JCSDA, Vol. 02, No. 1, 16–28
DOI: 10.69660/jcsda.02012502
ISSN 2959-6912

Improved Pilot Decontamination Scheme for Massive MIMO Networks

Habib Mohammed Hussien and Yeabtsega H.Gebrewold

Department of Electrical and Computer Engineering, Artificial Intelligence and Robotics Center of Excellence
Addis Ababa Science and Technology, Addis Ababa, Ethiopia
habib.mohammed@aastu.edu.et

Improved pilot reuse and channel estimation approaches are proposed in this study to mitigate pilot contamination in massive Multiple input multiple Input (MIMO) networks. Pilot contamination is a major issue in circumstances with a high user density, where interference from adjacent users limits system efficiency. We propose a solution to address this by classifying users into active and idle groups based on their resource needs and channel circumstances, hence prioritizing active users for pilot assignment. A weighted graph coloring approach is used to assign pilot symbols to active users, minimizing interference by allocating neighboring users to distinct pilots. Based on their channel gain, each user's weight indicates their respective signal strength. In order to improve the quality of channel state information and further minimize contamination, we further investigated channel estimation techniques. The findings of the simulation demonstrate that compared to the weighted graph coloring currently in use, the improved pilot contamination mitigation technique offers notable improvements in spectrum efficiency. In dense network environments, these results show how the suggested methodology may enhance the performance of MIMO systems, offering a workable method for system optimization and resource allocation.

Keywords: Massive MIMO, Pilot Contamination, Channel State Information, Soft Pilot Reuse Scheme (SPRS), Active user, idle user, Weighted Graph Coloring Pilot Decontamination (WGC-PD).

1. Introduction

A major development in wireless communication systems, the transition from Multiple Input Multiple Output (MIMO) to Massive MIMO was motivated by the need to boost data rates, improve network performance, and increase spectrum efficiency. One of the most exciting developments in the next generation of wireless networks is massive MIMO. It can provide a number of benefits, including decreased latency, enhanced resilience and reliability, spectrum efficiency, energy efficiency, and multiplexing gain. In practice, these advantages need precise Channel state information (CSI) at the Base Station for uplink detection and downlink beam shaping [1]-[4]. The phenomenon of pilot contamination has been found as a significant problem affecting the performance of multi-cell multi-user massive MIMO systems. This causes the networks' achievable rates and spectrum efficiency to decrease [7]. Numerous efforts have been made to reduce pilot contamination from a variety of angles, including precoding-

based techniques, channel estimation-based techniques, and several innovative pilot assignment strategies. of the work that was done via precoding. Reducing the CSI estimate error brought on by pilot pollution may be accomplished effectively by improving the current precoding algorithm [4].

The impact of the pilot sequence on the functionality of such multi-cell multiple antenna systems is described in a study in [8]. This new precoding method, which is based on multi-cell MMSE, reduces Pilot Contamination (PC). The study shows that when pilot sequences are used for uplink training, the channel between the base station in one cell and the users in other cells inadvertently distorts the precoding matrix used by the base station in that cell. However, it assumes that the users and the base station have perfect CSI.

The study in [10] developed a smart pilot assignment (SPA) scheme that sequentially assigns a pilot sequence to a user, prioritizing the most degraded channel. In [6], a pilot assignment scheme based on cell sectorization-based pilot allocation (CS-PA) was proposed. This method uses orthogonal pilots between adjacent sectors and has increased system throughput when base station antennas increase to infinity, but its performance is limited when the number of base stations is reduced. The suggested smart pilot assignment successively assigns a pilot sequence with the least inter-cell interference to the user with the most severely reduced channel quality, in contrast to traditional techniques that use random assignments. In terms of Signal to Interference Plus Noise (SINR), it performs better than the conventional techniques.

The Location-Aware Pilot Assignment approach, which uses mobile devices' updated positions, is the subject of the other research in [8]. The technique uses mobile device locations to estimate channel statistics between base stations and mobile devices. However, in situations when mobility is great, it has limits.

Furthermore, the approach measures the equity of each user in the network using the harmonic SINR utility function, which is based on the asymptotic SINR [14]. It characterizes the pilot assignment issue as a minimum-weight multi-index assignment. Users in the nearby cells, which are near the base station and have the lowest velocity, can partially reuse pilot sequences thanks to the work in [11]. A new multi-factor social spider optimization algorithm (MSSOA) is used in this approach.

