

Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO)

Amna Javed¹, Farzana Kulsoom^{2,✉}, Muhammad Iram Baig¹, Hassan Nazeer Chaudhry³

1. Department of Electrical Engineering, University of Engineering and Technology, Taxila, Taxila, PAK

2. Department of Telecommunication, University of Engineering and Technology, Taxila, Taxila, PAK

3. Department of Computer Science, Barani Institute of Information Technology (BIIT), Rawalpindi, PAK

Received: April 09, 2026 | Review began: April 19, 2026 | Review ended: August 08, 2026 | Published: October 05, 2026

© Copyright 2026

This is an open access article distributed under the terms of the Creative Commons Attribution License CC-BY 4.0., which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Abstract

Massive Multiple-Input Multiple-Output systems suffer from pilot contamination in uplink time-division duplex mode due to the limited availability of orthogonal pilots for channel estimation. This issue becomes more severe in dense networks where pilot reuse across cells is inevitable, leading to degraded channel estimation accuracy and system performance. Efficient pilot allocation strategies can mitigate this problem by minimizing pilot reuse across interfering channels. In this work, users are classified as edge or center users based on their large-scale fading coefficients. The center users are further grouped according to their channel correlation. Orthogonal pilots are assigned to all edge users, while one orthogonal pilot per group is allocated to the center users and reused within the group to reduce the reuse factor and limit contamination. A compressed sensing (CS)-based algorithm is then employed to estimate both the group-wise correlated center-user channels and the edge-user channels, exploiting joint sparsity and per-link sparsity. The CS scheme utilizes an extended discrete Fourier transform basis as the measurement matrix to convert spatial-domain channels into the angular domain, enabling non-overlapping angular supports between groups. Comparative evaluations against state-of-the-art methods demonstrate that the proposed scheme achieves lower channel estimation error and higher throughput, offering a 22.85% improvement in the Cumulative Distribution Function of uplink achievable rate over the SPRS+WGC-PD method at 15 dB Signal-to-Interference-plus-Noise Ratio.

Categories: Electronics Design and VLSI, Telecommunication Networks, Wireless Communication Systems

Keywords: soft pilot reuse (spr), pilot contamination channel estimation, channel state information (csi), sparse channel estimation, angular domain, discrete fourier transform

Introduction

Massive multiple-input multiple-output (MIMO) employs large antenna arrays at the base station (BS) to enhance spectral efficiency, capacity, and reliability. Transmit beamforming (TBF) requires accurate channel state information (CSI), typically obtained via pilots. In time-division duplex (TDD) systems, uplink pilots exploit reciprocity to reduce overhead, unlike frequency-division duplex (FDD), which suffers from excessive pilot costs with large arrays. However, TDD faces the challenge of pilot contamination (PC), caused by limited orthogonal sequences and pilot reuse across cells, which severely degrades CSI and system performance [1,2]. Several decontamination methods exist, including smart reuse, coordinated scheduling, and graph-based allocation [3], though they increase pilot overhead or rely on impractical assumptions. Soft Pilot Reuse (SPR) [4] reduces contamination by dividing center and edge users, while graph-coloring

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

schemes mitigate interference through pilot assignment. Recently, pilot contamination mitigation techniques have increasingly been integrated with sparse signal recovery techniques, where the inherent sparsity of massive MIMO channels is exploited to improve channel estimation while reducing pilot overhead. More advanced methods exploit spatial correlation and compressed sensing (CS), transforming correlated channels into the angular domain with extended discrete Fourier transform (DFT) bases to reduce leakage and enable joint channel estimation [5,6]. Classical greedy sparse recovery algorithms such as orthogonal matching pursuit (OMP) have been widely adopted because of their low computational complexity, whereas more recent structured compressive sensing techniques exploit group or block sparsity among channel coefficients to further improve estimation accuracy in correlated massive MIMO environments [7,8]. Sparse Bayesian learning (SBL)-based compressed sensing approaches have demonstrated excellent channel estimation accuracy by exploiting the sparse structure of massive MIMO channels. However, their iterative Bayesian inference and matrix inversion operations result in significantly higher computational complexity, limiting their suitability for real-time implementations [9]. Despite these advances, most existing pilot decontamination techniques do not jointly exploit SPR-based user grouping together with structured angular-domain sparsity during channel estimation. Motivated by this limitation, we propose a framework combining SPR, angular-domain decomposition, and CS-based joint estimation, achieving efficient pilot utilization and reduced contamination in massive MIMO uplink systems.

Our contribution

Our key contributions, and the main differences from the study [4], are summarized as follows:

- While users are still classified as center and edge users following the conventional approach, we introduce a new strategy for pilot assignment and center-user grouping.
- The proposed grouping and pilot assignment scheme significantly reduces pilot usage and effectively mitigates pilot contamination.
- All edge users are allocated orthogonal pilots, whereas each group of center users shares a single orthogonal pilot.
- To exploit spatial correlation, the center users' channel is transformed from the spatial domain to the angular domain using an extended DFT-based method, which differs from the approach proposed in [4].
- The angular domain representation yields non-overlapping channel supports, enabling efficient reuse of a common pilot within each group.
- Unlike the approach proposed in [4], where center pilots are reused across neighboring cells, in our framework, pilot reuse is restricted within each group only, further reducing interference.
- We develop a novel compressed-sensing-based algorithm that jointly estimates the channels of grouped center users and the individual edge users.
- Comprehensive simulations against [4] and [10] demonstrate that the proposed system achieves superior reliability and higher throughput.

The rest of our manuscript is structured as follows: First, we briefly discuss our system model, including pilot contamination, followed by our proposed technique, including the pilot assignment strategy and channel estimation. Next, we discuss our simulation results and their discussion. Finally, we conclude our article.

Materials And Methods

System model

The system under consideration is a TDD massive MIMO cellular network comprising J cells, as depicted in Figure 1. Each cell is served by a single BS equipped with M antennas and simultaneously supports K single-antenna users in the uplink. Consistent with the massive MIMO paradigm, the number of BS antennas is assumed to be significantly larger than the number of active users $M \gg K$. The wireless propagation channel is modeled by separating its characteristics into two components: large-scale fading, which captures path loss and shadowing, and small-scale fading, which represents rapid fluctuations caused by multipath propagation.

