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Research Article

Pilot Assignment for Cell Free Massive MIMO Systems: A Successive Interference Cancellation Approach

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ABSTRACT

In the contemporary era, considerable attention has been directed towards exploring cell-free massive multiple-input multiple-output (CF-M-MIMO) systems. A potential solution for tackling the persistent challenge of inter-cell interference prevalent in traditional cellular MIMO networks, this novel network paradigm has gained prominence. This study investigates a pilot assignment approach based on Successive Interference Cancellation (SIC) aimed at alleviating pilot contamination issues inherent in CF-M-MIMO systems. Through comprehensive numerical analyses and simulations, we demonstrate the efficacy and enhanced performance of the SIC-based approach competed with common random and greedy pilot assignment strategies. The proposed methodology addresses the critical challenge of pilot contamination, a phenomenon that severely impacts system performance and spectral efficiency. By iteratively decoding signals and canceling interference, the SIC algorithm optimizes pilot assignments, resulting in improved data rates and more efficient resource utilization. Our findings underscore the robustness and scalability of the SIC-based scheme across diverse system parameters and deployment scenarios, affirming its potential as a promising solution for enhancing the performance of CF-M-MIMO systems. Overall, this study contributes valuable insights into the design and optimization of pilot assignment strategies, offering a pathway for further research and development in the field of CF-M-MIMO systems.

Keywords: *Cell-free massive MIMO, Pilot assignment scheme, Successive interference cancellation (SIC), Spectrum efficiency*

Hücresiz Büyük MIMO Sistemleri için Pilot Atama: Ardışık Girişim İptali Yaklaşımı

ÖZET

Son yıllarda, hücresel MIMO ağlarında yaygın olan hücreler arası girişim sorununu hafifletmek için yeni bir ağ mimarisi olarak hücresiz devasa çoklu giriş-çoklu çıkış (CF-M-MIMO) sistemlerinin keşfi önemli ölçüde dikkat çekmektedir. Bu çalışma, CF-M-MIMO sistemlerinde yaygın olarak görülen pilot kirliliği sorunlarını hafifletmeyi amaçlayan Ardışık Girişim İptal (SIC) temelli yeni bir pilot atama şemasını incelemektedir. Kapsamlı sayısal analizler ve simülasyonlar yoluyla, SIC tabanlı yaklaşımın geleneksel rastgele ve açgözlü pilot atama şemalarına göre etkinliğini ve gelişmiş performansını gösteriyoruz. Önerilen şema, sistem performansı ve spektral verimlilik üzerinde ciddi etkisi olan pilot kirliliği sorununu ele almaktadır. Sinyalleri ardışık olarak çözerek ve girişimi iptal ederek, SIC algoritması pilot atamalarını optimize eder, bu da daha iyi veri oranlarına ve daha verimli kaynak

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kullanımına yol açar. Bulgularımız, SIC tabanlı şemanın çeşitli sistem parametreleri ve dağıtım senaryoları üzerindeki sağlamlığını ve ölçeklenebilirliğini vurgulayarak, hücresiz devasa MIMO sistemlerinin performansını artırmak için umut vadeden bir çözüm olarak potansiyelini doğrulamaktadır. Genel olarak, bu çalışma, pilot atama stratejilerinin tasarımı ve optimizasyonu konusunda değerli bilgiler sunarak, CF-M-MIMO sistemleri alanında daha fazla araştırma ve geliştirme için bir yol haritası sunmaktadır.

Anahtar Kelimeler: *Hücresiz büyük MIMO, Pilot atama şeması, Ardışık girişim iptali (SIC), Spektrum verimliliği*

I. INTRODUCTION

There has been an increasing focus on investigating cell-free multiple-input multiple-output (CF-M-MIMO) systems as an innovative architectural paradigm aimed at reducing inter-cell interference common in traditional cellular MIMO networks [1]–[5]. These systems involve the deployment of a multitude of distributed access points (APs) to collectively cater to a limited number of user equipments (UEs), diverging from the constraints imposed by conventional cell boundaries within the same time-frequency domain. Typically, CF-M-MIMO systems are characterized by their operation under a time-division duplex (TDD) mode [6].