In [22], a technique for channel estimation based on location is proposed. This approach lessens the inter-cell interference brought on by the reuse of the pilot sequence by allowing users in different cells utilizing the same pilot sequence to have various Angles of Arrival (AOAs) at the base station.

Using CsiNet, a novel CSI detection and recovery mechanism that learns to efficiently employ channel structure from training samples [14], recent research concentrating on deep learning approaches [16] seems to offer promising answers for pilot contamination mitigation systems.

By using a large-scale fading factor, the study that combines Weighted Graph Coloring Pilot Decontamination (WGC-PD) and Soft Pilot Reuse Scheme (SPRS) in [6] separates all users in the cell into center and edge users.

The edge-weighted interference graph (EWIG) will create a weighted graph for cen-

ter users by measuring their levels of attachment based on pilot contamination. The pilot will then be assigned using the graph as a guide. To reduce pilot contamination, edge users in the same category will employ orthogonal pilots.
The method used in [9]'s additional work on SPRS and WGCPD allocates pilots to users of various cells according to their LSF coefficients and by taking use of a straightforward matrix layout.
While significant studies have been made in mitigating PC through advanced pilot assignment, signal processing, and deep learning techniques [3], [5], [6], challenges related to finding a way to perform well in an uncertain environment and improving pilot decontamination accuracy remain unresolved. Incorporating the SPRS and WGCPD [12] with accurate channel estimation and pilot decontamination methods as a hybrid form into a large number of antennas
By assigning unique, orthogonal pilot sequences to active users based on their activity levels and channel conditions. Active Users are users currently engaged in data transmission or voice calls. These users require distinct pilot sequences to accurately estimate their channels. An idle User: Users not currently transmitting data but still connected to the network. These users can share pilot sequences with acceptable interference.
We establish thresholds for determining whether a user is active or idle. For example, if a user's signal power exceeds a certain threshold, we classify them as active. To classify users as active or idle based on their signal power, we can establish a threshold value.
The classification can be determined using a simple signal power measurement approach. For channel estimation and equalization in digital communication systems, the Least Squares (LS) method is frequently employed in communication engineering. When the receiver uses pilot symbols to estimate the channel for slow time-varying frequency-selective channels, LS is the most straightforward and popular frequency-domain channel estimating technique [18].
We assume $x \in C^{M\times 1}$, as the sent signal vector and $y \in C^{J\times 1}1$ as the received signal vector for a single antenna user. Consequently, it is possible to derive the received signal vector, $y = Hx + w$, where $H \in C^{J\times M}$
is the matrix that represents the channel response, $w \in C^{J\times 1}$ is the noise vector
The cost function is minimized to give the estimated channel matrix $H^{\hat{}}$.

$$(H^{\hat{}}) = ||y - Hx^{\hat{}}||^2 \tag{1}$$

Setting the derivative of the cost function with respect to H to zero yields the following results, which are the solutions to the least squares problem:

$$H^{\hat{}} = (x^H x)^{-1} x^H y \tag{2}$$

In reality, the broadcast signal x could contain a known pilot signal with which the channel response vector H is estimated [14]. The channel response vector h is determined using the corresponding received pilot signal after the pilot signal is periodically inserted into the transmission signal. The received signal is then

equalized by dividing it by the estimated channel response vector, which removes the channel's effect on the received signal.
To remove the effects of the channel distortion from the received signal, the channel impulse response may be estimated using the LS approach and used for equalization [6]. Time-varying channels can also be accommodated by expanding the LS approach by utilizing a sliding window methodology, which estimates the channel impulse response using a limited window of received signal samples at each time instant [5].
One popular technique for channel estimation is the Minimum Mean Square Error (MMSE) algorithm. The channel estimate is determined using the mean square error criteria, which is $J(h^\wedge) = E\ h\ ||y - xHh^\wedge||^2$. For the MMSE channel estimation technique, minimizing $J\ (h^\wedge)$ is the mean squared error criterion.
The MMSE solution is obtained by taking the partial derivative of $h^\wedge$ and setting it to zero:

$$H_{MMSE} = R_{hy} R_{yy}^{-1} y \tag{3}$$

where R_{hy} and R_{yy} can be acquired through:

$$R_{hy} = E[hY]^H = (R_{HH})y \tag{4}$$

$$R_{yy} = E\left[yy^H\right] = x\ (R_{HH})\ X^H + {}^2_w I \tag{5}$$

In this case, $\sigma^2 w$ is the wireless signal's noise variance, R_{HH} is the channel matrix's autocovariance matrix, $R_{\ yy}$ is the received data matrix Y's autocovariance matrix, and $R_{\ hy}$ is the cross-covariance matrix between the channel matrix H and the received data matrix Y. Therefore, the MMSE channel estimate solution may be found by combining Equations (2) and (3) as follows:

$$H^\wedge{}_{MMSE} = R_{HH}\left[R_{HH} + ,\sigma^2 w\ (XX)^{-1}\right]^{-1} H^\wedge \tag{6}$$