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

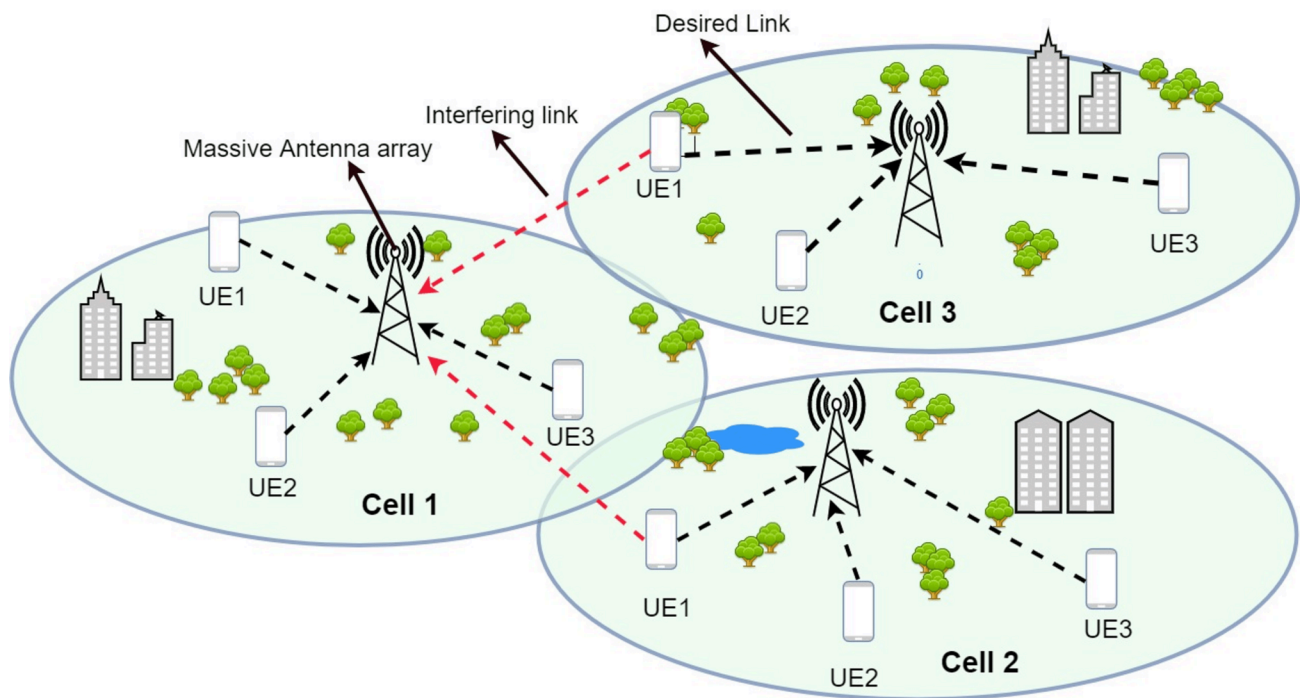


FIGURE 1: Multi-cell massive MIMO with desired and interfering link

MIMO, Multiple-Input Multiple-Output

Large-scale fading encompasses path loss and shadowing and is generally considered independent of the number of antennas at the BS. This assumption is justified by the relatively small spacing between antennas compared to the distance between the BS and a user, resulting in identical large-scale fading coefficients for all antennas associated with a given user. Hence, for each user-BS pair, a single large-scale fading coefficient represented as β is sufficient and does not vary across antenna indices or OFDM subcarriers [4].

Urban environments often present a rich scattering scenario, causing the transmitted signal to arrive at the receiver via multiple propagation paths. These multipath components undergo different attenuations and phase shifts, leading to either constructive or destructive interference. This phenomenon, which varies over small spatial displacements on the order of the carrier wavelength, is referred to as small-scale fading.

Pilot contamination

In the uplink transmission phase, the received signal at the base station (BS) after applying the combining vector is derived as follows. Following the conventional uplink massive MIMO signal model described in the studies [1,2], the received signal vector at the BS for the i -th cell can be expressed as:

$$\mathbf{y}_i = \sum_{j=1}^L \sum_{k=1}^K \sqrt{p_{j,k}} \mathbf{h}_{i,j,k} x_{j,k} + \mathbf{n}_i \quad (1)$$

where:

- L is the total number of cells,
- K is the number of users per cell,
- $p_{j,k}$ is the transmit power of the k -th user in cell j ,

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

- $\mathbf{h}_{i,j,k}$ is the channel between the k -th user in cell j and the BS in cell i ,
- $x_{j,k}$ is the uplink data symbol transmitted by the k -th user in cell j , with $\mathbb{E}[|x_{j,k}|^2] = 1$,
- $\mathbf{n}_i$ is the additive white Gaussian noise vector at BS i , distributed as $\mathcal{CN}(0, \sigma^2 \mathbf{I})$.

Proposed technique

The systematic procedure for mitigating inter-cell interference through pilot decontamination and the subsequent group-based pilot assignment strategy is illustrated in the system flow diagram in Figure 2.

Signal detection for user k in cell i is performed at the BS by applying a linear combining vector $\mathbf{v}_{i,k}$:

$$\mathbf{r}_{i,k} = \mathbf{v}_{i,k}^H \mathbf{y}_i \quad (2)$$

Substituting (1) :

$$\mathbf{r}_{i,k} = \sqrt{p_{i,k}} \mathbf{v}_{i,k}^H \mathbf{h}_{i,i,k} x_{i,k} + \sum_{(j,l) \neq (i,k)} \sqrt{p_{j,l}} \mathbf{v}_{i,k}^H \mathbf{h}_{i,j,l} x_{j,l} + \mathbf{v}_{i,k}^H \mathbf{n}_i \quad (3)$$

This expression includes:

- Desired signal: $\sqrt{p_{i,k}} \mathbf{v}_{i,k}^H \mathbf{h}_{i,i,k} x_{i,k}$
- Inter-cell and intra-cell interference: $\sum_{(j,l) \neq (i,k)} \sqrt{p_{j,l}} \mathbf{v}_{i,k}^H \mathbf{h}_{i,j,l} x_{j,l}$
- Noise term: $\mathbf{v}_{i,k}^H \mathbf{n}_i$.

Moreover, due to pilot reuse across cells, the BS may estimate the channel of user (i, k) with contamination from users in other cells sharing the same pilot. Let $\hat{\mathbf{h}}_{i,i,k}$ be the contaminated channel estimate used in $\mathbf{v}_{i,k}$.

The Signal-to-Interference-plus-Noise Ratio (SINR) [1,2] at the BS for user k in cell i is then given by:

$$\text{SINR}_{i,k} = \frac{p_{i,k} \left| \mathbb{E} \left[\mathbf{v}_{i,k}^H \mathbf{h}_{i,i,k} \right] \right|^2}{\sum_{(j,l) \neq (i,k)} p_{j,l} \mathbb{E} \left[\left| \mathbf{v}_{i,k}^H \mathbf{h}_{i,j,l} \right|^2 \right] + \sigma^2 \mathbb{E} \left[\left\| \mathbf{v}_{i,k} \right\|^2 \right]} \quad (4)$$

How to cite this article:

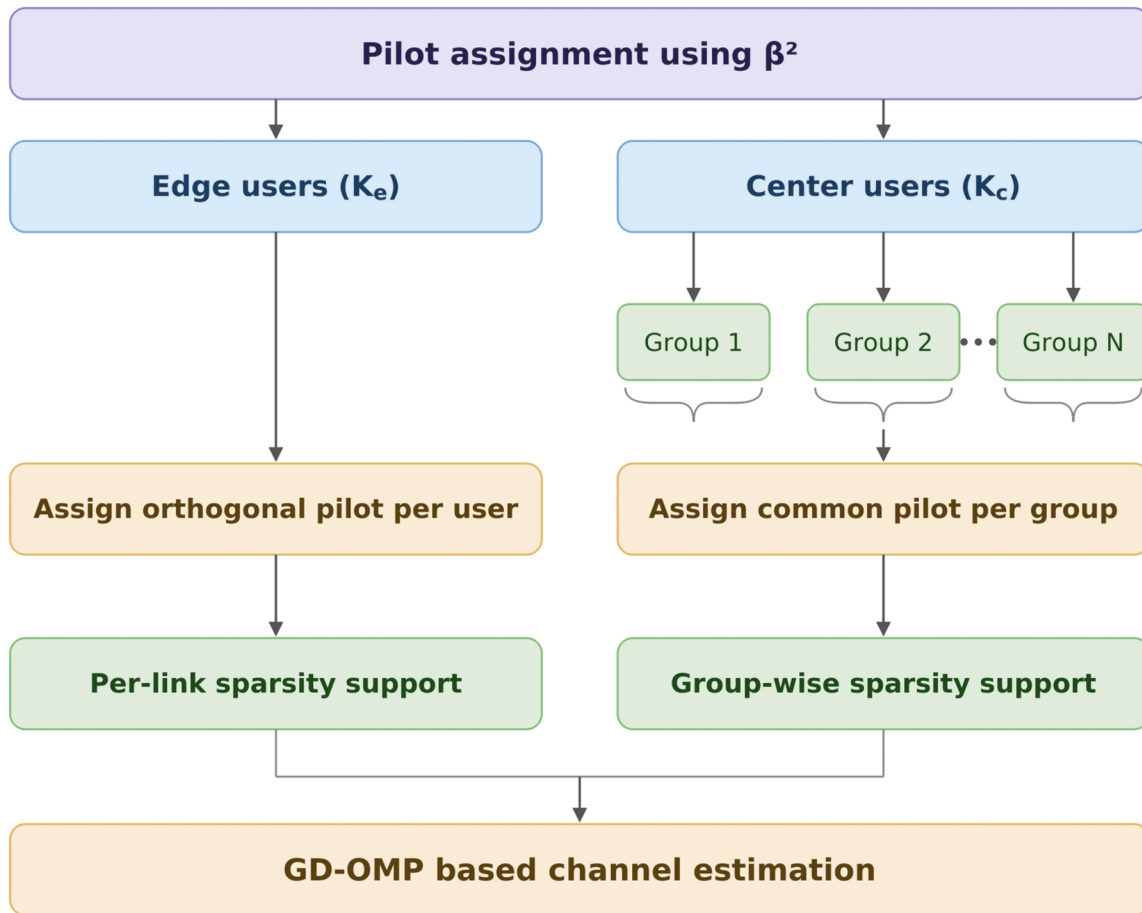


FIGURE 2: System flow diagram of pilot decontamination and group-based pilot assignment

GD-OMP, Group-based Distributed Orthogonal Matching Pursuit

The desired signal power appears in the numerator, while the denominator includes inter-cell and intra-cell interference, noise, and effects of channel estimation errors and pilot contamination. Using the SINR expression in (3), the achievable uplink sum-rate for cell i is given by the achievable rate of user k :

$$R_{i,k} = (1 - u) \mathbb{E} [\log_2(1 + \text{SINR}_{i,k})]$$

Here, u is the pilot fraction within a coherence interval. A larger u improves estimation but reduces spectral efficiency, while a smaller u increases data time but worsens estimation under pilot contamination. Since contamination arises from pilot reuse across cells, efficient allocation strategies can mitigate it. Thus, u reflects the trade-off between training and data, with lower contamination yielding higher SINR and better spectral efficiency.

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

Pilot Assignment Strategy

Following the concept of the SPR technique introduced in [4], users are classified into cell-center and cell-edge groups to reduce the impact of pilot contamination. The users are partitioned according to (5) before the classification process. Let K_i denote the total number of users in the i^{th} cell, partitioned as:

$$K_i = K_{i,c} + K_{i,e} \quad (5)$$

Here, $K_{i,c}$ and $K_{i,e}$ represent the number of center and edge users, respectively. The classification is based on the large-scale fading coefficient β , which represents the amplitude gain between the user and the BS. A user is categorized as a center or edge user based on the comparison of β_i with a threshold ρ_i :

$$\beta_i > \rho_i \rightarrow \begin{cases} \text{Yes} \rightarrow \text{Center user,} \\ \text{No} \rightarrow \text{Edge user.} \end{cases} \quad (6)$$

The threshold ρ_i is computed using:

$$\rho_i = \frac{\lambda}{K} \sum_{k=1}^K \beta_i^2 \quad (7)$$

Note that β_i is an amplitude gain; however, in equation (7), we use β_i^2 to reflect the power gain, as power is proportional to the square of amplitude. This ensures that the threshold ρ_i accurately represents the average received power across users in the cell. The squaring thus aligns with the physical interpretation of signal power. This clarification addresses the apparent inconsistency between equations (6) and (7).

The grouping parameter λ controls the strictness of this classification:

$\lambda = 1$: all users are edge users

$\lambda = 0$: all users are center users

After identifying the center users, they are partitioned into N groups, and all users within the same group are assigned a common orthogonal pilot sequence. This grouping strategy is motivated by practical deployment scenarios in which users located in close proximity, such as in offices, public transportation, stadiums, or conference halls, often exhibit similar scattering characteristics and spatial channel correlation. Such correlation enables multiple center users to share the same pilot while remaining distinguishable through sparsity-based joint channel estimation techniques. In contrast, each edge user is assigned a dedicated orthogonal pilot sequence to eliminate pilot contamination caused by severe inter-cell interference.

The proposed pilot allocation strategy exploits the inherently stronger received signal strength of center users, allowing them to better tolerate the additional interference introduced by intra-group pilot reuse. Furthermore, joint channel estimation algorithms can effectively separate the channels of users sharing the same pilot by leveraging their spatial-domain characteristics. Since edge users experience weaker signal conditions and are more vulnerable to inter-cell interference, allocating orthogonal pilots to these users ensures reliable channel estimation and improved communication quality.

To illustrate the reduction in pilot overhead, consider a network consisting of three cells, each serving 20 users. For $\lambda = 0.5$, each cell contains 10 center users and 10 edge users. Under conventional orthogonal pilot allocation, every user requires a unique pilot sequence, resulting in a total of 60 pilots. The SPR scheme in the study [4] reduces this requirement to 40 pilots. In the proposed approach, the 10 edge users in each cell retain dedicated pilot sequences, while the center users are divided into groups that share pilot sequences. When two center-user groups are formed per cell, the total pilot requirement is reduced to only 36 sequences, consisting of 30 edge-user pilots and 6 shared center-user pilots. Even when the number of center-user groups is increased to three per cell, the total pilot requirement becomes 39, which remains lower than that required by the SPR scheme.

How to cite this article:

The reduction in pilot overhead improves spectral efficiency without compromising channel estimation reliability. By restricting pilot reuse to carefully formed center-user groups and preserving orthogonal pilots for edge users, the proposed scheme effectively balances pilot utilization and interference mitigation. Consequently, it provides a scalable pilot allocation framework for dense cell-free massive MIMO deployments while maintaining high channel estimation accuracy and communication performance.

Sparse channel estimation and pilot decontamination

Angular Domain Channel Exploitation and Group-based GD-OMP Estimation

In a massive MIMO system, the spatial correlation between users belonging to the same group can be leveraged in the angular domain for improved channel estimation. If two users have correlated channels in the spatial domain, their angular domain representations will also be correlated after applying a suitable transformation, such as DFT. Since nearby users share similar scattering environments, their angles of arrival (AoAs) tend to be close but, due to unique geographical signatures, the angular supports remain largely non-overlapping [2,11]. Prior work [12] confirms that non-overlapping angular supports allow users to reuse pilots with minimal interference.

In this work, the BS is equipped with a uniform linear array (ULA). Following the uplink channel model described in the study [2], the uplink channel vector between the i -th user and the j -th BS can be expressed as:

$$\mathbf{h}_{ij} = \frac{1}{\sqrt{L_p}} \sum_{p=1}^{L_p} \alpha_{ij,p} \mathbf{a}(\varphi_{ij,p}) \quad (8)$$

where L_p denotes the number of propagation paths, $\alpha_{ij,p}$ is the complex path gain, $\varphi_{ij,p}$ is the AoA of the p -th path, and $\mathbf{a}(\varphi_{ij,p})$ is the ULA steering vector:

$$\mathbf{a}(\varphi_{ij,p}) = [1, e^{-j2\pi d \cos(\varphi_{ij,p})}, \dots, e^{-j2\pi d(M-1) \cos(\varphi_{ij,p})}] \quad (9)$$

Here, $d = D/\lambda$ is the normalized antenna spacing, and $\alpha_{ij,p}$ follows a complex Gaussian distribution with zero mean and variance β_{ij} . As given by the study [2], the spatial correlation matrix $\mathbf{R}_{ij} = E\{\mathbf{h}_{ij}\mathbf{h}_{ij}^H\}$ has entries:

$$[\mathbf{R}_{ij}]_{(m,n)} = \beta_{ij} \int e^{-j2\pi d(m-n) \cos(\varphi)} f(\varphi) d\varphi \quad (10)$$

where $f(\varphi)$ is the AoA probability density function. The derivation of equation (10) is given in Appendix A.