In CF-M-MIMO systems, the assurance of precise channel state information (CSI) at the APs are imperative, necessitating the employment of uplink (UL) training [7]–[9]. While the conventional approach to coordinated multipoint joint processing (CoMP) focuses on network-centric strategies, CF-M-MIMO systems depart from this norm by embracing a user-centric perspective. However, challenges ensue owing to the restricted coherence interval in wireless fading channels, posing obstacles to preserving orthogonality among training pilots for all UEs. This restriction results in pilot contamination, a phenomenon that can significantly degrade system performance and become a critical bottleneck in the effectiveness of CF-M-MIMO systems [10], [11].

Substantial initiatives have been directed towards alleviating the adverse effects of pilot contamination [1], [12]–[18]. Initially, researchers proposed a random pilot assignment strategy, which was subsequently iteratively refined to enhance performance by optimizing pilot assignments to maximize the minimum rate across all UEs [1]. In order to improve spectral efficiency through optimal pilot allocation, a Tabu-search-based approach is presented in [15]. This method utilizes a Tabu list to avoid local optima and enhance the effectiveness of pilot allocation. However, the efficacy of this approach hinges on a number of elements, with the size of the Tabu list and the choice of initial pilot assignment being particularly influential in determining its success. Another approach proposed in [16] suggests using a weighted graph to optimize uplink throughput. This is achieved by treating the pilot assignment as a max k-cut problem. Since max k-cut is typically an NP-hard problem, this method may encounter scalability challenges when applied to larger networks or more complex scenarios. Essentially, it’s a sophisticated way to allocate resources efficiently, but it might struggle to maintain that efficiency as the system grows. Pilot assignment strategies presented in [17], [18] centered on user grouping, wherein users are partitioned into groups based on shared serving APs. An iterative process is employed to determine a pre-defined threshold ensuring the equivalence between the number of user groups and available pilot numbers. Nonetheless, these iterative methods entail high computational complexity, often necessitating multiple iterations to identify an appropriate threshold. Furthermore, the implementation of the pilot assignment algorithm in [18] requires identifying centroid APs, a challenging task in CF-M-MIMO networks.

The pilot assignment procedure plays a pivotal role in the performance and efficiency of wireless communication systems, particularly in the context of MIMO deployments [19]–[21]. Efficient pilot assignment directly impacts the accuracy of channel estimation, which is essential for coherent signal detection and interference management. However, the presence of pilot contamination, arising from the reuse of pilot sequences among neighboring cells or users, poses significant challenges to system performance. Pilot contamination introduces inter-cell interference, leading to reduced signal-to-interference-plus-noise ratio (SINR), degraded user throughput, and overall system capacity limitations. Moreover, pilot contamination exacerbates the near-far effect, where users with stronger channel conditions dominate the system resources, further exacerbating interference for weaker users. Consequently, mitigating pilot contamination through intelligent pilot assignment schemes becomes imperative for ensuring reliable and efficient operation of wireless communication systems, particularly in dense urban environments where interference is prevalent.

The process of precoding and decoding operates efficiently when the channel estimation is precise, which is typically obtained through pilot signals sent by UEs throughout the uplink phase. Nevertheless, due to the scarcity of orthogonal pilot signals and the large number of UEs, these pilots must be reused. This reuse can result in pilot contamination (PC), a widespread problem that affects the accuracy of channel estimation and, consequently, the performance of the communication system. In essence, while pilot signals are essential for accurate channel estimation, their limited number and the necessity for reuse among numerous UEs create a significant challenge in maintaining the integrity of the signal information. This interference complicates channel state information estimation, inducing errors in the process. Consequently, spectrum efficiency (SE) in CF-M-MIMO systems suffers akin to multicell massive MIMO setups. Thus, the implementation of a meticulously devised pilot assignment strategy becomes imperative to ameliorate SE performance and effectively manage interference in densely populated CF-M-MIMO networks. Hence, this study examines a pilot assignment scheme founded on the successive interference cancellation (SIC) method. The numerical results unequivocally highlight the efficacy of the SIC-based pilot assignment strategy, highlighting its robust performance in CF-M-MIMO systems. This indicates that the SIC method is a promising solution for tackling the challenges of pilot assignment in environments with a high density of user equipment, contributing to the advancement of CF-M-MIMO technology.