2. Mathematical Modeling

3. Modeling MIMO Communication Systems

The channel from a user to the base station (BS) may be represented using the channel vector for a multi-cell system with L cells, where each BS has M antennas and serves K users:

$$h_{lik} = [h_{lik1}, h_{lik2} \ldots\ldots..h_{likM}] \tag{7}$$

In the l^{th} cell, the channel gain from the k^{th} user to the m^{th}antenna of the l^{th} BS is denoted as h_{likM} . In order to minimize the mean square error, MMSE channel estimation aims to estimate this channel vector from the received signals.
The autocorrelation matrix $R_{h_{lik}}$of channel vector can be represented as:

$$R_{h_{lik}} = E\left[h_{lik} h_{lik}^H\right] \tag{8}$$

Where E [·] denotes the expectation operator and ^{H} denotes the Hermitian transpose

Assuming that a certain correlation model explains the relationship between the channel gains h_{lik}

$$R_{h_{lik}} = \begin{bmatrix} \rho(0) & \rho(0) & \dots & \rho(\tau_{M-1}) \\ \rho(\tau) & \rho(0) & \dots & \rho(\tau_{M-2}) \\ \vdots & \vdots & \ddots & \vdots \\ \rho(\tau_{M-1}) & \rho(\tau_{M-2}) & \dots & (\rho(0)\ ) \end{bmatrix}$$

It is possible to describe the received uplink training sequences at the ith BS as a M × N matrix, which is defined as follows:

$$Y_i = \sqrt{p}\sum_{l=1}^{L} G_{il}\phi^H$$

where Ni is the M × N noise matrix with independently distributed components that are identically distributed after CN (0, 1), and p is the pilot power or average pilot signal-to-noise ratio.

$$Z_{ik} = \frac{1}{\sqrt{p}}Y_i = \sum_{l=1}^{L} f_{iik} + w_{lk} \tag{9}$$

4. Modeling Enhanced PR and MMSE Channel Estimation for MASSIVE MIMO Communication

Assume a multicellular L cells as in Fig. 1.4, in which every cell has a base station at its center, N antenna elements are present in the base station, and K randomly distributed single antenna users. Both users and antennas are considered to have separate Rayleigh fading channels. A multi-cell multi-user Massive-MIMO system with N non-cooperative hexagonal cells is shown in Fig. 1. K single-antenna users are served simultaneously by a single BS with N antennas, which supplies time-frequency resources for every cell. We assume a frequency-flat fading channel with mutually uncorrelated fading coefficients [10]. The two underlying assumptions of the model are that (1) the transmitter and receiver's antenna components are geographically well separated and that the channel gain will decrease with increasing spatial separation, leading to a decreased spatial channel correlation [9].

With reference to the observation Y_i at the ith BS, the MMSE channel estimator of φ_{iik} $\forall k$ is obtained by

$$\varphi_{iik}^{MMSE} = \frac{R_{iik}}{Q_{ik}}Z_{ik} = R_{iik}Q_{ik}^{-1}Z_{ik} \tag{10}$$

The channel estimate φ_{iik}^{MMSE} and the estimation error is caused by the Gaussian model's MMSE characteristics.

$$\widetilde{\varphi}_{iik}^{MMSE} = \varphi_{iik} - \widehat{\varphi}_{iik}^{MMSE} \tag{11}$$

Since both are simultaneously complex Gaussian-distributed, the estimator $\widehat{\varphi}_{iik}^{MMSE}$ is independent of the de-spread received vector Z_{ik} and does not correlate with it. For each antenna, the MMSE estimator's MSE is provided by

$$\eta_{ik}^{MMSE} = \frac{1}{M} E \left\{ \left\| \widehat{\varphi}_{iik}^{MMSE} - \varphi_{iik} \right\|^2 = \frac{1}{M} Tr[R_{iik} - R_{iik} Q_{ik}^{-1} R_{iik}\,] \right. \tag{12}$$

