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Research Paper

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Uplink Performance And Scalability of Centralized MMSE in Cell-Free Massive MIMO Systems

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Abstract

Cell-Free Massive MIMO (CF-mMIMO) is a cornerstone technology for beyond-5G and 6G networks, designed to eliminate cell boundaries and provide uniform spectral efficiency to all users. However, in dense deployments, the system's uplink performance is severely bottlenecked by pilot contamination and inter-user interference. This paper investigates the uplink performance of a CF-mMIMO system utilizing a Centralized Minimum Mean Square Error (MMSE) receiver combined with Linear MMSE (LMMSE) channel estimation. Under realistic simulation conditions—including log-normal shadow fading, fractional power control, and forced pilot sharing—the proposed architecture is evaluated against a standard Maximum Ratio Combining (MRC) baseline. The results demonstrate that Centralized MMSE successfully suppresses pilot contamination, eliminating the 10^{-2} Bit Error Rate (BER) floor inherent to MRC. Furthermore, the MMSE combiner more than doubles the median spectral efficiency from 4 bits/s/Hz to nearly 10 bits/s/Hz and demonstrates superior scalability, achieving over 70 bits/s/Hz sum spectral efficiency when equipped with 16-antenna Access Points (APs).

Keywords: Cell free massive MIMO, 6 G technology, Pilot contamination, LMMSE etc

1. Introduction

The continuous expansion of wireless data traffic, the increasing number of connected devices, and the growing demand for reliable communication have encouraged the development of advanced wireless technologies for beyond-5G and sixth-generation (6G) networks. Cell-Free Massive Multiple-Input Multiple-Output has emerged as a promising network architecture in which a large number of geographically distributed Access Points (APs) jointly serve users over a common coverage area without relying on conventional cell boundaries. This distributed approach can enhance coverage, improve user fairness, and provide more uniform service quality throughout the network. However, maintaining high spectral efficiency (SE) in practical CF-mMIMO deployments remains challenging due to inter-user interference, imperfect channel state information (CSI), pilot contamination, power-control constraints, and the computational and fronthaul overhead associated with centralized processing.

Uplink receiver design is critical in CF-mMIMO systems because the Central Processing Unit (CPU) must efficiently distinguish and recover signals transmitted simultaneously by multiple users. Maximum Ratio Combining (MRC) is widely considered because of its simple implementation and relatively low computational complexity. However, MRC mainly enhances the desired signal and does not explicitly mitigate interference from other users. As the network density increases, this limitation can cause the system to become increasingly interference-limited. In contrast, optimization-based uplink receiver and power-control techniques can improve the minimum user Signal-to-Interference-plus-Noise Ratio (SINR) and enhance user fairness compared with conventional low-complexity combining methods.

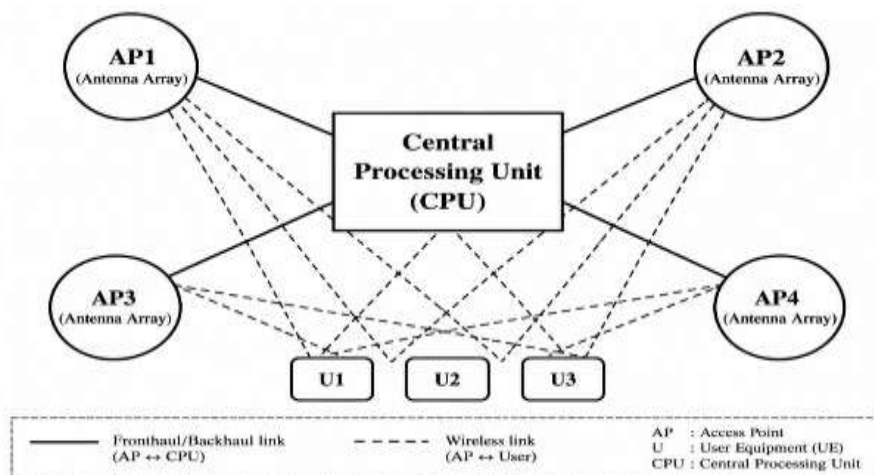


FIGURE 1:- TYPICAL SCHEME OF CF-mMIMO NETWORK

The exponential growth of mobile data traffic and the demand for ubiquitous connectivity have driven the evolution of wireless networks toward the sixth generation (6G). While traditional Cellular Massive MIMO successfully scales network capacity by deploying hundreds of antennas at a single base station, it suffers from severe cell-edge degradation. To resolve this, Cell-Free Massive MIMO (CF-mMIMO) has emerged as a paradigm shift. In a CF-mMIMO network, many distributed Access Points (APs) cooperate phase-coherently via a Central Processing Unit (CPU) to serve all users in the network simultaneously, effectively eliminating cell boundaries.