Virtual Angular Domain Representation

Based on the channel model in (8) and the correlation matrix in (10), the spatial-domain channel is transformed into the angular domain using (11). Based on the approach described in the study [13], spatially correlated channels can be transformed into the angular domain using a virtual channel representation:

$$\mathbf{H}_i^a = \mathbf{P}_i^H \mathbf{H}_i \mathbf{P}_{T_i} \quad (11)$$

where $\mathbf{P}_i$ and $\mathbf{P}_{T_i}$ are unitary DFT matrices at the BS and user sides, respectively. Each non-zero element in $\mathbf{H}_i^a$ corresponds to a specific quantized angular direction between the BS and the user. Due to the rich scattering environment, users within the same group often share part of their angular support (joint sparsity), while each individual link exhibits per-link sparsity.

In practice, the DFT basis may lead to leakage when signal directions are arbitrary. Therefore, we employ an extended DFT dictionary [6,13]. To reduce basis mismatch, the extended DFT dictionary defined in (12) is adopted.

How to cite this article:

$$\mathbf{D} = \begin{bmatrix} e^{-j2\pi k_1 \tau_1} & & e^{-j2\pi k_1 \tau_{L_d}} \\ e^{-j2\pi k_2 \tau_1} & & e^{-j2\pi k_2 \tau_{L_d}} \\ \vdots & \ddots & \vdots \\ e^{-j2\pi k_M \tau_1} & & e^{-j2\pi k_M \tau_{L_d}} \end{bmatrix} \quad (12)$$

where τ is the normalized delay, L_d is the dictionary length, and k refers to Fourier bins.

Compressed Sensing Model

Using the dictionary $\mathbf{D}$, the received pilot signal at BS is:

$$\mathbf{Y}_{pi} = \mathbf{A} \mathbf{D} \mathbf{B}_{si} + \mathbf{N}_i \quad (13)$$

where $\mathbf{A} = \mathbf{X}_p^H \otimes \mathbf{D}$ is the sensing matrix, $\mathbf{B}_{si}$ contains the sparse angular domain channel coefficients, and $\mathbf{N}_i$ is noise. Channel recovery can be posed as:

$$\min_{\{\mathbf{B}_{si}\}} \sum_{i=1}^K \|\mathbf{Y}_{pi} - \mathbf{A} \mathbf{D} \mathbf{B}_{si}\|_2 \leq \epsilon \quad (14)$$

$$\& \text{ s.t. } \bigcap_{i=1}^{K_c} \text{supp}(\mathbf{B}_{si}) = \Theta_c \quad (15)$$

Here, Θ_c represents the common angular support among center users.

Group-based Distributed Orthogonal Matching Pursuit (GD-OMP)

To solve (15), we employ GD-OMP, a greedy compressed sensing algorithm adapted for joint and per-link sparsity recovery. Center users' channels are jointly estimated by exploiting shared angular support, while edge users' channels are recovered individually (Table 1).

How to cite this article:

Algorithm 1 GD-OMP for Joint and Individual Channel Estimation	
1:	Input: Received pilots $\mathbf{Y}_{pi}$, sensing matrix $\mathbf{A}$, dictionary $\mathbf{D}$, group info, threshold ϵ
2:	Initialize residual: $\mathbf{R} = \mathbf{Y}_{pi}$, common support $\Theta_c = \emptyset$
3:	For each iteration until stopping criterion do
4:	Find column in $\mathbf{A}$ with max correlation across all center users
5:	Update Θ_c with selected index
6:	Solve LS: $\mathbf{B}_{si} = (\mathbf{A}_{\Theta_c})^\dagger \mathbf{Y}_{pi}$
7:	Update residual: $\mathbf{R} = \mathbf{Y}_{pi} - \mathbf{A}_{\Theta_c} \mathbf{B}_{si}$
8:	end For
9:	For each edge user do
10:	Run OMP individually to find Θ_i (excluding Θ_c)
11:	Combine supports: $\Theta_i = \Theta_i \cup \Theta_c$
12:	Estimate channel: $\hat{\mathbf{H}}_i = \mathbf{D} \mathbf{B}_{si}$
13:	end For
14:	Output: $\hat{\mathbf{H}}_i$ for all users

TABLE 1: Algorithm 1

The GD-OMP ensures that no dictionary atom (column of $\mathbf{A}$) is selected more than once, thereby reducing the likelihood of pilot contamination. Joint recovery among center users reduces pilot resource usage, while individual recovery for edge users mitigates inter-cell interference.

Results And Discussion

Performance analysis

The effectiveness of the proposed pilot contamination reduction framework is presented and benchmarked against several widely used pilot allocation techniques given in the literature. The comparison includes the following reference schemes:

Random Pilot Assignment (Baseline 1): Pilot sequences are distributed arbitrarily among users without considering spatial information or inter-cell interference.

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

Soft Pilot Reuse (SPR) (Baseline 2) [4]: Users are classified into cell-center and cell-edge groups. A common pilot pool is reused by center users, whereas orthogonal pilot sequences are reserved for edge users to alleviate severe interference.

Weighted Graph Coloring Pilot Design (WGC-PD) (Baseline 3) [3]: Pilot allocation is formulated as a weighted graph-coloring problem, where interference relationships between users determine pilot assignment.

Hybrid SPR-WGC-PD (Baseline 4) [10]: This method integrates soft pilot reuse with weighted graph coloring to further optimize pilot allocation and reduce pilot contamination.

The simulation environment consists of a seven-cell cellular layout. A pilot reuse factor of seven is employed for edge users to suppress inter-cell interference, while center users use a reuse factor of one because their channel conditions are less affected by pilot contamination. To further improve channel estimation accuracy, CS is combined with angular-domain processing so that the virtual angular supports of correlated users become sufficiently separated, thereby minimizing overlap and reducing estimation errors.

Although the hybrid SPR-WGC-PD technique reported in the study [10] improves pilot assignment by combining two complementary strategies, it requires additional computational effort due to its multi-stage processing. In contrast, the proposed framework delivers better overall performance with a substantially lower computational burden, demonstrating a more efficient balance between estimation accuracy and implementation complexity.

Figure 3 illustrates the average achievable data rate per user as the number of BS antennas increases. As expected, reducing the antenna array size leads to a decline in spectral efficiency for all compared methods because of the lower spatial diversity. Nevertheless, the proposed scheme consistently achieves the highest achievable rate throughout the evaluated antenna range. Furthermore, the performance advantage becomes increasingly significant as the number of BS antennas grows, highlighting the effectiveness of the proposed sparsity-aware channel estimation approach in mitigating pilot contamination under massive MIMO conditions.

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). *Cureus J Eng* 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

