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A Dynamic Optimization based Algorithm for Pilot Assignment in Massive MIMO

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In this study, we propose an efficient algorithm for the optimization of pilot assignment to reduce pilot contamination in multi-cell multi-user massive multiple-input multiple-output (MIMO) systems. The object function of the proposed optimization approach is based on the cumulative average uplink Signal to Interference plus Noise Ratio (SINR) values. This method effectively optimizes pilot-user matchings using an efficient search which wisely reduces both search spaces of users and pilots. It dynamically calculates search space reductions after updating each cell iteratively. This reduction is performed by selecting only the users whose SINR value is below the average SINR of the each cell. On the other hand, the pilot's search space is reduced by choosing only the least-used pilots within close neighboring cells' pilot usages. This calculation is performed for each cell to increase the cumulative average SINR (global SINR) value. Pilot contamination is reduced to minimum levels with less complexity and memory requirements with the proposed method in this manner. The simulation results indicate that the proposed method outperforms the recent popular analytical and deep learning-based pilot assignment approaches. The achieved improvement is even more prominent when all the pilots are fully used.

Keywords: dynamic optimization, massive MIMO, pilot assignment, pilot contamination, capacity optimization

1. INTRODUCTION

Massive MIMO system has been a very popular type of wireless communication technologies recently. It plays a significant role in 5G and beyond wireless communication systems. In massive MIMO, base stations have a huge number of antenna elements to improve spectral and energy efficiency. The large number of antennas also provides a more accurate channel estimation for all users. Each user transmits a sequence of known symbols to the base station for the channel estimation. These sequences are called as *uplink pilot sequences*. Users in different cells may use the same pilot sequences, since there is a limited number of pilot sequences to be assigned. It basically leads to interference between the users using the same pilots. This problem is called as *pilot contamination* in wireless communication. In this study, a new approach has been developed to reduce efficiently the pilot contamination in a unique way.

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As mentioned in [1–3], the pilot contamination problem has been studied extensively and various approaches are developed. In [4], channel estimation performance is investigated for the massive MIMO systems having serious pilot contamination. They propose a scheme to mitigate pilot contamination in time division duplexing (TDD) cellular networks.

A partial pilot power control scheme has been proposed in [5] by dividing the time slot of the pilots into two parts. In the first part, only the pilots leading to the interference are transmitted while in the second part, other pilots are transferred. Therefore, they do not overlap, and the whole pilots are transferred for each time interval. The effectiveness of pilot utilization in neighboring cells to obtain better channel estimates by shifting them in time frames was examined in [6]. The requirements for the comparison and superiority of the time-shifted pilot transmission method over the time-synchronized method with spatial multiplexing are presented in [7]. In [8], it proposes a method to prevent simultaneous transmissions of non-orthogonal pilot from adjacent cells. The effects of power allocation are also investigated in this interferenced scenario. It is reported that the combination of these two techniques are realized in that study.

In another technique [9], the edge and center users are decomposed to focus on the contamination in edges. The soft pilot reuse scheme (SPRS) is used to handle the contamination in the cell edges. However, this study requires relatively more pilot sequences. In the smart pilot assignment (SPA) [10] method, pilot sequences are randomly assigned to users, and then they are optimized using the aim of the smallest inter-cell interference. In [11], a hybrid pilot assignment method is proposed. This hybrid structure was formed by combining SPRS and weighted coloring graph pilot decontamination (WCG-PD) [17] techniques. A weighted coloring graph-based technique has been proposed to reduce pilot contamination, especially for edge users. As a heuristic approach, in [18], it is proposed a hybrid pilot assignment method by combining SPRS (Soft Pilot Reuse Scheme) and Munkres pilot assignment methods for reducing pilot contamination. In [19], it is achieved a pilot contamination reduction success by using ant colony optimization as a metaheuristic approach that creates a pilot assignment scheme. In [13], the Deep Learning-based Pilot Assignment Scheme (DLPAS) focuses on learning the relationship between pilot assignment and the users' position patterns. This study allows only 4 users for each cell due to high dimension output like (number of users)$\times$(number of cells). Therefore, the number of cells is only 7 while other system simulations of [10–12] use 19 cells to get a more realistic massive MIMO system model. For many users and cells, as in real-life scenarios, this output representation does not seem feasible to implement.