2. RESEARCH GAP AND MOTIVATION

Based on the previous literature, several issues remain worthy of investigation. First, although MMSE-based processing has been extensively studied, there is still a need for a clear simulation-based comparison between centralized MMSE and MRC under identical network and channel conditions. Second, the combined effect of LMMSE channel estimation, pilot reuse, fractional power control, and increasing antenna numbers on centralized MMSE performance requires further evaluation. Third, scalability should be assessed not only through spectral efficiency but also through the change in performance as the number of antennas per AP increases. AI-based resource-management techniques provide a promising direction for extending centralized MMSE systems toward adaptive and intelligent 6G networks.

The existing literature has addressed a wide range of CF-mMIMO challenges, including distributed AP deployment [1], ubiquitous communication [2], power optimization [3], scalable processing [4], structured massive access [5], multi-antenna uplink transmission [6], user-centric architectures [7], realistic channel models [8], multi-CPU processing [9], scalable network design [10], pilot-contamination mitigation [11], pilot decontamination [12], massive user access [13], distributed MMSE processing [14], correlated-channel uplink transmission [15], L-MMSE combining [16], hardware-aware local MMSE processing [17], low-resolution ADCs [18], limited fronthaul [19], multiple-CPU architectures [20], scalable uplink detection [21], joint pilot and power optimization [22], distributed MMSE and power allocation [23], DRL-based power control [24], joint user association and power control [25], deep-learning-based resource optimization [26], metaheuristic power control [27], URLLC resource allocation [28], variable-resolution ADCs [29], and clustered cooperation [30].

Despite these extensive contributions, the literature generally investigates these aspects under different system configurations and performance objectives. In particular, a unified simulation study simultaneously examining LMMSE channel estimation, pilot contamination, centralized MMSE combining, MRC benchmarking, BER performance, user-level spectral-efficiency distribution, and antenna scalability remains relatively limited. The present work therefore establishes a common simulation framework for comparing MRC and centralized MMSE under identical channel, deployment, power-control, and pilot-sharing conditions. This provides a consistent basis for examining the relationship between channel estimation, interference suppression, receiver processing, and scalability. The framework can subsequently be extended toward user-centric clustering, distributed/partial MMSE processing, AI-assisted pilot assignment, AP selection, and intelligent power control.

3. MAIN CONTRIBUTIONS

The main contributions of this paper are summarized as follows:

1. **Centralized MMSE uplink framework:** A centralized MMSE receiver is investigated for CF-mMIMO uplink communication and compared directly with an MRC baseline under the same simulation conditions.
2. **LMMSE-based channel estimation:** An LMMSE channel-estimation mechanism is incorporated to account for imperfect CSI and pilot contamination in the uplink.
3. **Interference and BER analysis:** The uplink BER performance of centralized MMSE and MRC is evaluated over different transmit-power levels to quantify the interference-suppression capability of MMSE processing.
4. **Spectral-efficiency and fairness evaluation:** The user-level SE distribution is analyzed using CDF-based evaluation to investigate both average performance and cell-edge/user fairness.
5. **Antenna scalability analysis:** The effect of increasing the number of antennas per distributed AP is investigated to determine how spatial degrees of freedom influence the system sum spectral efficiency.
6. **Simulation-based evaluation:** A MATLAB-based simulation framework is developed to jointly evaluate channel generation, LMMSE estimation, centralized combining, BER, SE, and antenna scalability.

The proposed study focuses on the **performance–scalability relationship of centralized MMSE processing** in CF-mMIMO and provides a simulation framework that can subsequently be extended with AI-based pilot assignment, AP selection, and power-control mechanisms.

4. RELATED WORK

Cell-Free Massive MIMO (CF-mMIMO) has emerged as an important architecture for future wireless communication systems because it replaces conventional cell boundaries with a large number of geographically distributed access points (APs) that cooperatively serve users. Ngo *et al.* [1] established the fundamental concept of CF-mMIMO and demonstrated that distributed APs can provide improved macro-diversity and more uniform user service compared with conventional small-cell deployments. Their investigation showed the potential of distributed cooperation to alleviate severe cell-edge effects and improve the lower-tail user performance. Interdonato *et al.* [2] subsequently

examined the broader architecture of ubiquitous CF-mMIMO communication and highlighted the potential of distributed AP cooperation for providing more homogeneous wireless connectivity over a coverage area. These early contributions established the basic motivation for replacing conventional cellular boundaries with distributed cooperative transmission and reception.