II. SYSTEM MODEL

In the context of uplink transmissions within CF-M-MIMO architectures, the considered topology comprises M single-antenna APs and K single-antenna UEs, where ($K \ll M$). These UEs are dispersed stochastically across an expansive geographic expanse. Each AP maintains a connection to a Central Processing Unit (CPU) via a hypothetical ideal fronthaul link, as delineated in reference [22]. This configuration is postulated to optimize uplink communication efficacy by capitalizing on the distributed deployment of APs to serve a relatively diminutive cohort of UEs, with the presupposed flawless fronthaul connectivity precluding any potential throughput constraints between the APs and the CPU. The channel propagation coefficient g_{mk}, representing the link between the mth AP and the kth UE, is modeled as $g_{mk} = \sqrt{\beta_{mk}} h_{mk}$, where β_{mk} encapsulates the influence of large-scale fading phenomena such as path loss and shadowing, while h_{mk} embodies the small-scale fading characteristics through an independent and identically distributed (i.i.d.) complex normal (CN) distribution with zero mean and unit variance.

A. UPLINK PILOT TRAINING

During the initial phase of uplink pilot training in CF-M-MIMO systems, all K users concurrently transmit pilot signals to the APs. These pilot signals, characterized by their length τ_p, serve as crucial reference signals for channel estimation. Every UE k transmits a pilot signal denoted as $\sqrt{\tau_p}\boldsymbol{\varphi}_k$, where $||\boldsymbol{\varphi}_k||^2 = 1$, implying unit power. These signals propagate through the wireless medium and are acquired by the APs.

The signal received during pilot training at AP m, represented by $\mathbf{Y}_{p,m}$, encompasses contributions from the desired signal as well as the additive noise as [15]:

$$\mathbf{Y}_{p,m} = \sqrt{\tau_p \rho} \sum_{k=1}^{K} \mathbf{g}_{mk} \boldsymbol{\varphi}_k^H + \mathbf{n}_{p,m} \tag{1}$$

here, ρ symbolizes the normalized signal-to-noise ratio (SNR) of individual pilot symbols, capturing the trade-off between signal power and noise contamination. The coefficient $\mathbf{g}_{mk}$ characterizes the channel link between user k and AP m, while $\mathbf{n}_{p,m}$ stands for the additive white Gaussian noise (AWGN) present between them. The elements of $\mathbf{n}_{p,m}$ are drawn from a complex Gaussian distribution $\mathcal{CN}(0,1)$.

Leveraging the received pilot training signals, AP m performs channel $\mathbf{g}_{mk}$ between itself and each user k. This estimation is crucial for subsequent data transmission and reception. Utilizing the minimum mean square error (MMSE) method, AP m computes the channel estimate $\hat{\mathbf{g}}_{mk}$ as a linear combination of the received signal components:

$$\hat{\mathbf{g}}_{mk} = c_{mk} \hat{\mathbf{y}}_{p,mk} \tag{2}$$

here, $\hat{\mathbf{y}}_{p,mk}$ represents the projection of the received signal onto the pilot signal $\boldsymbol{\varphi}_k$, encapsulating the channel information. The scaling factor c_{mk} is determined to optimize the balance between signal power and noise contamination, ensuring accurate channel estimation.

However, the existence of pilot contamination, stemming from the shared usage of pilot signals among users, complicates the estimation process. Strategies aimed at mitigating pilot contamination and enhancing the accuracy of channel estimation remain active areas of research within the realm of massive MIMO systems. Fig.1 shows a CF-M-MIMO network.