For every i, l, and k, if the components of φ_{iik} are circularly-symmetric complex normal variables. Then

$$Q_{ik} = \zeta_{ik} I_M = (\sum_{L=1}^{L} \beta_{iik} + \left(\frac{1}{p}\right) I_M \text{ , } \mathit{and} \tag{13}$$

$$R_{iik} = \beta_{iik} I_M$$

Therefore: $\eta_{ik}^{MMSE} = \beta_{iik} - \beta_{iik}^2 / \zeta_{ik}$ due to pilot contamination

$$\eta_{ik}^{MMSE} \approx \frac{1}{M} Tr[R_{iik} - \frac{R_{iik}^2}{\sum_{l=1}^{L} R_{iik}}] \tag{14}$$

As p $\rightarrow \infty$ and if φ_{iik} is an i.i.d. complex Gaussian vector, then

$$\eta_{ik}^{MMSE} = \beta_{iik} \left(1 - \frac{\beta_{iik}}{\sum_{l=1}^{L} \beta_{iik}} \right) \tag{15}$$

If R_{iik} is invertible, then we say that:

$$\widehat{\varphi}_{iik}^{MMSE} = R_{iik} R_{iik}^{-1} \widehat{\varphi}_{iik}^{MMSE} \tag{16}$$

As demonstrated by the authors [16], if R_{iik} Channels are not parallel vectors if they are mutually asymptotically linearly independent. As a result, the BS can divide users sending the same pilot sequence. The basis for estimating $Q_{ik}$is the fact that

$$E \left[Z_{ik} Z_{ik}^H \right] = Q_{ik} \tag{17}$$

$$\hat{Q}_{ik} = \frac{1}{N_Q} \sum_{n=1}^{N_Q} Z_{ik}(n) Z_{ik}^H(n) \tag{18}$$

Where $Z_{ik}(n)$, n = 1... N_Q Are the N_Q different observations
We see that:

$$E \left[\hat{Q}_{ik} \right] = Q_{ik} \tag{19}$$

$$A = \begin{bmatrix} User & pilot1 & pilot2 & \cdots & pilot\ p \\ user1 & a_{11} & a_{12} & \cdots & a_{1p} \\ user2 & a_{21} & a_{22} & \cdots & a_{1p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ userk & a_{k1} & a_{k2} & \cdots & a_{kp} \end{bmatrix}$$

Where a_{kl}=1 if user k is assigned to pilot l, otherwise $a_{kl} = 0$
The following is a mathematical expression for user I's classification:

$$\text{Activity (i)} = \left\{ \begin{array}{c} \text{Active, if } p_i > p_{th} \\ \text{idle if } p_i < p_{th} \end{array} \right\}$$

There are two subsets of the entire orthogonal pilot resource set, one for active users and one for idle users. Idle users share the remaining orthogonal pilots, while active users are given priority.

$$q_{all} = q_{ac} + q_{id} \tag{20}$$

$$f_{all} = \left[f_{act}^T f_{id}^T\right]^T \tag{21}$$

Where f_{act} , is the pilots for active users and f_{id} is the pilot for active users
Pilot contamination occurs when several users share the same pilot sequence, altering the channel estimates' correlation structure. If N_l active users share pilot l, the effective channel correlation matrix can be modified to account for this contamination.

$$R_{y_{lik}}^{effective} = \sum_{m=1}^{N_l} R_{h_{lki}}(a_{km} = 1) \tag{22}$$

This changes the received signal correlation matrix to:

$$R_{y_{lik}}^{effective} = P_k R_{h_{lik}}^{effective} + s^2 I \tag{23}$$

$$MSE_{lki}^{contaminated} = Tr(R_{h_{lik}}^{effective} - R_{h_{lik}}^{effective}(P_k R_{h_{lik}}^{effective} + s^2 I)^{-1}) \tag{24}$$

Received signal strength, which influences their priority for pilot assignment.