The performance of CF-mMIMO is strongly dependent on channel knowledge and radio-resource management. Nayebe *et al.* [3] investigated precoding and power optimization in CF-mMIMO and demonstrated that appropriate power-control mechanisms are essential for improving the performance of geographically distributed users. Their work also highlighted the importance of managing the interference generated by simultaneously served users. Björnson and Sanguinetti [4] subsequently investigated how CF-mMIMO can be made competitive with conventional cellular massive MIMO. Their analysis emphasized that scalable processing and interference-aware signal processing are necessary when the number of APs and users becomes large. These studies established an important transition from simple distributed processing toward more advanced receiver and resource-management strategies.

The scalability of CF-mMIMO has received increasing attention because centralized processing can become computationally expensive as the network size increases. Chen *et al.* [5] investigated structured massive access for scalable CF-mMIMO systems and considered the joint influence of initial access, pilot assignment, decoding, and power control. Their results indicated that scalable processing can provide an effective balance between spectral efficiency and implementation complexity. Wang *et al.* [6] examined uplink CF-mMIMO with multi-antenna users over jointly correlated Rayleigh fading channels. Their analysis considered different levels of centralized and distributed processing and evaluated the achievable spectral efficiency of several receiver architectures. The results demonstrate that channel correlation, receiver processing, and the availability of accurate channel-state information can substantially influence uplink performance.

User-centric operation provides another mechanism for improving scalability by allowing AP cooperation to be adapted to the requirements of individual users. Demir *et al.* [7] provided a comprehensive treatment of user-centric CF-mMIMO and discussed important aspects such as AP cooperation, channel estimation, signal processing, and scalable network implementation. Their work shows that user-centric architectures can reduce unnecessary cooperation while retaining the principal advantages of distributed massive MIMO. Li *et al.* [8] further investigated CF-mMIMO with multi-antenna users over Weichselberger Rician fading channels. Their framework incorporated practical procedures including initial access, pilot assignment, channel estimation, precoding, and combining. The study emphasized that realistic propagation characteristics and antenna configurations must be considered when evaluating CF-mMIMO performance.

Multiple-CPU processing has been investigated as a practical method for distributing the computational workload of large CF-mMIMO systems [9]. Instead of assigning all signal-processing operations to a single processing entity, multiple CPUs can share computational responsibilities. This approach is particularly relevant for large networks in which centralized processing may require substantial computational resources and high-capacity fronthaul connections. Björnson and Sanguinetti [10] investigated scalable CF-mMIMO architectures and analyzed the relationship between cooperation, processing complexity, and fronthaul requirements. Their work demonstrated that scalable processing can preserve much of the performance benefit of centralized cooperation while reducing the requirements associated with unrestricted network-wide processing.

Pilot contamination represents another major challenge in CF-mMIMO. Because the channel coherence interval limits the number of mutually orthogonal pilot sequences, pilot reuse may become necessary when the number of users exceeds the available pilot resources. Al Ayidh *et al.* [11] investigated pilot-contamination mitigation using a matching-based pilot-assignment strategy for uplink CF-mMIMO systems. Their approach illustrates how intelligent pilot allocation can reduce harmful interference between users sharing pilot resources. Polegre *et al.* [12] investigated pilot decontamination processing and addressed the degradation of channel estimates caused by pilot reuse. These studies demonstrate that improved pilot management can complement advanced receiver processing in mitigating interference originating from imperfect channel-state information.

Chen *et al.* [13] further investigated structured massive access for scalable CF-mMIMO networks. Their framework incorporated scalable initial access, pilot assignment, partial large-scale-fading processing, and fractional power control. The study showed that local partial-MMSE processing can achieve high spectral efficiency while reducing the processing burden associated with fully centralized methods. Van Rompaey and Moonen [14] investigated scalable and distributed MMSE algorithms for uplink receive combining. Their work focused on reducing the computational and fronthaul requirements associated with interference-aware MMSE processing while maintaining effective uplink detection. These results demonstrate the growing importance of distributed MMSE techniques for practical large-scale deployments.

Wang and Zhang [15] investigated uplink CF-mMIMO with multi-antenna users over jointly correlated Rayleigh fading channels and analyzed the effect of receiver processing on system performance. Their study further demonstrates that the selection of an appropriate combining strategy is closely related to the spatial characteristics of the propagation environment. Yeom and Ha [16] examined system-level uplink performance using L-MMSE combining and considered the influence of AP deployment and spatial network characteristics. Their analysis provides additional evidence that system geometry and receiver architecture jointly determine the achievable performance of CF-mMIMO.