The main contributions of this work are summarized as follows,

- The proposed Dynamic Optimization Algorithm for Pilot Assignment Schemes (DOAPAS) *dynamically* calculates the reduced pilot and users search spaces for the efficiency of algorithm.
- It always assert providing more optimal pilot assignment than initial assignment by progressively updating and checking cumulative SINR value.
- Simulations are performed by 10 users and 19 cells which are more realistic to real life scenarios.

The remainder of this paper is organized as follows: Section 2 describes the system model with several mathematical details. Section 3 explains the proposed approach along with important assumptions. In Section 4, results and related analyses are presented. Section 5 summarizes the study with concluding remarks and possible future extension.

2. SYSTEM MODEL

In this article, an uplink massive MIMO system with a multi-cell model is utilized to investigate the effects of pilot contamination. The maximum number of active mobile users having single-antennas within a cell is denoted by K; furthermore, the number of cells in this massive MIMO system is represented by L, and the antenna number in the base stations is individually M assuming that M goes to infinity.

Wireless channels between users and base stations are assumed to have large-scale fading (LSF) and small-scale fading (SSF) characteristics. The LSF channel can be modeled by path-loss and shadowing factors. The LSF coefficient is formulated as,

$$\beta_{i,j,k} = \frac{z_{i,j,k}}{r_{i,j,k}^{\gamma}} \tag{1}$$

where γ is the path-loss exponent [14]. $r_{i,j,k}$ and $z_{i,j,k}$ represent the distance and the shadowing effects between ith base station (BS) and kth user of the jth cell respectively.

Lastly, $\mathbf{h}_{i,j,k}$ as seen in Fig. 1 denotes the channel vector between the kth user in the jth cell and the ith BS in the ith cell. It can be written as

$$\mathbf{h}_{i,j,k} = \mathbf{g}_{i,j,k}\sqrt{\beta_{i,j,k}} \tag{2}$$

where $\mathbf{g}_{i,j,k} \sim CN(\mathbf{0}, \mathbf{I}_M)$ is the SSF vector [14]. $\beta_{i,j,k}$ values can be easily tracked because $\beta_{i,j,k}$ values are frequency-dependent and changing slowly. This kind of assumption has already been made by different massive MIMO studies in [15, 16].

In this study, it is also assumed that orthogonal pilots are used in all network cells to reduce the complexity of interference. Therefore, the interference only occurs in inter-cells. Additionally, the number of pilots is limited for each cell, and the same pilots can be used only in different cells as in [11].

Notations used in this paper are summarized in Table 1.

Table 1. Nomenclature.

K	Number of users for each cell
L	Number of cells
M	Number of antennas in BS
$\beta_{i,j,k}$	LSF coefficient
$z_{i,j,k}$	Shadowing effects
$r_{i,j,k}^{\gamma}$	Distance
γ	Path-loss exponent
$\mathbf{h}_{i,j,k}$	Channel vector
$\mathbf{g}_{i,j,k}$	SSF vector

2.1 Uplink Pilot Transmission Phase

In the massive MIMO system, the uplink pilot signal matrix received at the BS in the ith cell is modeled as follows, similar to [20,23]:

$$\mathbf{Y}_i = \sum_{j=1}^{L} \sum_{k=1}^{K} \sqrt{\rho_{up}} \mathbf{h}_{ijk} \psi_k^H + \mathbf{N}_i \tag{3}$$

where ρ_{up} represents transmission power of the pilots. The additional noise matrix $\mathbf{N}_i \in \mathbb{C}^{M\times\tau_p}$ is expressed as $\mathbf{N}_\mathrm{i} \sim \mathbb{CN}\left(\mathbf{0}, \sigma^2 \mathbf{I}_M\right)$ with σ^2 noise variance. The uplink pilot signal $\mathbf{Y}_i \in \mathbb{C}^{M\times\tau_p}$ received during pilot transmission is expressed as in [20] and the length of the orthogonal pilot arrays is τ_p. The pilot matrix used by K users is expressed as follows,

$$\Psi = [\psi_1 \ldots \psi_K] \in \mathbb{C}^{\tau_p\times K}. \tag{4}$$

After the receiving pilot sequences, the channel vector between the kth user in the ith cell and the BS in the ith cell is estimated by correlating the received pilot signal with the pilot sequence as in [10],

$$\begin{aligned} \widehat{\mathbf{h}}_{iik} &= \mathbf{Y}_i \psi_k \\ &= \sqrt{\rho_{up}} \sum_{j=1}^{L} \mathbf{h}_{ijk} + N_i \psi_k \\ &= \sqrt{\rho_{up}} \mathbf{h}_{iik} + \sqrt{\rho_{up}} \sum_{j\neq i}^{L} \mathbf{h}_{ijk} + N_i \psi_k. \end{aligned} \tag{5}$$

2.2 Uplink Data Transmission Phase

The uplink data transmission phase is performed after channel estimation, where the BS aims to detect only signals sent by its K users. Therefore, signals from users in other cells are detected as intercellular interference and eventually considered as additional noise.