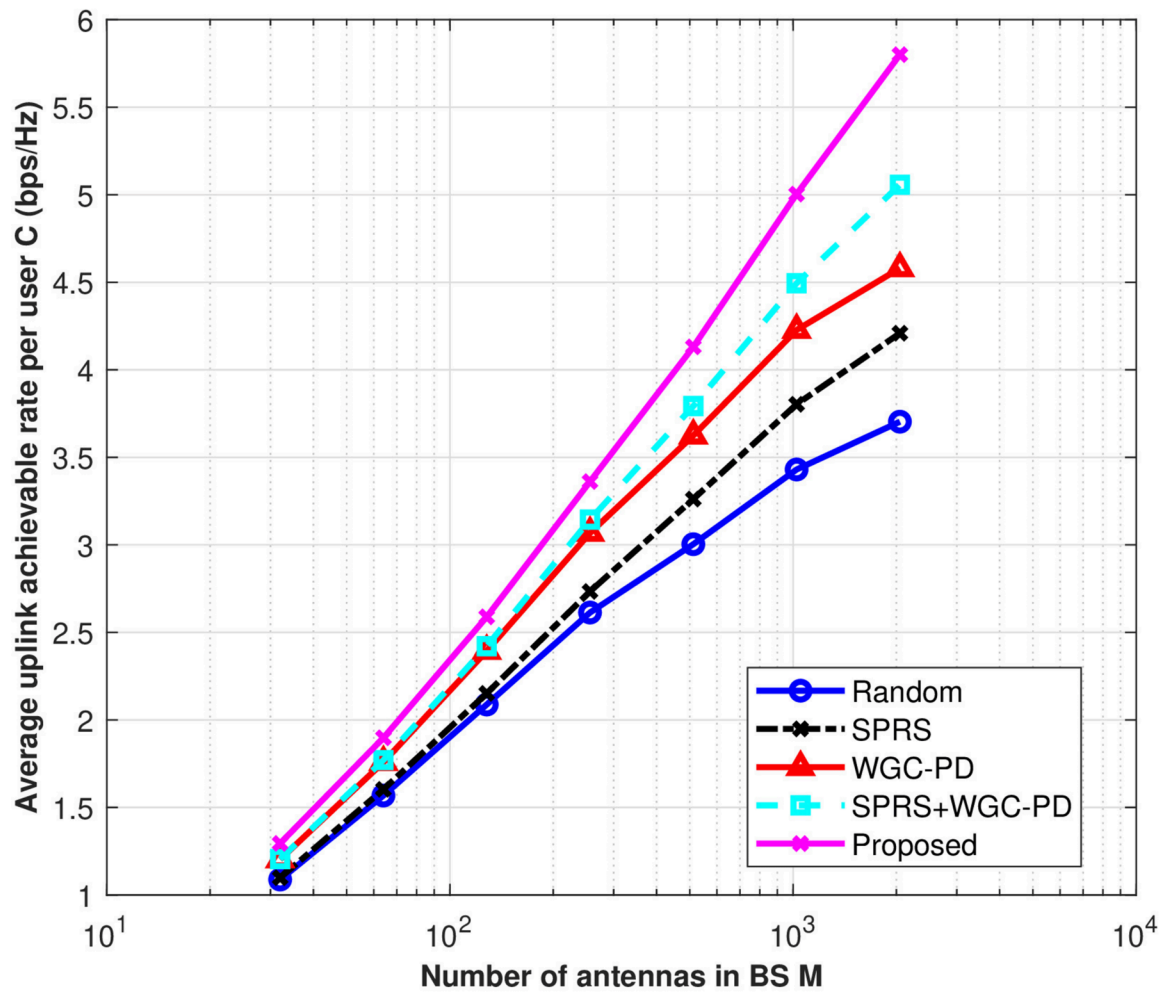


FIGURE 3: Average achievable sum rate per user vs number of BS antennas

BS, Base Station; WGC-PD, Weighted Graph Coloring Pilot Design; SPRS, Soft Pilot Reuse Scheme

Figure 4 illustrates the Cumulative Distribution Function (CDF) of the achievable rate per user. Our method achieves higher rates due to optimized pilot reuse and non-overlapping angular supports within groups, which reduces both inter-cell and intra-group contamination.

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

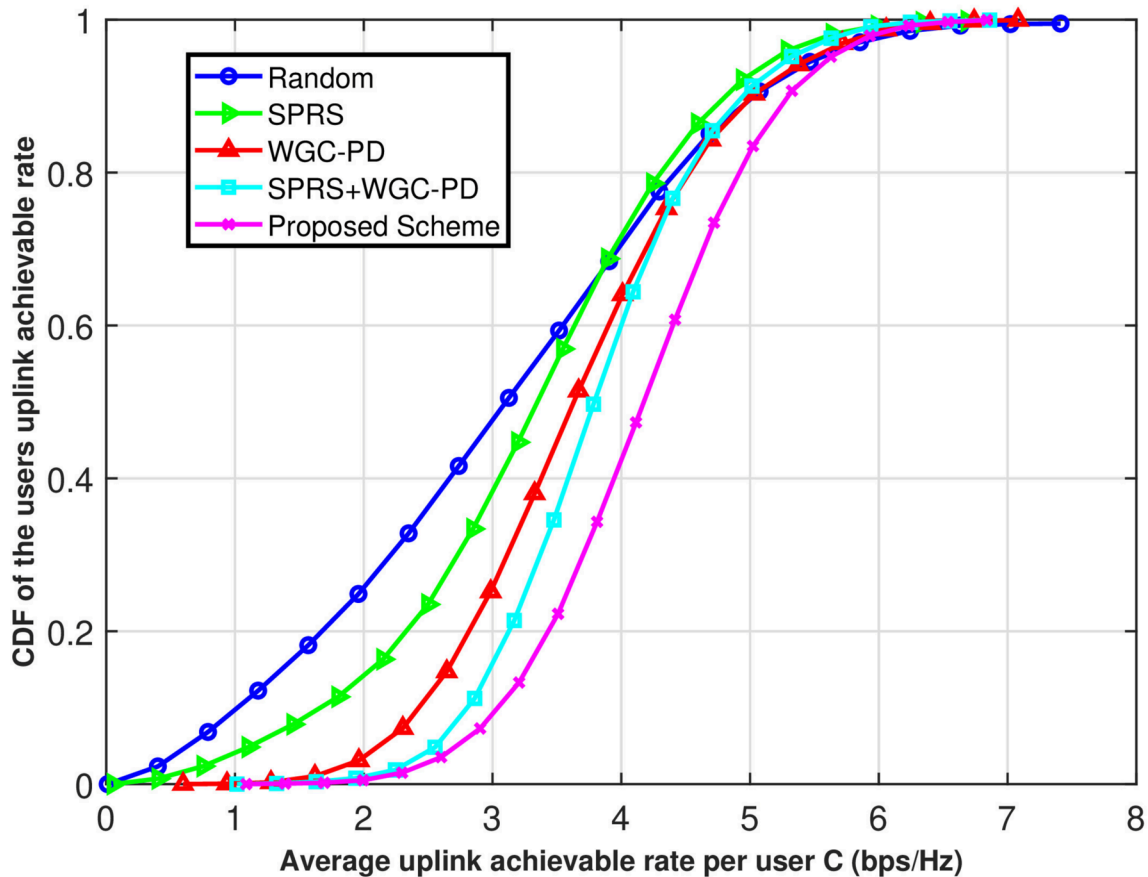


FIGURE 4: CDF of uplink achievable rate vs average rate per user

CDF, Cumulative Distribution Function; WGC-PD, Weighted Graph Coloring Pilot Design; SPRS, Soft Pilot Reuse Scheme

Figure 5 compares average cell throughput against the grouping parameter λ . Here, $\lambda = 0$ means all users are center users, and $\lambda = 1$ means all are edge users. The study [4] shows that throughput drops sharply with increasing λ (to 10~bps/Hz), while our method remains stable. This robustness comes from not reusing pilots across neighboring cells and from more accurate channel estimation within groups. GD-OMP has significantly lower computational complexity than SBL because it performs greedy support selection followed by least-squares estimation over a small support set. Consequently, the matrix inversion is limited to a $K \times K$ system, where $K \ll M$. In contrast, SBL repeatedly estimates hyperparameters through Bayesian inference and requires inversion of an $M \times M$ covariance matrix at every iteration, resulting in substantially higher computational cost. Although SBL may provide slightly improved channel estimation accuracy, GD-OMP offers a more favorable trade-off between estimation performance and computational efficiency, making it more suitable for real-time massive MIMO pilot decontamination.