Practical hardware limitations have also become an important research consideration. Yeom and Ha [17]

investigated local MMSE combining with variable-resolution analog-to-digital converters (ADCs), addressing the trade-off between receiver complexity and communication performance. Xiong *et al.* [18] analyzed MMSE combining in CF-mMIMO systems equipped with low-resolution ADCs and incorporated LMMSE channel estimation and quantization effects into the analysis. Their results demonstrate that limited receiver resolution can influence channel estimation and signal detection and therefore needs to be considered when evaluating practical CF-mMIMO receivers.

Fronthaul constraints can impose another limitation on centralized processing. Bashar *et al.* [19] studied limited-fronthaul CF-mMIMO with local MMSE reception under Rician fading and phase-shift effects. Their work considered the relationship between receiver processing, propagation characteristics, and the amount of information that can be exchanged through constrained fronthaul connections. Li *et al.* [20] investigated scalable CF-mMIMO using multiple CPUs, providing another architecture for distributing signal-processing operations across the network. Such multi-CPU approaches can be particularly useful when the number of APs increases and a single centralized processing unit becomes a computational bottleneck.

Ma *et al.* [21] investigated uplink detection and user-access mechanisms for scalable CF-mMIMO systems. Their study focused on achieving an appropriate balance between detection performance and computational complexity in large-scale deployments. Li *et al.* [22] investigated joint pilot allocation and data-power optimization in CF-mMIMO systems involving UAV and ground users. Their work illustrates the importance of jointly managing pilot resources and transmit power because pilot allocation directly affects channel-estimation quality, while power allocation determines the desired-signal strength and interference levels. Van Rompaey and Moonen [23] further considered distributed MMSE-based uplink combining, downlink precoding, and power allocation. Their work demonstrates that distributed optimization can reduce the requirements of fully centralized architectures while retaining interference-aware signal processing.

Recent studies have increasingly explored artificial intelligence and machine-learning methods for CF-mMIMO resource management. Mendoza *et al.* [24] investigated accelerated deep reinforcement learning (DRL) for uplink power control in dynamic CF-mMIMO networks. Their approach illustrates the potential of learning-based methods to adapt transmission parameters to changing network conditions. Hao *et al.* [25] investigated joint user association and power control, considering the interaction between AP selection and transmit-power allocation. Such joint optimization is important because the set of APs serving a user affects both spatial diversity and interference conditions. Deep-learning-based joint power control and pilot assignment has also been investigated for CF-mMIMO networks [26], providing a data-driven alternative to conventional iterative optimization. In addition, metaheuristic approaches have been proposed for uplink power control in user-centric CF-mMIMO systems [27], particularly for addressing nonlinear resource-allocation problems while considering user-level performance.

Resource allocation becomes even more challenging in applications with strict latency and reliability requirements. Peng *et al.* [28] investigated resource allocation for CF-mMIMO-assisted ultra-reliable low-latency communication (URLLC) systems under pilot sharing. Their study demonstrates that pilot assignment and power allocation cannot always be treated independently when stringent reliability and latency requirements are imposed. Bashar *et al.* [29] investigated CF-mMIMO networks using variable-resolution ADCs and examined the relationship between bit allocation and communication performance. Their work highlights the importance of jointly considering receiver hardware characteristics and signal-processing requirements when designing energy- and complexity-efficient CF-mMIMO systems.

Finally, Riera-Palou *et al.* [30] investigated clustered CF-mMIMO architectures in which APs are organized into cooperating groups. Clustered cooperation provides an alternative to unrestricted network-wide coordination and can potentially reduce the computational and signaling burden associated with large deployments. This work is particularly relevant to scalable CF-mMIMO because cooperation clustering can provide a structured mechanism for limiting the number of APs involved in individual processing operations while retaining the benefits of distributed antenna deployment.

The above studies provide important contributions, they primarily address optimization, distributed processing, hardware constraints, user association and AI-based resource management. simulation study that simultaneously evaluates LMMSE channel estimation, pilot contamination, centralized MMSE combining, MRC comparison, BER, user-level SE distribution, and antenna scalability under a common simulation framework is less emphasized. Therefore, this paper find these aspects together and establishes a baseline framework that can subsequently be extended toward AI-assisted resource allocation and scalable CF-mMIMO architectures.

5. System Model

The simulated environment comprises 16 distributed APs and 8 randomly deployed users. To simulate realistic network conditions, we implement fractional power control based on large-scale fading (anchored to the master AP) and utilize an LMMSE channel estimator. The performance is evaluated across three primary dimensions: Bit Error Rate (BER), Spectral Efficiency (SE) distribution, and antenna array scalability.