The uplink data vector received in BS in ith cell is given as

$$\begin{aligned} \mathbf{y}_i &= \sqrt{\rho_{ud}} \sum_{j=1}^{L} \sum_{k=1}^{K} \mathbf{h}_{ijk} s_{jk} + \mathbf{n}_i \\ &= \sqrt{\rho_{ud}} \mathbf{h}_{iik} s_{ik} + \sqrt{\rho_{ud}} \sum_{j\neq i}^{L} \sum_{k=1}^{K} \mathbf{h}_{ijk} s_{jk} + \mathbf{n}_i \end{aligned} \tag{6}$$

where the data symbol from the kth user in the jth cell is represented by s_{jk} and uplink data transmission power is denoted by the $\sqrt{\rho_{ud}}$. $\mathbf{n}_i \in \mathbb{C}^M$ is the additional Gaussian noise vector. The detected signal of kth user in BS in ith cell can be calculated by methods such as linear maximum-ratio combining (MRC) detector used in some studies [21, 23] as follows,

$$
\begin{aligned}
\widehat{s}_{ik} &= \widehat{\mathbf{h}}_{iik}^{H}\mathbf{y}_i \\
&= (\sum_{j=1}^{L}\sqrt{\rho_{up}}\mathbf{h}_{ijk} + \mathbf{N}_i\psi_k)^H(\sqrt{\rho_{ud}}\sum_{j=1}^{L}\sum_{k=1}^{K}\mathbf{h}_{ijk}s_{jk} + \mathbf{n}_i) \\
&= (\sqrt{\rho_{up}}\mathbf{h}_{iik} + \sqrt{\rho_{up}}\sum_{j\neq i}^{L}\mathbf{h}_{ijk} + N_i\psi_k)^H(\sqrt{\rho_{ud}}\mathbf{h}_{iik}s_{ik} + \sqrt{\rho_{ud}}\sum_{j\neq i}^{L}\sum_{k=1}^{K}\mathbf{h}_{ijk}s_{jk} + \mathbf{n}_i) \\
&= \sqrt{\rho_{ud}}(\sqrt{\rho_{up}}\mathbf{h}_{iik}^{H}\mathbf{h}_{iik}s_{ik} + \sum_{j\neq i}^{L}\sqrt{\rho_{up}}\mathbf{h}_{ijk}^{H}\mathbf{h}_{ijk}s_{jk}) + \varepsilon_{ik}
\end{aligned}
\tag{7}
$$

where combined term of uncorrelated interference and noise are indicated by ε_{ik} [20].