To further highlight the computational trade-offs between the proposed GD-OMP algorithm and SBL, Table 2 summarizes the theoretical computational complexity of both methods. The total computational complexity of GD-OMP is given by ($\mathcal{O}(T(MN + K^3))$), where T denotes the number of greedy iterations, M is the number of measurements, N is the dictionary size, and K is the sparsity level, as reported in the study [14]. In contrast, the computational complexity of SBL is ($\mathcal{O}(IM^3)$), where I represents the number of Bayesian convergence iterations. This higher complexity arises from the repeated estimation of hyperparameters and inversion of an $M \times M$ covariance matrix during each iteration of the

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

Bayesian inference process [15]. As shown in Table 2, the significantly lower computational complexity of GD-OMP makes it a more practical choice for real-time massive MIMO channel estimation while maintaining competitive estimation performance.

Feature	GD-OMP (proposed scheme)	Sparse Bayesian Learning (SBL)
Recovery strategy	Greedy pursuit	Bayesian iterative
Per-iteration complexity	$(O(MN + K^3))$	$(O(M^3))$
Total complexity	$(O(T(MN + K^3)))$	$(O(I.M^3))$

TABLE 2: Comparison Table GD-OMP vs SBL

M: Number of Measurements / Observations
N: Dictionary / Grid Size (Dimension of the sparse vector)
K: Sparsity Level (Number of dominant active propagation paths)
T: Total Sparsity Iterations (Number of loops executed by the greedy algorithm)
I: Total Convergence Iterations (Number of outer loops executed by the Bayesian framework)
GD-OMP, Group-based Distributed Orthogonal Matching Pursuit; SBL, Sparse Bayesian Learning

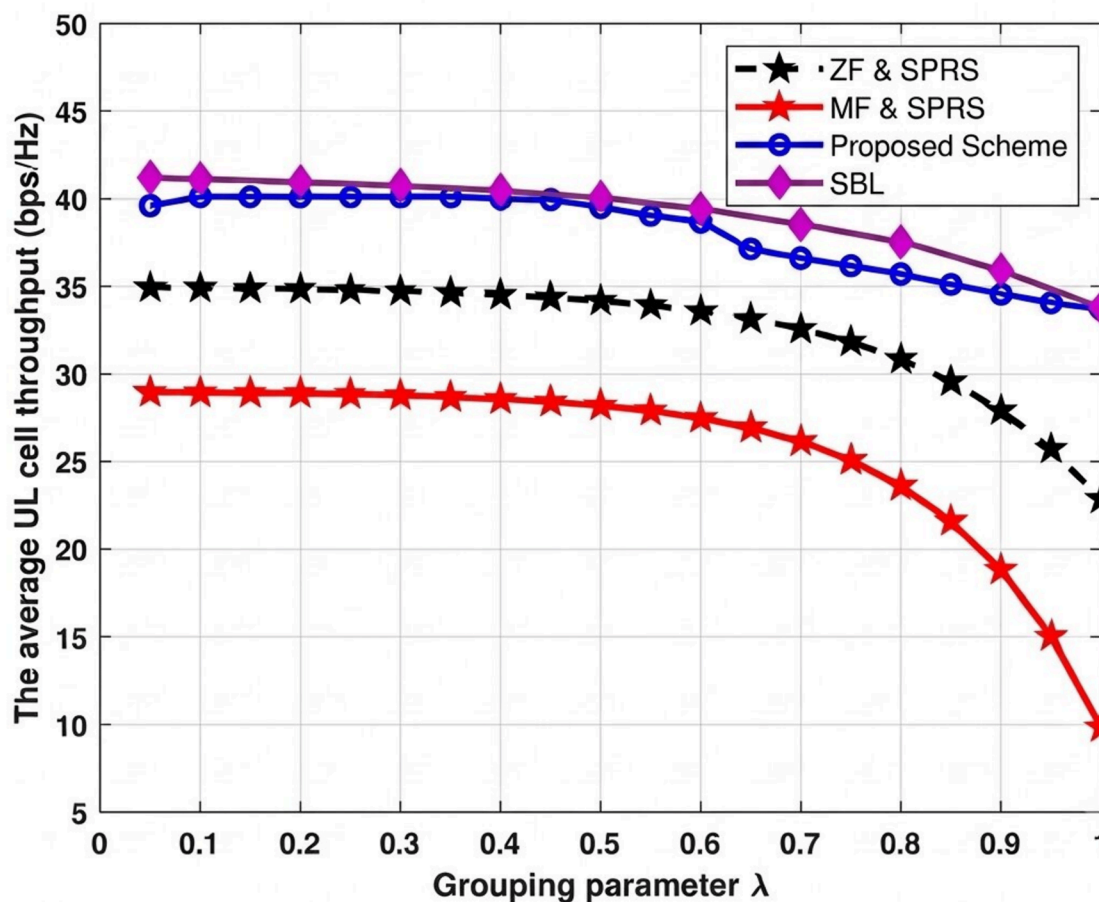


FIGURE 5: Average throughput vs grouping parameter λ

SPRS, Soft Pilot Reuse Scheme; SBL, Sparse Bayesian Learning

In Figure 6, increasing the number of center-user groups improves throughput. More groups allow the use of additional orthogonal pilots, enhancing performance. Throughput also improves with more BS antennas.

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

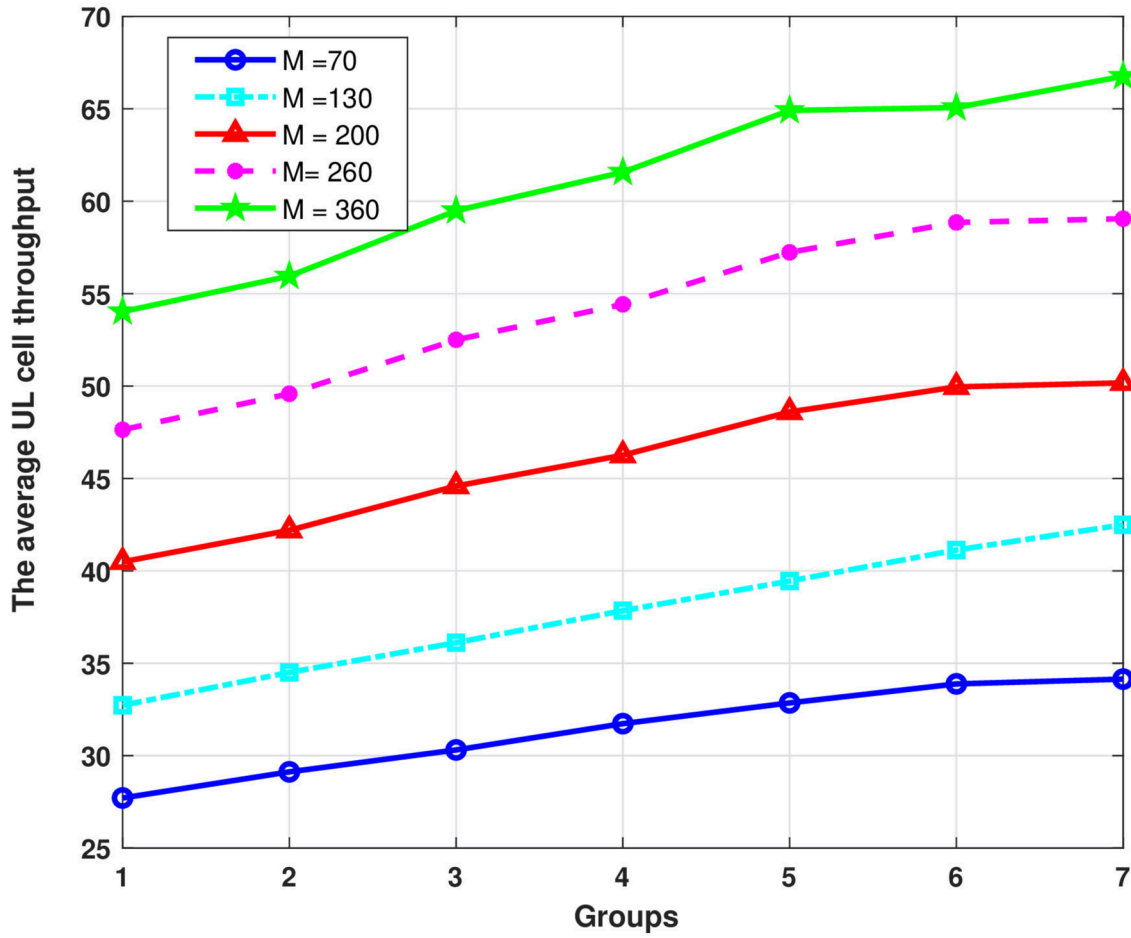


FIGURE 6: Average throughput vs number of center-user groups

Figure 7 shows the MSE for edge and center users as λ increases. For edge users, MSE is calculated as:

$$\text{MSE}^e = \mathbb{E} \left[\frac{1}{K_e} \sum_{i=1}^L \sum_{k=1}^{K_{i,e}} \frac{\|\hat{h}_{i,i,k}^e - h_{i,i,k}^e\|_2^2}{\|h_{i,i,k}^e\|_2^2} \right] \quad (16)$$