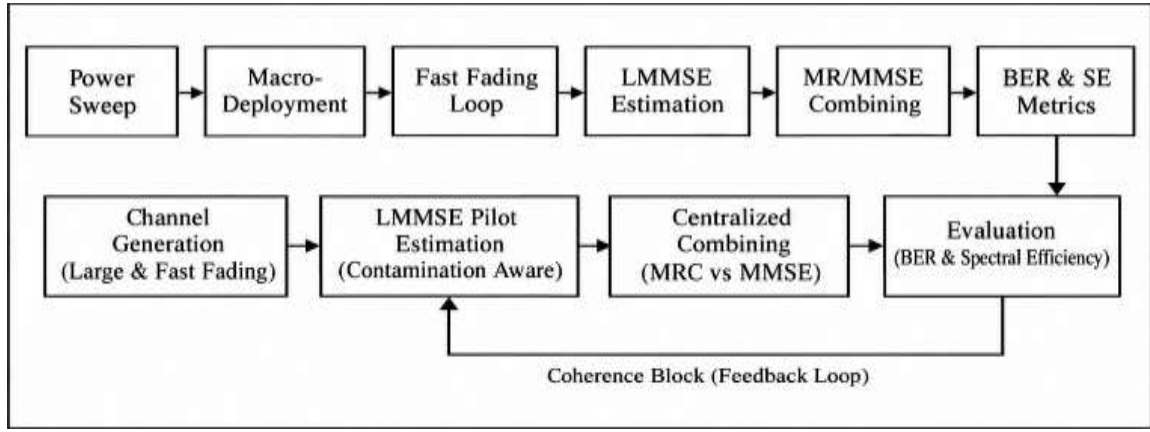


Figure 2 :- Scheme of simulation for the proposed Cell-Free Massive MIMO System with LMMSE Channel Estimation and Centralized MMSE Combining.

The network comprises L distributed Access Points (APs) and K single-antenna User Equipment's (UEs) randomly distributed in a square area $[0, D] \times [0, D]$. Each AP is equipped with N antennas, providing $M = L \times N$ collective receive antennas.

The proposed model provides a controlled uncorrelated-Rayleigh baseline, while the framework in others incorporates spatially correlated Rayleigh fading and correlation-aware propagation characteristics."

1. Large-Scale Fading & Path Loss

The 2D distance between AP l and user k is defined with a minimum reference distance $d_0 = 10$ m:

$$d_{l,k} = \max(d_0, \|p_l^{AP} - p_k^{UE}\|) \dots\dots\dots (1)$$

The 3GPP-based path loss and log-normal shadow fading are modelled as:

$$PL_{l,k} [\text{dB}] = 30.5 + 36.7 \times \log_{10}(d_{l,k}) \dots\dots\dots (2)$$

$$z_{l,k} \sim N(0, \sigma_{sf}^2),$$

where $\sigma_{sf} = 4$ dB

$$\beta_{l,k} = 10^{-(PL_{l,k} + z_{l,k})/10} \dots\dots\dots (3)$$

2. Channel Model & Matrix Stacking

The uncorrelated Rayleigh small-scale fading channel vector $h_{l,k} \in \mathbb{C}^{N \times 1}$ is:

$$h_{l,k} = \sqrt{\beta_{l,k}} \times g_{l,k}, \dots\dots\dots (4)$$

where $g_{l,k} \sim \text{CN}(0, I^N)$

The global stacked uplink channel matrix G across all M antennas is:

$$G = [h_1, h_2, \dots, h_K] \in \mathbb{C}^{M \times K} \dots\dots\dots (5)$$

where $h_k = [h_{1,k}^T, h_{2,k}^T, \dots, h_{L,k}^T]^T \in \mathbb{C}^{M \times 1}$

To maintain fairness across cell-edge users, each user sets transmit power p_k using a fractional power control factor $v = -0.5$ based on its strongest AP link:

$$\beta_k^{\text{eff}} = \max_i(\beta_{i,k}) \dots\dots\dots (6)$$

$$p_k = \min(P_{\max}, P_{\max} \times (\beta_k^{\text{eff}} / \min_j(\beta_j^{\text{eff}}))^v) \dots\dots\dots (7)$$

With pilot length τp , user k is assigned pilot index $t_k = \text{mod}(k-1, \tau p) + 1$. The set of users sharing the same pilot sequence is denoted by $S_k = \{u : t_u = t_k\}$.