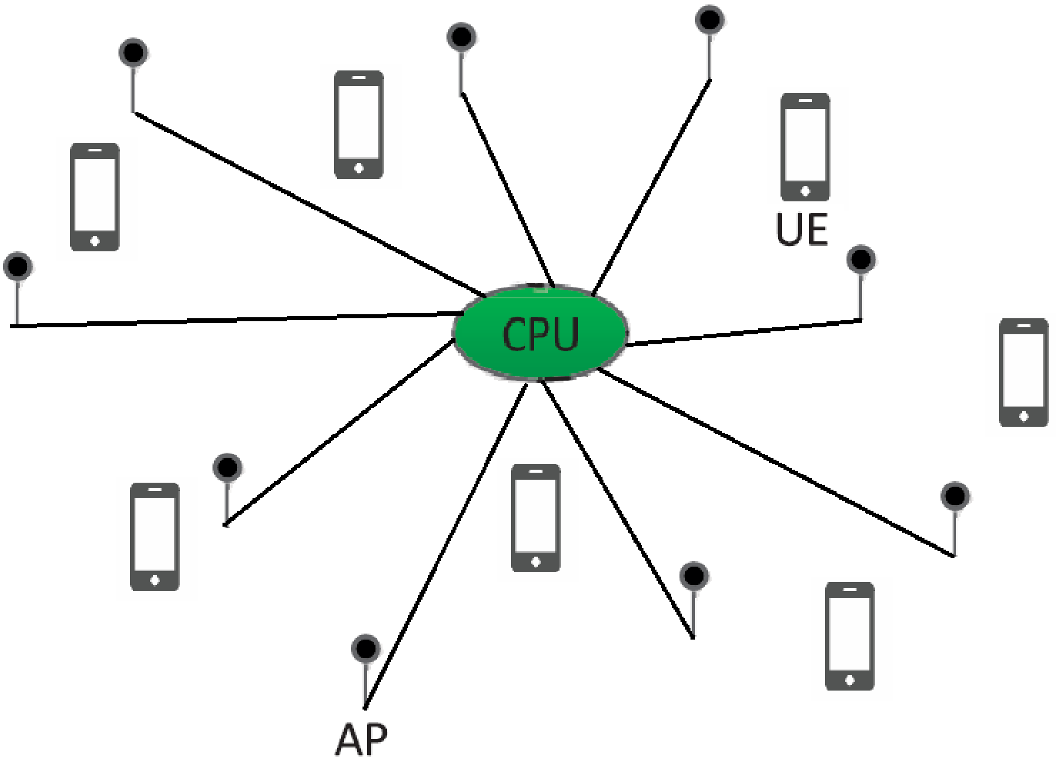

Figure 1. *A cell-free massive MIMO system*

B. UPLINK DATA TRANSMISSION PHASE

During the uplink data transmission phase, each of the k users concomitantly send their data symbols to the m APs. Before transmission, each user k adjusts the power of its data symbol to ensure that the expected value of the squared magnitude of the symbol is 1, employing a power control coefficient $\sqrt{\eta_k}$, where $0 \leq \sqrt{\eta_k} \leq 1$. The data signal received at AP m is expressed as [23]:

$$\mathbf{y}_{u,m} = \sqrt{\rho_u} \sum_{k=1}^{K} \mathbf{g}_{mk} s_k + \mathbf{n}_{u,m} \tag{3}$$

here, ρ_u represents the SNR for uplink data transmission, and $\mathbf{n}_{u,m}$ stands for the AWGN characterized by elements with a mean of zero and a variance of one.

To retrieve the signal transmitted by user k, AP m performs multiplication between the received signal $\mathbf{y}_{u,m}$ and the conjugate transpose of the channel estimate $\hat{\mathbf{g}}_{mk}^{*}$, sending the resulting data to the CPU via the backhaul network. The mathematical expression for the received data signal at the CPU can be articulated as follows:

$$\mathbf{y}_{u,CPU} = \sum_{m=1}^{M} \hat{\mathbf{g}}_{mk}^{*} \mathbf{y}_{u,m} \tag{4}$$