5. Simulation and results

In this part, we use a series of Monte Carlo simulations to assess how well the two approaches of interest perform in mitigating PC in Massive MIMO. With a BS of M antennas at the center of each cell, we consider a system of L hexagonal cells serving K single-antenna users. Our simulation parameters are listed in Table 4.1. Here, we contrast the advantages of our suggested algorithms with those of the weighted graph coloring WGC scheme, which has been shown to be one of the most effective ways to reduce PC, and the conventional strategy, which is the random allocation approach.
Table 4.1 Parameters in Simulation

users in one cell (K)	10
Number of cells (J)	19
Pilot sequences (Q)	K≤Q≤KJ 20 if fixed
Spectral efficiency loss ($_0$)	0.06
Number of Antennas in a base station	42∼2048 256 if fixed
Threshold ()	0.06≤≤1 0.1 if fixed
Transmit power (d_p)	6∼30 dB 16 if fixed
Shadow fading (σ)	6dB

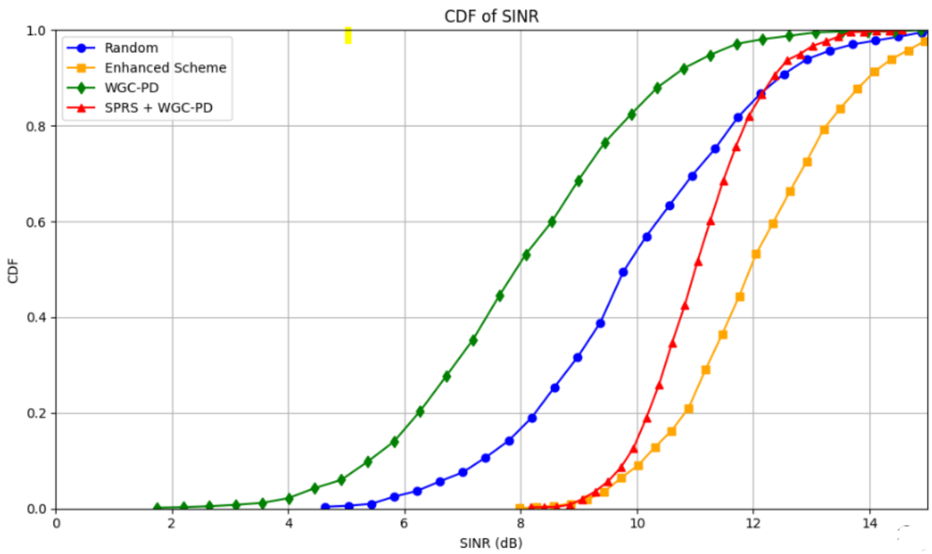

Fig. 1. CDF of average uplink achievable rate per

The average uplink rate per user achievable for the several methods under consideration is shown in Fig. 2. The simulation findings unequivocally demonstrate that, in comparison to the WGC-PD and SPRS+WGC-PD approaches, respectively, the suggested strategy delivers a comparatively higher average uplink attainable rate per user. It is evident that the Random pilot approach has the lowest performance.

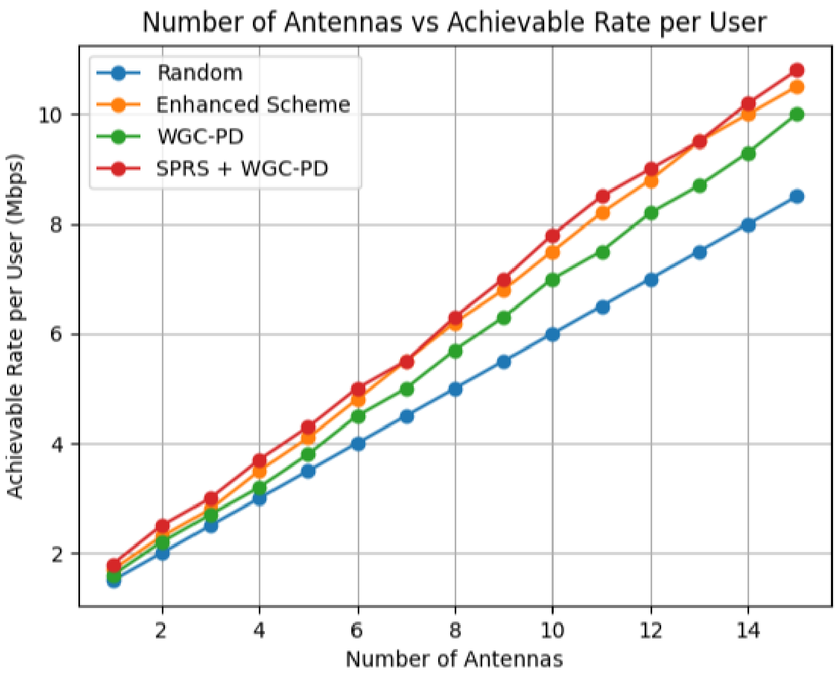

Fig. 2. Number of antennas vs achievable rate per user

Comparison in Performance of Enhanced pilot allocation and Random WGC-PD SPRS+WGC-PD for the number of antennas vs Achievable Rate per user