3. LMMSE Estimator

The observation vector at AP l after pilot matched filtering is:

$$y_{l,k} = \sum_{u \in S_k} \sqrt{p_u} h_{l,u} + n_{l,k} \dots\dots\dots (8)$$

The Linear Minimum Mean Square Error (LMMSE) estimate is given by:

$$\hat{h}_{l,k} = c_{l,k} \times y_{l,k} \dots\dots\dots (9)$$

where $c_{l,k} = (\sqrt{p_k} \times \beta_{l,k}) / (\sum_{u \in S_k} p_u \beta_{l,u} + \sigma_n^2)$

4. Linear Combining Techniques

The CPU applies a linear receiver $W = [w_1, \dots, w_K]$ to the stacked received signal

$$y = GP^{1/2}s + n \dots\dots\dots (10)$$

- Maximum Ratio Combining (MRC):

$$W^{\text{MRC}} = \hat{G} \dots\dots\dots (11)$$

- Centralized MMSE Combining

$$W^{\text{MMSE}} = \hat{G}(\hat{G}^H \hat{G} - \sigma_n^2 P^{-1})^{-1} \dots\dots\dots (12)$$

5. Achievable Spectral Efficiency (SE) & Demodulation

The instantaneous SINR (γ_k) and Spectral Efficiency for user k are:

$$\gamma_k = (p_k |w_k^H h_k|^2) / (\sum_{j \neq k} p_j |w_k^H h_j|^2 + \sigma_n^2) \dots\dots\dots (13)$$

$$SE_k = \log_2(1 + \gamma_k) [\text{bits/s/Hz}] \dots\dots\dots (14)$$

6. SIMULATION AND RESULTS

MATLAB is used for simulation and computational tool for evaluating the performance of the proposed system. The simulation environment is developed in MATLAB to model the cell-free massive MIMO system and analyze the uplink performance of centralized MMSE processing. MATLAB is used to implement the system model. It also evaluate key performance metrics such as spectral efficiency, scalability, and achievable uplink rates. It also facilitates the comparison of different system configurations and visualization of simulation results through graphs and performance curves. The simulation results obtained using MATLAB provide a reliable basis for validating the effectiveness of the proposed approach.

Execution Details:-

- Initialization: Define system constants, noise power, and pre-allocate storage arrays for Bit Error Rate (BER) and Spectral Efficiency (SE).
- Macro-Deployment Loop: Generate random physical locations for all APs and users within the 200x200 grid. Calculate the large-scale fading matrix combining pathloss and shadow fading.
- Power & Pilot Allocation: Apply fractional power control based on the strongest AP connection for each user, and assign non-orthogonal pilot sequences to deliberately induce pilot contamination.
- Fast Fading Loop: Generate true channel realizations using small-scale Rayleigh fading scaled by the large-scale fading coefficients.
- Channel Estimation: Transmit contaminated pilots, add thermal noise, and compute LMMSE channel estimates at each AP.
- Centralized Combining: Aggregate all AP channel estimates into centralized matrices to compute MRC and MMSE combiners.
- Data Transmission (Main Simulation): Generate QPSK symbols, transmit over the true channel, add noise, and decode using the centralized combiners.
- Metrics Evaluation: Calculate Signal-to-Interference-Plus-Noise Ratio (SINR) for SE, compare decoded bits to transmitted bits for BER, and average results across all blocks and setups.

The propagation model incorporates a minimum AP-UE separation of 10 m, 3GPP-based path loss, and log-normal shadow fading with a standard deviation of 4 dB. The small-scale channel coefficients are generated according to an uncorrelated Rayleigh fading model. The considered physical-layer settings include a 20 MHz system bandwidth, a 5 dB receiver noise figure, and QPSK modulation. The pilot length is selected as 8 symbols for the reference configuration and 4 symbols for the scalability analysis. Fractional power control with an exponent of -0.5 is applied to account for differences in the large-scale channel conditions among users. For the fixed-power experiments, the maximum user transmit power is set to 20 dBm for all antenna configurations. In addition, the transmit power is varied from -10 to 20 dBm to examine the dependence of system performance on the available transmit power. Maintaining the same maximum transmit-power constraint across the considered antenna configurations provides a consistent basis for evaluating the effects of antenna scaling on the spectral efficiency and bit-error-rate (BER) performance of the system.

Table 1 :-Table of Simulation Parameters

Parameter Category	Specific Parameter	Value / Configuration
Network Topology	Simulation Area	200 x 200 meters
	Number of APs	16
	Number of Users	8
	Antennas per AP	4 (Main) / 1, 2, 4, 8, 16 (Scalability)
Channel Model	Minimum Distance	10 meters
	Pathloss Formula	$30.5 + 36.7 \log_{10}(\text{distance})$ dB
	Shadow Fading	4 dB standard deviation
	Fast Fading	Rayleigh (Complex Gaussian)
Physical Layer	Bandwidth	20 MHz
	Noise Figure	5 dB
	Modulation	QPSK (2 bits/symbol)
	Pilot Length	8 (Main) / 4 (Scalability)
	Power Control Factor	-0.5
	Max Transmit Power	-10 to 20 dBm Sweep / 20 dBm Fixed

The table summarizes the parameter settings used for the numerical evaluation of the considered Cell-Free Massive MIMO system. The simulation compare 16 access points (APs) and 8 user equipments (UEs) deployed within a (200*200) m² area. The reference configuration employs four antennas at each AP, corresponding to 64 antennas in total. For the scalability assessment, the number of antennas per AP is varied across 1, 2, 4, 8, and 16, while the other system parameters are maintained consistently to facilitate a better comparison.