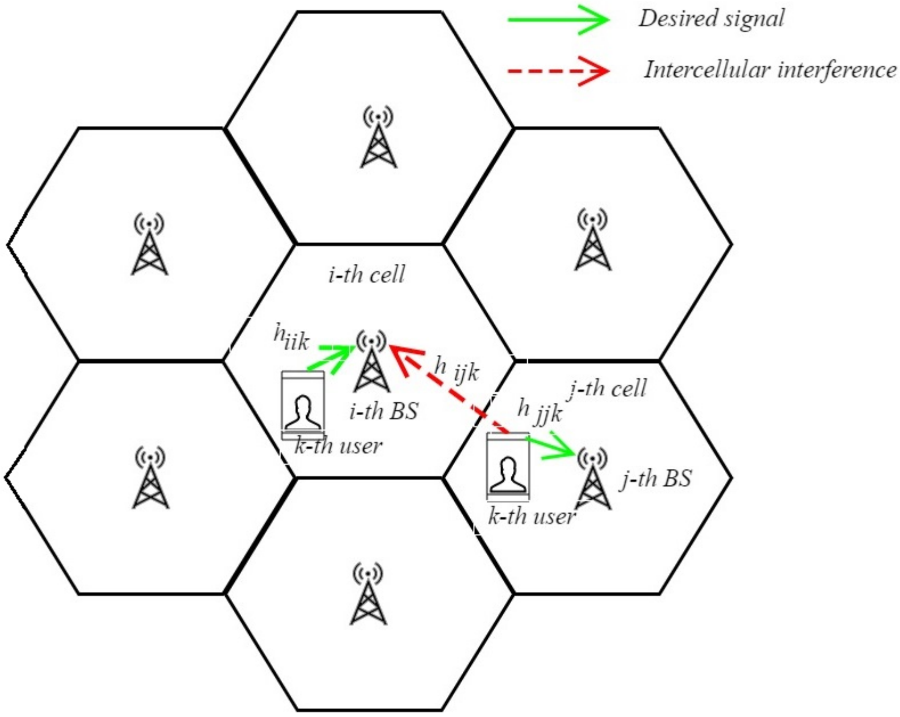

Fig. 1. Signal detection in massive MIMO uplink system.

In the Massive MIMO uplink system as seen in Fig. 1, the SINR expression is shown as follows as stated in [20, 22].

$$
SINR_{i,k}^{u} = \frac{\rho_{up}|\mathbf{h}_{iik}^{H}\mathbf{h}_{iik}|^2}{\sum_{j\neq i}\rho_{up}|\mathbf{h}_{ijk}^{H}\mathbf{h}_{ijk}|^2 + \frac{|\varepsilon_{ik}|^2}{\rho_{ud}}} \tag{8}
$$

Assuming [12, 13, 22] $M \to \infty$, SINR value is reduced to

$$SINR^u_{i,k} \to \frac{\beta^2_{i,i,k}}{\sum_{j \neq i} \beta^2_{i,j,k}}. \tag{9}$$

By leveraging the uplink SINR in Eq. (9), the average uplink capacity (uplink achievable rate) of the kth user of ith cell is formulated as

$$C^u_{i,k} = E\{\mu \log_2(1 + SINR^u_{i,k})\} \tag{10}$$

where μ is the constant changing with bandwidth and system/channel parameters [13]. Since the channel parameters are random variables, the corresponding capacity value is also a random variable. Therefore, the SINR value is the expected value of the SINR random variable.

Lastly, the whole network capacity for L cells can be defined as

$$C^u_{net} = \sum_{i=1}^{L} \sum_{k=1}^{K} C^u_{i,k}. \tag{11}$$

The joint optimization of whole cells inside the network should be ensured simultaneously to maximize the capacity of the system [13].

3. PROPOSED METHOD

In this section, this novel method is elucidated in detail. It is a hybrid version of dynamic programming and a heuristic optimization. Our approach firstly simulates pilot assignment algorithms and environment. Then, the proposed algorithm optimize these pilot assignments effectively.

The *cumulative average SINR* (global SINR) value is the objective function of the proposed optimization. The uplink capacities of all pilot assignment schemes are calculated regarding their pilot sequences and users' β values. After the calculation of the capacities, it detects the *users with low SINR values* then, calculates the *least used pilots* within neighboring cells. Then, it calculates the most optimal pilot-users matching to increase the average channel capacity.

3.1 Dynamic Optimization Algorithm for Pilot Assignment Schemes (DOAPAS)

DOAPAS is an algorithm inspired of the dynamic programming approach and smart searching. In the searching part, as the search area expands, the computation time increases exponentially. Therefore, DOAPAS basically focuses on reducing the search areas of pilots and users.

Before the algorithm steps, it is essential to define some mathematical expressions and parameters which are used in the Algorithm 1. Let c_j represents the jth cell. m_j is the *number of neighbouring cells* of the c_j. $\mathcal{N}_j$ are *neighboring cells* of c_j including itself such as $\mathcal{N}_j = [c_{j,1}, ..., c_{j,m_j}]$ for all $j = 1, 2, ...L$.

The algorithm dynamically calculates the average SINR (*AvgSINR*) value of each cell. It detects the users whose SINR values are below the average SINR. These users are