From equation (4), the signal received at the CPU undergoes further processing to extract the desired signal from user k:

$$\mathrm{DS}_k + \mathrm{BU}_k - \mathrm{UI}_{kk'} + \mathrm{NO}_k \tag{5}$$

here, the terms DS_k, refers to the desired signal pertaining to user k, representing the signal intended to be transmitted by the user and accurately received by the receiver. BU_k, represents the beamforming uncertainty associated with user k, stemming from the uncertainty in the estimated channel state by the receiver and reflecting the challenge of forming an accurate beam. $\mathrm{UI}_{kk'}$ denotes the mutual interference of user k with user k', arising from the transmissions of other users affecting the transmission of user k. and NO_k signifies the additive white Gaussian noise (AWGN) specific to user k, originating from random thermal noise in the channel and receiver hardware. These terms are defined as follows as [23]:

$$DS_k = \sqrt{\rho_u \eta_k} \sum_{m=1}^{M} \mathbb{E}\{\hat{\mathbf{g}}_{mk}^{H} \mathbf{g}_{mk}\} \tag{6}$$

$$BU_k = \sqrt{\rho_u \eta_k} \Big(\sum_{m=1}^{M} \hat{\mathbf{g}}_{mk}^{H} \mathbf{g}_{mk} - \sum_{m=1}^{M} \mathbb{E}\{\hat{\mathbf{g}}_{mk}^{H} \mathbf{g}_{mk}\} \Big) \tag{7}$$

$$UI_{kk'} = \sum_{m=1}^{M} \sqrt{\rho_u \eta_{k'}} \hat{\mathbf{g}}_{mk}^{H} \mathbf{g}_{mk'} \tag{8}$$

$$\mathrm{NO}_k = \sum_{m=1}^{M} \hat{\mathbf{g}}_{mk}^{H} \mathbf{w}_{u,m} \tag{9}$$

By employing the method proposed in [24] for bounding channel capacity, we further analyze equation (5) to obtain a closed-form expression for the SINR, as detailed in equation (10) and elaborated upon in [23].

$$\mathrm{SINR}_k = \frac{|\mathrm{DS}_k|^2}{\mathbb{E}\{|\mathrm{BU}_k|^2\} + \sum_{k' \neq k}^{K} \mathbb{E}\{|\mathrm{U}|_{kk'}|^2\} + \sum_{m=1}^{M} \mathbb{E}\{|A_{mk} \hat{g}_{mk}^{*} w_{u,m}|^2\}} \tag{10}$$

This formulation, coupled with the definition of the SINR specific to user k, enables the determination of the uplink ergodic rate for that user:

$$\mathrm{Rate}_k = \Big(1 - \frac{\tau_c}{\tau_p}\Big) \log_2(1 + \mathrm{SINR}_k) \tag{11}$$

The uplink ergodic rate is contingent upon various factors including the characteristics of the large-scale fading coefficients, which account for phenomena like path loss and shadowing, as well as the statistical attributes of the channel estimates. These channel estimates capture the complex dynamics of the wireless channel, incorporating information about signal propagation, interference, and noise. By considering these factors comprehensively, the uplink ergodic rate offers profound insights into the overall performance and efficiency of the communication system.

III. SUCCESSIVE INTERFERENCE CANCELLATION BASED PILOT ASSIGNMENT

In this section, we delve into the intricate mechanics of the Successive Interference Cancellation (SIC) algorithm for pilot assignment, a method extensively utilized within wireless communication systems [25]. The Successive Interference Cancellation (SIC) algorithm presents a compelling solution to the challenges posed by pilot contamination in CF-M-MIMO systems. One of the primary reasons for its preference lies in its ability to effectively mitigate interference by iteratively decoding signals and canceling interference from neighboring users. Unlike conventional random or greedy pilot assignment schemes, which may result in inefficient resource allocation and reduced spectral efficiency, the SIC algorithm optimally assigns pilots to users based on their channel conditions, thereby maximizing the overall system throughput. Moreover, the SIC-based pilot assignment scheme demonstrates robustness and scalability across diverse deployment scenarios and varying system parameters. By leveraging the inherent spatial diversity of massive MIMO systems, the SIC algorithm offers improved spectral efficiency and enhanced performance, particularly in dense wireless environments. Overall, the SIC algorithm emerges as a promising solution for improving the reliability, efficiency, and capacity of cell-free massive MIMO systems, making it a preferred choice for next-generation wireless communication networks. In recent years, SIC-based methods have been observed to be employed in systems such as non-orthogonal multiple access (NOMA), multi-user mobile underwater acoustic communication, and massive ultrareliable low-latency communications [26]–[28].