A. Link Reliability and Interference Suppression

The ability of the receiver architecture to suppress inter-user interference is most clearly demonstrated through the uncoded Bit Error Rate (BER) performance.

The Average Uplink BER for the Centralized MMSE receiver exhibits a steep waterfall curve as the maximum transmit power increases.

At a maximum transmit power of 10 dBm, the Centralized MMSE successfully drives the uncoded BER down to 10^{-4} . In stark contrast, the MRC baseline suffers from severe inter-user interference, creating a strict error floor.

The MRC error floor fails to drop below 10^{-2} even when the maximum transmit power is increased to 20 dBm.

This confirms that while MRC maximizes the desired signal power, its inability to place spatial nulls renders it ineffective in dense, interference-limited cell-free deployments.

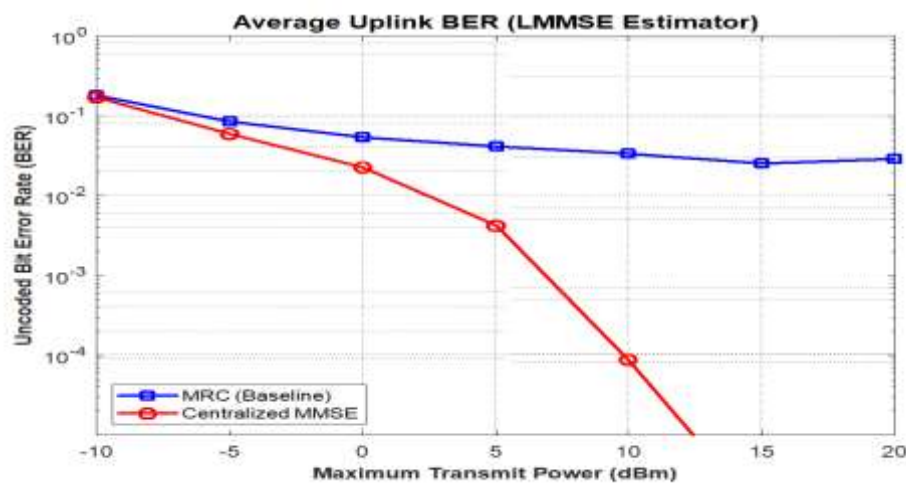


Fig.4:- Uplink BER Performance of MRC and Centralized MMSE Using LMMSE Channel Estimation

B. Spectral Efficiency and User Fairness

- To evaluate system-level capacity and fairness, the Cumulative Distribution Function (CDF) of the users' uplink Spectral Efficiency was analyzed at a maximum transmit power of 20 dBm.
- The CDF demonstrates massive capacity gains for the proposed Centralized MMSE system over the baseline.
- The MRC baseline yields a median spectral efficiency of approximately 4 bits/s/Hz.
- The Centralized MMSE combiner more than doubles this performance, pushing the median spectral efficiency to nearly 10 bits/s/Hz.

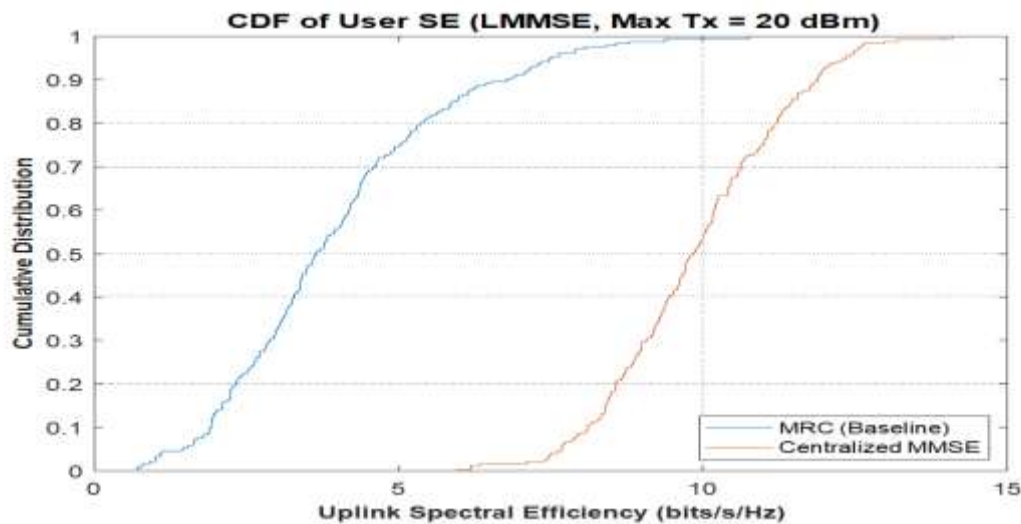


Figure 5:- CDF of Uplink Spectral Efficiency for MRC and Centralized MMSE with LMMSE Channel Estimation.