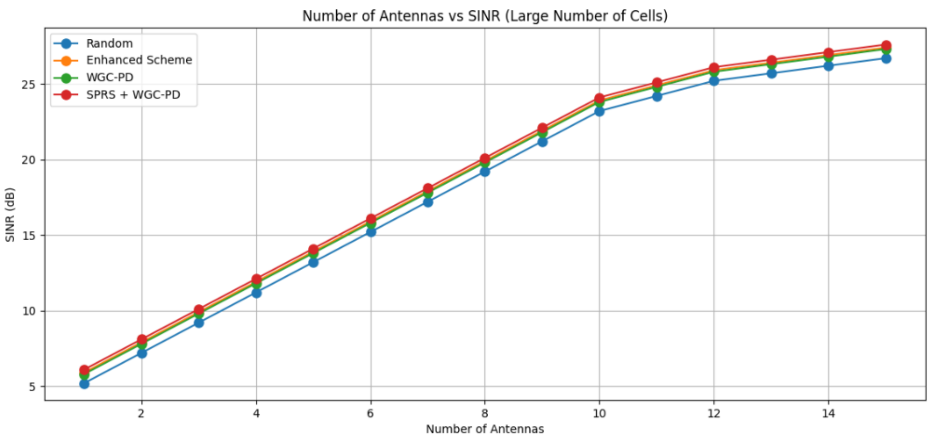

Fig. 4. Number of antennas vs SINR

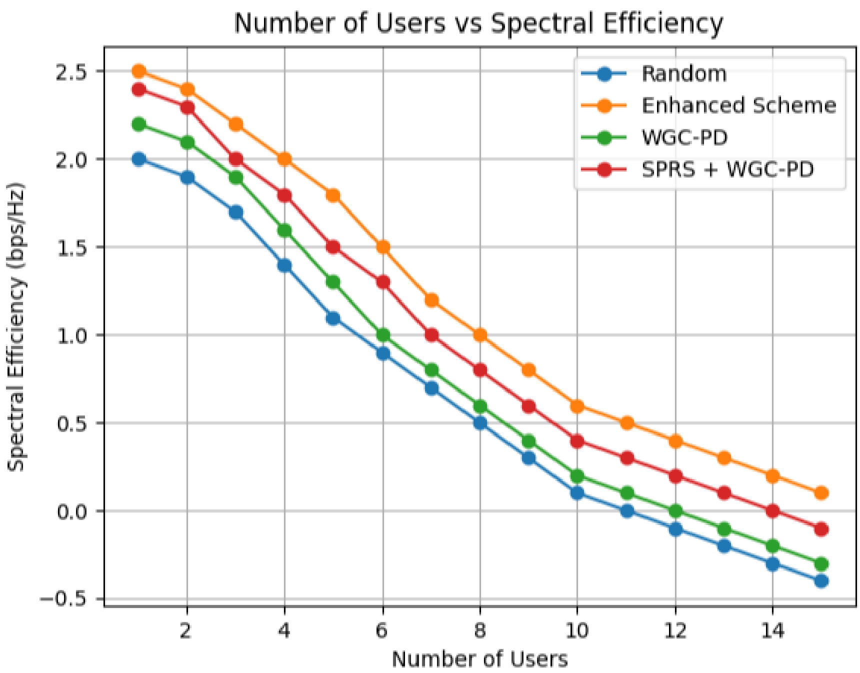

Fig. 3. Number of users vs Spectral Efficiency

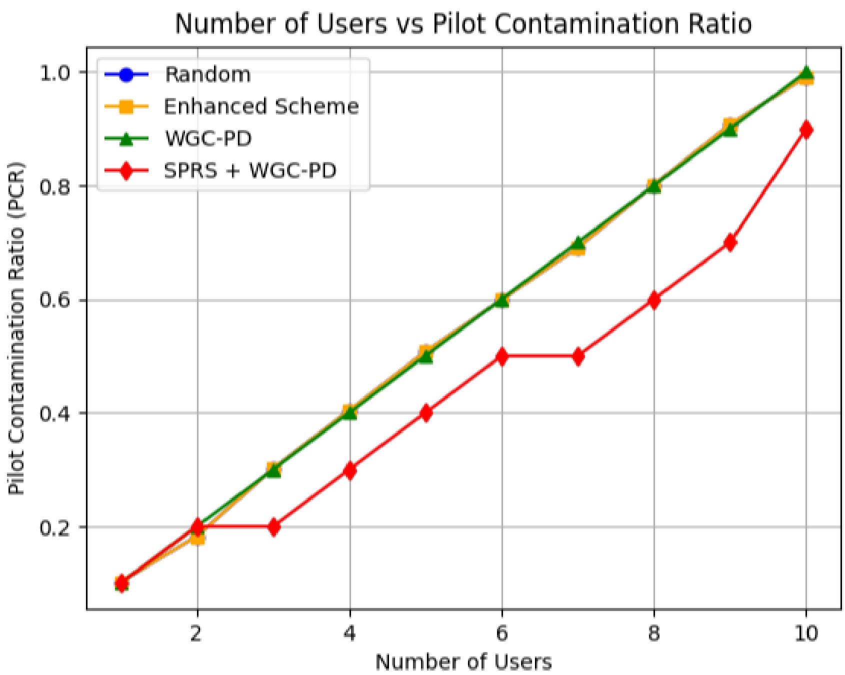

Fig. 5. Number of users vs pilot contamination ratio

The simulation's findings indicate that the recommended Enhanced Pilot Reuse Scheme performs noticeably better than other methods, such as Weighted Graph Coloring with Pilot Decontamination (WGC-PD) and Random Pilot assignment (SPRS). The Enhanced Scheme delivers greater spectrum efficiency, improved channel estimate accuracy, and improved network performance across a range of simulation scenarios by cleverly allocating pilots and minimizing inter-cell interference. This strong performance demonstrates how well the plan can reduce pilot contamination in large MIMO networks.

6. Conclusion

This research examines the critical issue of pilot contamination in large MIMO networks and proposes an enhanced pilot allocation strategy as a solution. The study showed the higher performance of the suggested method while examining the drawbacks of traditional schemes like Weighted Graph Coloring with Pilot Decontamination (WGC-PD), Random Pilot Allocation, and Soft Pilot Reuse Schemes (SPRS). The improved spectrum efficiency, increased channel prediction accuracy, and successful inter-cell interference mitigation were all attained by the Enhanced Pilot allocation scheme through