Similarly, for center users:

$$\text{MSE}^c = \mathbb{E} \left[\frac{1}{\left(\sum_{i=1}^L K_i \right) - K_e} \sum_{i=1}^L \sum_{k=1}^{K_{i,c}} \frac{\|\hat{h}_{i,i,k}^c - h_{i,i,k}^c\|_2^2}{\|h_{i,i,k}^c\|_2^2} \right] \quad (17)$$

How to cite this article:

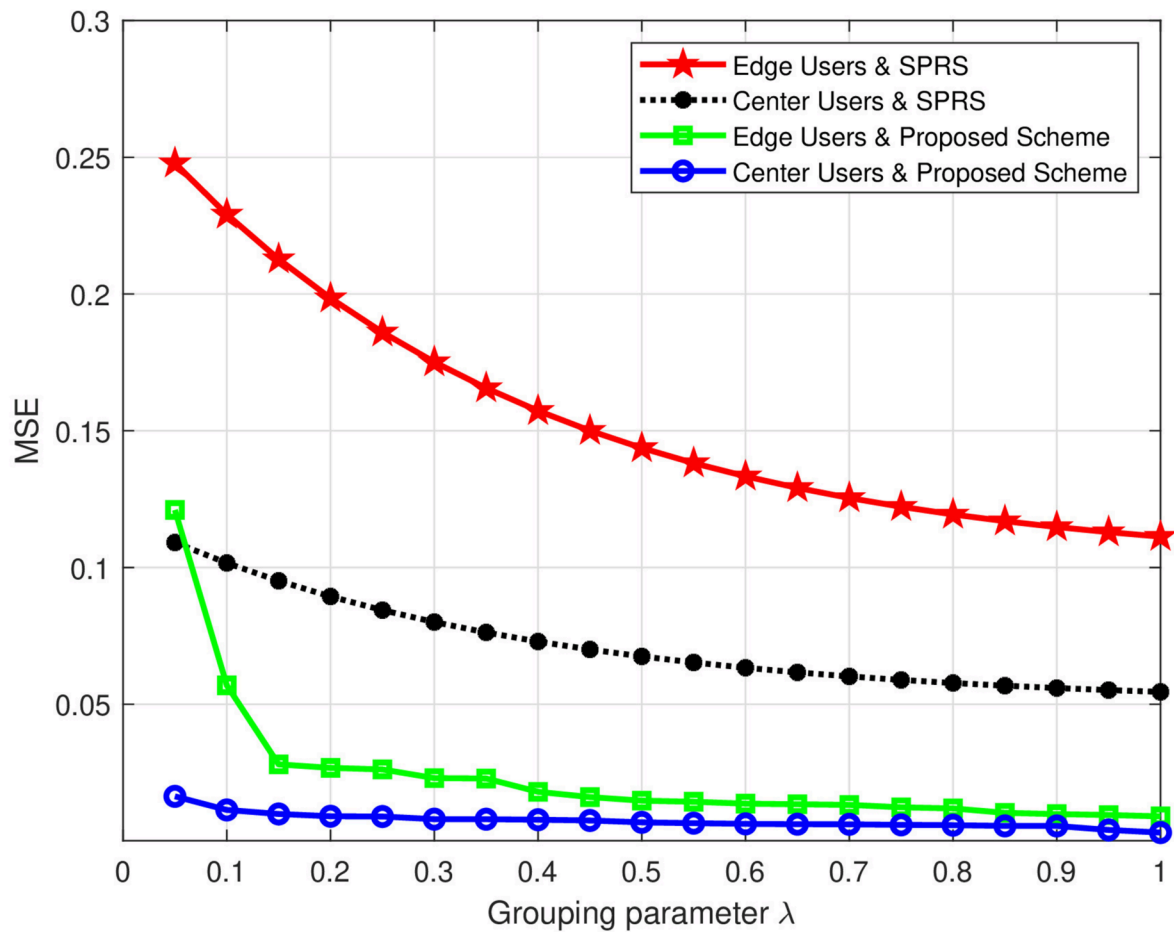


FIGURE 7: Mean square error (MSE) vs λ for center and edge users

SPRS, Soft Pilot Reuse Scheme

As anticipated, center users achieve lower channel estimation error because of their favorable propagation conditions and stronger received signal strength. More importantly, the proposed pilot grouping strategy substantially reduces the disparity in estimation accuracy between center and edge users compared with the SPR scheme in the study [4], resulting in a more balanced channel estimation performance across the network.

In summary, the proposed framework consistently outperforms the benchmark schemes by providing higher achievable data rates, sustaining robust throughput over a wide range of center-user ratios λ , and improving channel estimation accuracy. These performance gains are achieved with reduced pilot overhead and without introducing excessive computational complexity, making the proposed approach an efficient and scalable solution for cell-free massive MIMO systems.

Conclusions

This paper presents a pilot assignment and reuse scheme for massive MIMO uplink systems that leverages spatial correlation to mitigate pilot contamination. By transforming user channels into the angular domain using an extended DFT basis, the proposed approach enables separation through non-overlapping angular supports, improving channel estimation accuracy. Center users are grouped based on channel correlation, and a single orthogonal pilot is reused

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

within each group. Due to their lower susceptibility to contamination and distinct angular characteristics, intra-group interference remains limited. The proposed strategy effectively reduces the overall pilot reuse factor, allowing more efficient pilot utilization across neighboring cells. Although pilot reuse within a group may introduce minor power leakage, its impact is negligible under high channel correlation, making the scheme both practical and effective for dense massive MIMO deployments. Furthermore, the proposed framework maintains a favorable balance between estimation accuracy and pilot overhead, which is critical for scalable network design. The results also suggest that exploiting angular-domain sparsity can be a promising direction for future pilot design strategies. Overall, the scheme provides a low-complexity and efficient solution for improving uplink performance in next-generation wireless systems.

Appendices

Appendix A: Derivation of the Correlation Matrix

The uplink channel vector between the i -th user and the j -th BS, assuming a ULA at the BS, is given in (8) as:

$$\mathbf{h}_{ij} = \frac{1}{\sqrt{L_p}} \sum_{p=1}^{L_p} \alpha_{ij,p} \mathbf{a}(\varphi_{ij,p}) \quad (\text{A1})$$

where L_p is the number of multipath components, $\alpha_{ij,p}$ is the complex path gain for the p -th path, and $\mathbf{a}(\varphi_{ij,p})$ is the ULA steering vector as defined in (9).