Neighborhood Definition:
The set $\mathcal{N}(\mathbf{p})$ defines the neighborhood of a specific pilot assignment result vector $\mathbf{p}$ within the context of the SIC algorithm. Unlike some others algorithms, which defines neighborhoods based on pilot usage frequency, SIC focuses on canceling interference iteratively. In SIC, the neighborhood consists of pilot assignment vectors where one UE's pilot assignment is modified while keeping other assignments intact. Each neighboring vector represents a different interference cancellation strategy.

Stopping Rule:
Similar to Tabu Search (TS) algorithm [15], the search iteration stops when it reaches a predefined maximum number of iterations N_{iter}.

Aspiration Criterion:
In SIC, the aspiration criterion is defined based on the achieved SINR improvement. The algorithm aims to improve SINR iteratively by cancelling interference from previously decoded signals. The aspiration criterion compares the SINR improvement of the current candidate solution with the historical best solution.

SIC-based Pilot Assignment Steps:
Initialization: Start with an initial pilot assignment solution $\mathbf{p}^0 = \{p_1, p_2, \dots, p_K\}$.

Iterative Interference Cancellation: For each UE in the system, decode its signal using the assigned pilot and cancel interference from other signals using SIC. After decoding, update the interference covariance matrix to remove interference from the decoded signal. Iterate this process for all UEs in the system, progressively cancelling interference from previously decoded signals.

Pilot Reassignment: After interference cancellation, reassign pilots to UEs based on the updated interference covariance matrix and SINR improvement. Each UE is assigned a pilot that maximizes its SINR while minimizing interference to other UEs.

Stopping Criterion: Terminate the algorithm when the maximum number of iterations N_{iter} is reached or when the SINR improvement falls below a predefined threshold.

SIC-based Pilot Assignment Algorithm: The SIC-based pilot assignment algorithm iteratively improves SINR by cancelling interference from previously decoded signals. The algorithm aims to maximize overall system throughput by optimizing pilot assignments.

Table 1. *Algorithm 1: Successive Interference Cancellation (SIC) Algorithm-based Pilot Assignment.*

```
Require: $K, M, \tau, N_{\text{iter}}$, initial pilot assignment $\mathbf{p}^0$.
Ensure: Final pilot assignment $\mathbf{p}^*$ and throughput.
Initialize interference covariance matrix.
Decode signals using assigned pilots and cancel interference iteratively.
for $n = 1$ to $N_{\text{iter}}$ do
    Reassign pilots based on updated interference covariance matrix and SINR improvement.
end for
return Final pilot assignment $\mathbf{p}^*$.
```

IV. NUMERICAL RESULTS

We analyze a setup featuring M distributed APs and K UEs evenly distributed within a 1 km^2 area. To alleviate the impact of boundary effects, the square region is handled as if it wraps around its edges, ensuring the presence of additional access points surrounding it. For our simulation framework, we employ an uncorrelated shadowing model along with a three-slope path loss model, consistent with the approach detailed in reference [1]. Additionally, noise power parameters akin to those outlined in [1] are employed. The power levels designated for pilot signals $(\overline{\rho}_p)$ and data transmission $(\overline{\rho}_u)$ are consistently configured at 100mW for each. Furthermore, to enhance throughput efficiency across the network, a max-min power control scheme is incorporated. The per-user throughput $(SE_{u,k})$ is calculated considering channel estimation overhead, represented by the formula $SE_{u,k} = B\frac{1-\frac{\tau_c}{\tau_p}}{2}\log_2(1+\text{SINR}_{u,k})$ as [15], where $\tau_c = 200$ samples.

The proposed methodology undergoes rigorous evaluation against several established pilot assignment strategies. Among these, the random pilot assignment scheme [1] stands out, wherein users are allocated pilots randomly by establishing connections with all available APs. This strategy is denoted as "RPA" in the figures. Furthermore, we explore the greedy-based pilot assignment known as "GPA," in which every user establishes connections with all APs. Subsequently, the data rate for the least performing user is iteratively optimized using a greedy algorithmic approach.