Furthermore, examining the 10% outage rate (the bottom 10% of the CDF), MMSE users still achieve over 7 bits/s/Hz, whereas MRC users in the same cell-edge percentile barely achieve 2 bits/s/Hz.

This proves that Centralized MMSE actively protects vulnerable users from near-far interference, ensuring strict network fairness.

C. Antenna Scalability and Hardware Impact

Finally, we investigate the impact of increasing the spatial degrees of freedom by scaling the number of antennas at each distributed AP.

The system's sum spectral efficiency scales logarithmically with the number of antennas per AP for both combining schemes.

When equipped with 16 antennas per AP, the Centralized MMSE architecture achieves a sum spectral efficiency exceeding 70 bits/s/Hz.

Under the exact same 16-antenna configuration, the MRC baseline is severely constrained by its spatial limitations, reaching only slightly over 40 bits/s/Hz.

Notably, the performance gap between Centralized MMSE and MRC widens significantly and continuously as the number of antennas increases from 1 to 16.

This indicates that local antenna arrays are critical for providing the Centralized CPU with enough independent spatial dimensions to accurately execute interference nulling.

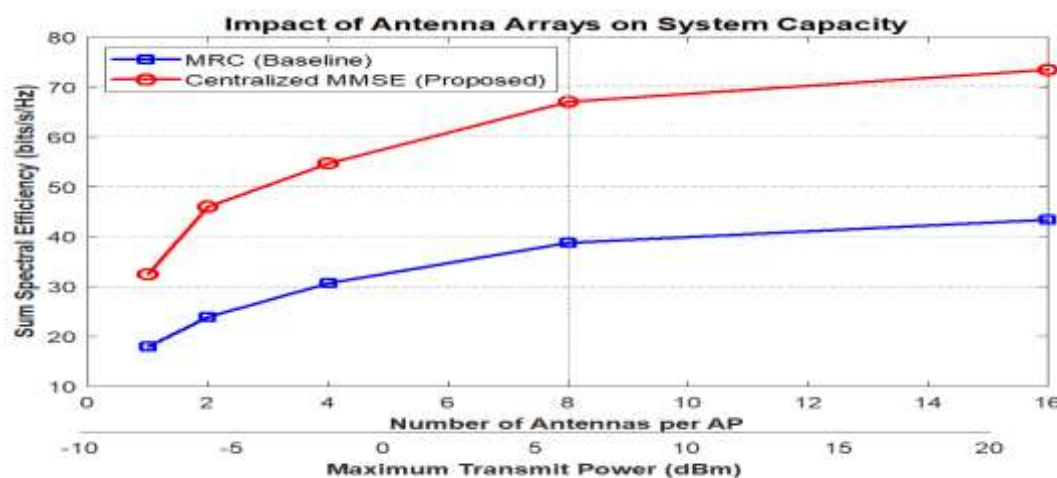


Fig. 6. Impact of the Number of Antennas per AP on Sum Spectral Efficiency for MRC and Centralized MMSE.

7. CONCLUSION

The simulation results definitively prove that relying on simple MRC in a Cell-Free Massive MIMO network leads to saturated error floors and poor spectral efficiency due to unmitigated interference. By implementing LMMSE channel estimation coupled with Centralized MMSE combining, the system can leverage multi-antenna APs to mathematically suppress interference, resulting in superior link reliability, doubled median spectral efficiency, and robust user fairness.

8. FUTURE SCOPE

Future work can improve the proposed framework by evaluating correlated and Rician fading channels to assess its robustness under more realistic propagation conditions. The effect of adaptive pilot-length selection and pilot-assignment strategies can also be investigated to further reduce pilot contamination. Larger AP-UE deployments and different antenna configurations may be considered to examine scalability beyond the present system settings. The fixed and fractional power-control schemes can be extended toward adaptive or AI-assisted power allocation for dynamic network conditions.

Further studies may incorporate limited-fronthaul constraints, low-resolution ADCs, and user-centric/clustered processing to evaluate practical implementation trade-offs. Finally, joint optimization of spectral efficiency, BER, energy efficiency, and computational complexity can provide a more comprehensive assessment of future CF-mMIMO systems.

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