The spatial correlation matrix $\mathbf{R}_{ij}$ is defined as:

$$\mathbf{R}_{ij} = \mathbb{E}\{\mathbf{h}_{ij} \mathbf{h}_{ij}^H\} \quad (\text{A2})$$

Substituting (A1) into the above expression:

$$\begin{aligned} \mathbf{R}_{ij} &= \mathbb{E} \left\{ \frac{1}{L_p} \left(\sum_{p_1=1}^{L_p} \alpha_{ij,p_1} \mathbf{a}(\varphi_{ij,p_1}) \right) \left(\sum_{p_2=1}^{L_p} \alpha_{ij,p_2} \mathbf{a}(\varphi_{ij,p_2}) \right)^H \right\} \\ &= \frac{1}{L_p} \sum_{p_1=1}^{L_p} \sum_{p_2=1}^{L_p} \mathbb{E} \{ \mathbf{a}(\varphi_{ij,p_1}) \mathbf{a}^H(\varphi_{ij,p_2}) \} \mathbb{E} \{ \alpha_{ij,p_1} \alpha_{ij,p_2}^* \} \end{aligned}$$

Assuming the path gains are uncorrelated across different paths, we have:

$$\mathbb{E} \{ \alpha_{ij,p_1} \alpha_{ij,p_2}^* \} = \beta_{ij} \delta(p_1 - p_2) \quad (\text{A3})$$

where β_{ij} is the large-scale fading coefficient (power gain).

This reduces the double summation to:

$$\mathbf{R}_{ij} = \frac{\beta_{ij}}{L_p} \sum_{p=1}^{L_p} \mathbb{E} \{ \mathbf{a}(\varphi_{ij,p}) \mathbf{a}^H(\varphi_{ij,p}) \} \quad (\text{A4})$$

If the AoA distribution is identical for all paths, then the summation yields L_p identical terms, which cancel with the $1/L_p$ factor:

$$\mathbf{R}_{ij} = \beta_{ij} \mathbb{E} \{ \mathbf{a}(\varphi_{ij}) \mathbf{a}^H(\varphi_{ij}) \} \quad (\text{A5})$$

From (9), the (m, n) -th element of $\mathbf{R}_{ij}$ becomes:

$$[\mathbf{R}_{ij}]_{(m,n)} = \beta_{ij} \mathbb{E} \left\{ e^{-j2\pi d(m-n) \cos(\varphi_{ij})} \right\} \quad (\text{A6})$$

How to cite this article:

Finally, expressing the expectation in terms of the AoA probability density function $f(\varphi)$, we have:

$$[\mathbf{R}_{ij}]_{(m,n)} = \beta_{ij} \int_0^{2\pi} e^{-j2\pi d(m-n)\cos(\varphi)} f(\varphi) d\varphi \quad (\text{A7})$$

Equations (A6)-(A7) provide the closed-form expression for the correlation matrix entries in terms of large-scale fading β_{ij} , antenna spacing d , and AoA distribution $f(\varphi)$.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Amna Javed, Farzana Kulsoom, Muhammad Iram Baig, Hassan Nazeer Chaudhry

Acquisition, analysis, or interpretation of data: Amna Javed, Farzana Kulsoom

Drafting of the manuscript: Amna Javed, Farzana Kulsoom, Hassan Nazeer Chaudhry

Critical review of the manuscript for important intellectual content: Farzana Kulsoom, Muhammad Iram Baig, Hassan Nazeer Chaudhry

Supervision: Farzana Kulsoom, Muhammad Iram Baig, Hassan Nazeer Chaudhry

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.

Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.

Conflicts of interest: In compliance with [the ICMJE uniform disclosure form](#), all authors declare the following:

- **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work.
- **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work.
- **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

References

1. Bjornson E, Larsson EG, Debbah M: [Massive MIMO for maximal spectral efficiency: How many users and pilots should be allocated?](#). IEEE Transactions on Wireless Communications. 2016, 15:1293-1308. [10.1109/twc.2015.2488634](#)
2. Sanguinetti L, Björnson E, Hoydis J: [Toward massive MIMO 2.0: Understanding spatial correlation, interference suppression, and pilot contamination](#). IEEE Transactions on Communications. 2019, 68:232-257. [10.1109/tcomm.2019.2945792](#)
3. Zhu X, Dai L, Wang Z, Wang X: [Weighted-graph-coloring-based pilot decontamination for multicell massive MIMO systems](#). IEEE Transactions on Vehicular Technology. 2016, 66:2829-2834. [10.1109/tvt.2016.2572203](#)

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>

4. Zhu X, Wang Z, Qian C, et al.: [Soft pilot reuse and multicell block diagonalization precoding for massive MIMO systems](#). IEEE Transactions on Vehicular Technology. 2015, 65:3285-3298. [10.1109/tvt.2015.2445795](#)
5. Haghighatshoar S, Caire G: [Pilot decontamination through compressive wideband channel estimation](#). 2016 50th Asilomar Conference on Signals, Systems and Computers, Pacific Grove, CA, USA. 2016:979-983. [10.1109/ACSSC.2016.7869513](#)
6. Kulsoom F, Vizziello A, Chaudhry HN, Savazzi P: [Joint sparse channel recovery with quantized feedback for multi-user massive MIMO systems](#). IEEE Access. 2020, 8:11046-11060. [10.1109/access.2020.2965280](#)
7. Lee J, Gil GT, Lee YH: [Exploiting spatial sparsity for estimating channels of hybrid MIMO systems in millimeter wave communications](#). 2014 IEEE Global Communications Conference, Austin, TX, USA. 2014. 3326-3331. [10.1109/GLOCOM.2014.7037320](#)
8. Gao Z, Dai L, Dai W, Shim B, Wang Z: [Structured compressive sensing-based spatio-temporal joint channel estimation for FDD massive MIMO](#). IEEE Transactions on Communications. 2016, 64:601-617. [10.1109/tcomm.2015.2508809](#)
9. Zhou L, Cao Z, Dai J: [Real-valued sparse Bayesian learning approach for massive MIMO channel estimation](#). IEEE Wireless Communications Letters. 2020, 9:311-315. [10.1109/lwc.2019.2953265](#)
10. Yuan W, Yang X, Xu R: [A novel pilot decontamination scheme for uplink massive MIMO systems](#). Procedia Computer Science. 2018, 131:72-79. [10.1016/j.procs.2018.04.187](#)
11. Mei Y, Gao Z: [CS-based CSIT estimation for downlink pilot decontamination in multi-cell FDD massive MIMO](#). 2021 IEEE/CIC International Conference on Communications in China (ICCC), Xiamen, China. 2021:1-5. [10.1109/ICCC52777.2021.9580398](#)
12. Rupasinghe N, Yapici Y, Iscar J, Guvenc I: [Impact of angular spread in moderately large MIMO systems under pilot contamination](#). IEEE Transactions on Vehicular Technology. 2018, 67:10631-10644. [10.1109/tvt.2018.2866799](#)
13. Kulsoom F, Vizziello A, Chaudhry HN, Savazzi P: [Pilot reduction techniques for sparse channel estimation in massive MIMO systems](#). 2018 14th Annual Conference on Wireless On-demand Network Systems and Services (WONS), Isola 2000, France. 2018, 111-116. [10.23919/WONS.2018.8311671](#)
14. Pati YC, Rezaiifar R, Krishnaprasad PS: [Orthogonal matching pursuit: recursive function approximation with applications to wavelet decomposition](#). Proceedings of 27th Asilomar Conference on Signals, Systems and Computers, Pacific Grove, CA, USA. 1993. 1:40-44. [10.1109/ACSSC.1993.342465](#)
15. Wipf DP, Rao BD: [Sparse Bayesian learning for basis selection](#). IEEE Transactions on Signal Processing. 2004, 52:2153-2164. [10.1109/tsp.2004.831016](#)

How to cite this article:

Javed A, Kulsoom F, Baig M, et al. (October 05, 2026) Joint Sparsity Exploitation and Angular Separation for Pilot Contamination Reduction in Massive Multiple-Input Multiple-Output (MIMO). Cureus J Eng 3 : es44388-026-00307-z. DOI <https://doi.org/10.7759/s44388-026-00307-z>