Fig. 2 depicts the cumulative distribution of per-user uplink throughput, providing insights into the performance of various pilot assignment strategies across the network under the conditions of $M = 100, K = 40, \tau_p = 30, \tau_c = 200$, and a bandwidth of $B = 20$ MHz. It is evident from the plot that the performance achieved by the SIC-PA scheme closely matches that of the exhaustive scheme. This suggests that SIC-PA is capable of exploring solutions in close proximity to the optimal solution, thereby enhancing the system's overall performance. Furthermore, it effectively addresses the challenge of pilot contamination, surpassing traditional pilot assignment methods in performance.

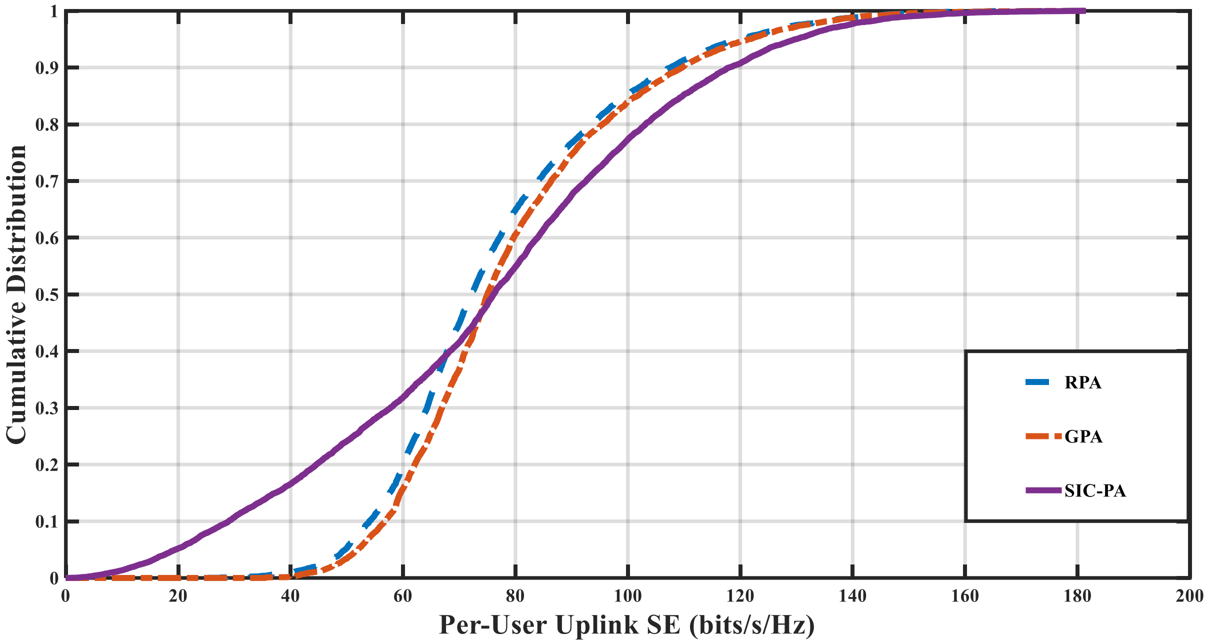

Figure 2. *The per-user uplink throughput distribution is examined across different pilot assignment strategies, considering a scenario with 100 access points (APs) and 40 user equipments (UEs).*

Figure 3 investigates how the average uplink throughput is affected by varying the number of APs M. The trend reveals that as the number of APs M increases, the average uplink throughput of all pilot assignment schemes also increases. This phenomenon stems from the amplified received signal strength resulting from the densification of the network. Moreover, our proposed SIC-PA scheme consistently surpasses alternative approaches in terms of average uplink throughput, underscoring its effectiveness and superiority across diverse AP layout scenarios. Figure 2 demonstrates the average uplink throughput as a function of the number of APs M, while maintaining $K = 40$ and $\tau_p = 30$. The increase in the number of access points M contributes significantly to the improvement in the average uplink throughput across all pilot assignment strategies. This enhancement is attributed to the broader macro diversity gain facilitated by a larger AP deployment, which consequently boosts the received signal strength owing to the densification of the network. Additionally, our proposed AP selection algorithm prioritizes APs with higher gains for users as the number of APs increases, leading to an average uplink throughput exceeding that of the Greedy Pilot Assignment (GPA) scheme and the Random Pilot Assignment (RPA) scheme by approximately 1.02 bits/s and 1.04 bits/s, respectively. Furthermore, our proposed SIC-PA scheme consistently outperforms alternative approaches in terms of average uplink throughput. This observation underscores the efficacy and superiority of our scheme, particularly in scenarios characterized by a broad deployment of access points.