rigorous simulations. The results demonstrate how intelligent pilot reuse and sophisticated channel estimate methods may improve large MIMO systems' performance, scalability, and reliability while meeting the needs of next-generation wireless communication networks.

References

1. Z. Zhao, Z. Chen, & Y. Liu (2015). Cell Sectorization-Based Pilot Assignment Scheme in Massive MIMO Systems. In the 2015 Wireless Telecommunications Symposium. (pp. 1– 5). New York, NY: IEEE. https://doi.org/10.1109/WTS.2015.7117245
2. B. Gopalakrishnan and N. Jindal, "An analysis of pilot contamination on multi-user MIMO cellular systems with many antennas," in IEEE 12th International Workshop on Signal Processing Advances in Wireless Communications. IEEE, June 2011, pp. 381–385, 10.1109/SPAWC.2011.5990435.
3. H. Yin, D. Gesbert, M. Filippou, and Y. Liu, "A coordinated approach to channel estimation in large-scale multiple-antenna systems," IEEE Journal of Selected Areas in Communications, vol. 31, no. 2, pp. 264– 273, February 2013
4. H. Wang, Z. Pan, J. Ni, S. Wang, and C.-L. I, "A temporal domain-based method against pilot contamination for multi-cell massive MIMO systems," in IEEE Vehicular Technology Conference (VTC) spring, Seoul, Korea, May 2014.
5. V. Saxena, G. Fodor, E. Karipidis, "Mitigating Pilot Contamination by Pilot" Reuse and Power Control Schemes for Massive MIMO Systems," article in IEEE Vehicular Technology Conference · July 2015

