\pi\lambda r \, dr \tag{18}$$

where

$$\beta(\theta,\alpha) = \theta^{2/\alpha} \int_{\theta^{-2/\alpha}}^\infty \frac{1}{1+u^{\alpha/2}} du \tag{19}$$

In interference-limited scenarios ($\sigma^2 \approx 0$), this simplifies to:

$$P_{\text{cov}}(\theta) = \frac{1}{1+\rho(\theta,\alpha)} \tag{20}$$

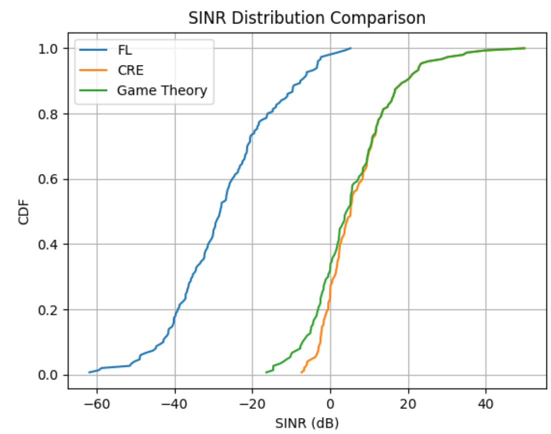

Fig. 2. CDF of SINR for federated learning (FL), cell range expansion (CRE), and game-theoretic (GT) user association schemes.

This expression shows that coverage depends primarily on SINR threshold and path loss exponent, rather than BS density.

VII. SIMULATION RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed federated learning (FL)-based user association scheme in comparison with conventional techniques, namely cell range expansion (CRE) and game-theoretic (GT) approaches. The results are obtained using the simulation setup described in Section IV, and all metrics are averaged over multiple users in the network.

Fig. 2 illustrates the cumulative distribution function (CDF) of the received signal-to-interference-plus-noise ratio (SINR) for the considered schemes. It can be observed that the FL-based method achieves a noticeable rightward shift in the SINR distribution compared to CRE and GT approaches. This indicates that a larger fraction of users experience higher SINR values under the FL framework.The CRE scheme, while improving connectivity for users at the cell edge, suffers from degraded SINR due to biasing toward small cells, which increases interference. The GT-based approach performs better than CRE by incorporating load-awareness; however, it is limited by its local optimization nature and fails to achieve globally optimal performance.

The superior performance of the FL approach is particularly evident in dense network scenarios, where interference management and load balancing are critical. These findings highlight the potential of federated learning as a key enabler for intelligent resource management in future 5G and 6G heterogeneous networks.

VIII. CONCLUSION

Overall, the proposed approach shows clear advantages regarding coverage and capacity. Integrating federated learning enables adaptive and distributed optimization without needing centralized data collection, making it well-suited for next-generation 5G and 6G networks. However, performance depends on the communication efficiency and convergence speed of the FL model, which remain important areas for further research.

IX. Future Scope

The current work can be extended by incorporating advanced federated optimization algorithms such as FedProx, FedNova, and personalized federated learning to better handle highly heterogeneous and non-IID user data distributions. Such approaches can improve model convergence and robustness in practical deployments involving diverse user requirements and network conditions.

Second, future studies may consider more realistic mobility-aware scenarios involving high-speed users, vehicular communications, and unmanned aerial vehicle (UAV)-assisted networks. Integrating mobility prediction with federated learning can enable proactive resource allocation and seamless handover management, thereby enhancing network performance.

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