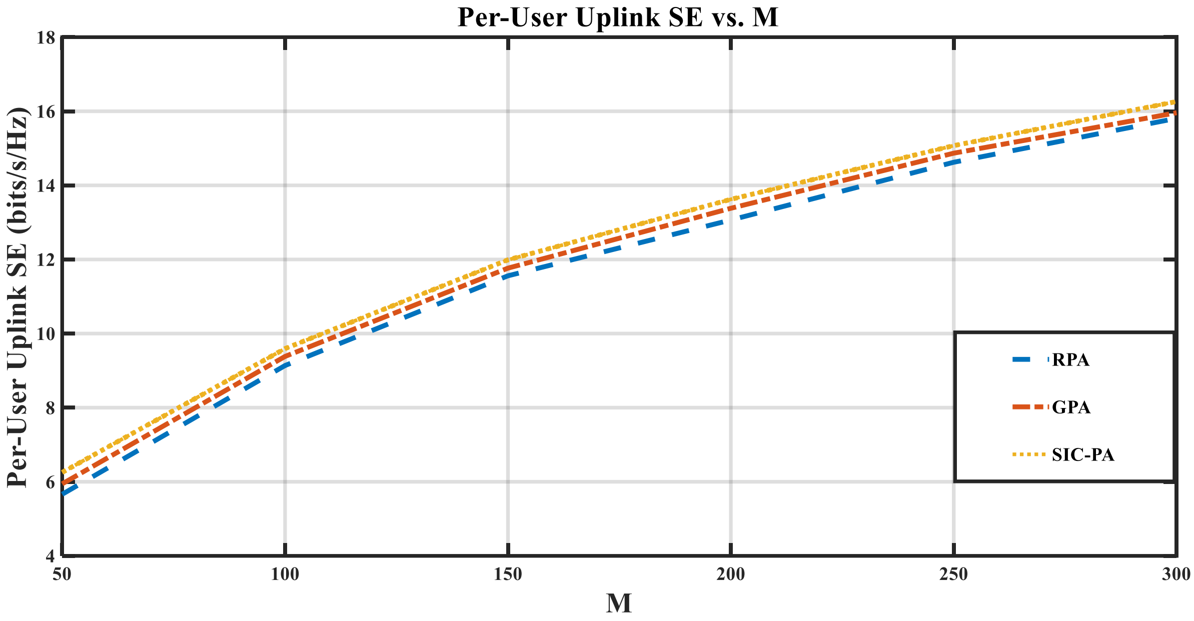

Figure 3. *Uplink throughput in relation to the AP count M.*

V. CONCLUSION

This study delves into the exploration of a novel pilot assignment strategy grounded in SIC to address the pervasive issue of pilot contamination challenges in CF-M-MIMO systems. Through comprehensive numerical analyses and simulations, we have unveiled the substantial benefits and enhanced performance brought forth by the SIC-based strategy, significantly surpassing conventional random and greedy pilot assignment methods.

Our investigation underscores that the employment of the SIC-based pilot assignment approach successfully mitigates the adverse ramifications of pilot contamination, resulting in notable improvements in both system throughput and spectral efficiency. By iteratively decoding signals and canceling interference, the SIC algorithm optimally assigns pilots to users, leading to enhanced data rates and improved utilization of system resources.

Furthermore, our simulations elucidate the robustness and scalability of the SIC-based scheme across varying system parameters and deployment scenarios. The scheme exhibits superior performance in achieving higher spectral efficiency and mitigating interference, particularly in dense wireless environments.

In conclusion, our study underscores the considerable promise of employing the SIC-based pilot assignment scheme to bolster the effectiveness of cell-free massive MIMO systems. This approach emerges as a notable avenue for future investigations and advancements in the realm of wireless communication technologies. The outcomes shed valuable light on an in-depth exploration of the design and optimization of pilot assignment strategies, paving the way for further research and development in this area.

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