6. X. Zhu, Z. Wang, L. Dai,& C. Qian (2015). Smart Pilot Assignment for Massive MIMO. IEEE Communications Letters, 19(9), 1644–1647. https://doi.org/10.1109/ LCOMM.2015.2409176
7. A. Ashikhmin and T. Marzetta, “Pilot contamination precoding in multicell large-scale antenna systems,” in IEEE International Symposium on Information Theory Proceedings. IEEE, 2012, 978-1-4673-2579-0/12/.
8. J. Ma, C. Liang, C. Xu, & L. Ping (2017). On Orthogonal and Superimposed Pilot Schemes in Massive MIMO NOMA Systems. IEEE Journal on Selected Areas in Communications, 35(11),2696–2707. https://doi.org/ 10.1109/JSAC.2017.2726019
9. S. J. Mingmei Li and X. Gao, “Spatial orthogonality-based pilot reuse for multi-cell massive MIMO transmission,” in 2013 International Conference on Wireless Communications & Signal Processing (WCSP), Hangzhou, October 24-26, 2013, doi:10.1109/WCSP.2013.6677139
10. K. Upadhya, S. Vorobyov, & M. Vehkapera (2017). Superimposed pilots are superior for mitigating pilot contamination in massive MIMO. IEEE Transactions on Signal Processing, 65(10), 2917–2932. https://doi. org/10.1109/TSP.2017.2675859
11. A . Ashikhmin and T. Marzetta, “Pilot contamination precoding in multi-cell large scale antenna systems,” in IEEE International Symposium on Information Theory Proceedings. IEEE, 2012, 978-1-4673-2579-0/12/.
12. H. Yan, & Y. Chen(2020). A pilot assignment scheme for a multi-cell massive MIMO system. In 2020 International Conference on Electronics, Information, and Communication (ICEIC) (pp. 1–4). IEEE. https:// doi.org/10.1109/ICEIC49074.2020.9051104
13. H. Wang, Z. Pan, J. Ni, S. Wang, and C.-L. I, “A temporal domain-based method against pilot contamination for multi-cell massive MIMO systems,” in IEEE Vehicular Technology Conference (VTC) spring, Seoul, Korea, May 2014.
14. S.M. Shaabi, M.A. Mosleh,& M. Ardebilipour (2020). Low-complexity AoA-driven pilot assignment for multi-cell massive MIMO systems. Physical Communication, 42, 101118. https://doi.org/10.1016/ j.phycom.2020.101118
15. R. Muller, L. Cottatellucci, and M. Vehkapera, “Blind pilot decontamination,” IEEE Journal of Selected Topics in Signal Processing, 2014, doi: 10.1109/JSTSP.2014.2310053.
16. E. Bjönson (2016). Massive MIMO for maximal spectral efficiency: how many users and pilots massive MIMO for maximal spectral efficiency: How many users and pilots should be allocated? IEEE Transactions on Wireless Communications, 15(2), 1293–1308. https:// doi.org/10.1109/TWC.2015.2488634
17. L. Su,& C. Yang (2015). Fractional frequency reuse aided pilot decontamination for massive MIMO systems. IEEE Vehicular Technology Conference, 2015. https:// doi.org/10.1109/VTCSpring.2015.7145845

18. R. Zho, Y. Fu, & H. Wang (2018). Uplink Asynchronous Fractional Pilots Scheduling in Massive MIMO System. In 2018, IEEE 18th IEEE International Conference on Communication Technology. Chongqing, China (pp. 402–406). IEEE. https://doi.org/10.1109/ICCT.2018. 8600231
19. L. Sanguinetti, A. Moustakas, and M. Debbah, "Interference management in 5G reverse TDD HetNets with wireless backhaul: A large system analysis," IEEE J. Sel. Areas Commun., vol. 33, no. 6, pp. 1187–1200, Jun. 2015.
20. E. Björnson, J. Hoydis, M. Kountouris, and M. Debbah, "Massive MIMO systems with nonideal hardware: Energy efficiency, estimation, and capacity limits," IEEE Trans. Inf. Theory, vol. 60, no. 11, pp. 7112–7139, Nov. 2014.
21. E. Björnson, E. G. Larsson, and M. Debbah, "Massive MIMO for maximal spectral efficiency: How many users and pilots should be allocated?" IEEE Trans. Wireless Communication, vol. 15, no. 2, pp. 1293–1308, Feb. 2016.
22. X. hu, Z. Wang, L. Dai, and C. Qian, "Smart pilot assignment for massive MIMO," IEEE Commun. Lett., vol. 19, no. 9, pp. 1644–1647, Sep. 2015
23. C.-K. Wen, W.-T. Shih, & S. Jin (2018). Deep learning for massive MIMO CSI feedback