Algorithm 1 : Optimization Algorithm for Pilot Assignment

Input: initialized pilots
Output: optimized pilots
Initialization:
$optimalPilots = initPilots$
for $i = L$ to 1 **do**
  $Glob\_SINR = \frac{1}{K*L} * \sum_{i=1}^{L} \sum_{k=1}^{K} SINR_{i,k}$
  $AvgSINR_i = \frac{1}{K} * \sum_{k=1}^{K} SINR_{i,k}$
  $nou_i = 0,\ nop\_user_i = \{\}$
  for $k = 1$ to K **do**
    if $(SINR_{i,k} < AvgSINR_i)$ **then**
      $nop\_user_i.append(k)$
      $nou_i = nou_i + 1$
    end if
  end for
  $least\_plts = find\_N\_Smallest(hist(\mathcal{N}_i), nou_i)$
  $all\_perms = Perm(least\_plts)$
  while $j = 1,\ j{+}{+}, j == all\_perms.lenght$ **do**
    $pilots' = optimalPilots(:,:)$
    $pilots'(i, nop\_user_i) = all\_perms(j)$
    $Cum\_SINR = calculateAvgSINR(pilots'(:,:))$
    if $Cum\_SINR > Glob\_SINR$ **then**
      $optimalPilots = pilots'$
      $Glob\_SINR = Cum\_SINR$
    end if
  end while
end for
return $optimalPilots(L,K)$

called non-optimal users (nop_user_i). Only non-optimal users are concentrated to reduce the user search space. On the other hand, the histogram of used pilots for each cell is calculated to get the least-used ones with the number of non-optimal users (nou_i). In this calculation, the amount of pilot usages within close neighboring cells are also included to get a more comprehensive distribution. The pilot search space is reduced by selecting least used pilots.

The algorithm calculates the most optimal user-pilot matches in these reduced user and pilot search spaces. This calculation is performed for each cell to increase the cumulative average SINR ($Glob\_SINR$) value. A new cumulative average SINR (Cum_SINR) is calculated after the optimization to compare with the previous SINR value. When the new average SINR is greater than previous one, the pilots of these users are updated with the pilots of the best match $pilots'(i, nop\_user_i)$. Therefore, the average cumulative SINR of the whole cells is increased progressively. The main idea of the algorithm is to balance the numbers of pilots' usage while selecting the non-optimal users for the dynamically changing environment. All steps and details are also exhibited in Algorithm 1 for a better explanation.

Table 2. Essential simulation parameters.

Name	Value
Number of users for each cell	10 users
Number of base stations	19 BS and 19 cells
Number of antennas in BS	512
Radius of cells	1000 m
Minimum distance to base stations	100 m
Sigma shadowing fading	8 dB
Uplink transmission power	$10^{15/10}$ for 15 dB
Uplink pilot power	$10^{15/10}$ for 15 dB

4. SIMULATION FRAMEWORK AND RESULTS

In this study, all system modeling and pilot assignments schemes are realized on MATLAB regarding the assumptions mentioned in Section 2. Monte Carlo methodology is employed in the simulations.[1]

4.1 System Simulation

Massive MIMO system simulations have played a significant role in academic wireless communication researches. The success of the study is very dependent to the proximity of simulation to reality. Therefore, it is quite important to simulate the system taking into account environmental and human impacts. In these simulations, the base stations, users and interactions between them are simulated according to the system modeling assumptions of this study. System parameters are as shown in Table 2. Users are located with respect to the random Poisson distribution for each simulation. Channel coefficients and pilot assignments between base stations and users are calculated depending on system modeling. These simulations are carried out using the codes in [11] for the simulations and pilot assignments. The selected pilot assignment schemes in study [11] and random pilot assignment algorithm methodically allocates the pilots to all users for each simulation. After the algorithms are run, the occurring assignments, SINR values and relevant environmental system data are stored. In addition, thanks to these data, the performance of the proposed optimization algorithm can be compared with the performances of other algorithms.

4.2 Performance Evaluation

After all pilot assignment schemes are performed for each simulation case, their assignments are compared regarding the corresponding SINR values of theoretical calculation. All graphs plotted below are the results of the 10K simulations.

As seen in Figs. 2 and 3, the proposed methodology outperforms other algorithms especially in Fig. 3. The order of algorithms SINR values for the same CDF value is RANDOM $<$ DLPAS $<$ SPRS $<$ WCG-PD $<$ WCG-PD+SPRS $<$ DOAPAS. In other words, DOAPAS provides much more channel capacity possibility. For example in Fig.

[1] The whole scripts written for this study can be found at https://gitlab.com/xxxxx/pilot_assignment of the study's GitLab page.

2, the $P(SINR > 4)$ is 0.6 in WCG-PD+SPRS while this value is 0.7 in DOAPAS where $P(SINR = x)$ represents the probability of $SINR = x$. This difference in performance is getting much more when the number of users is equal to the number of pilots as seen in Fig. 3.

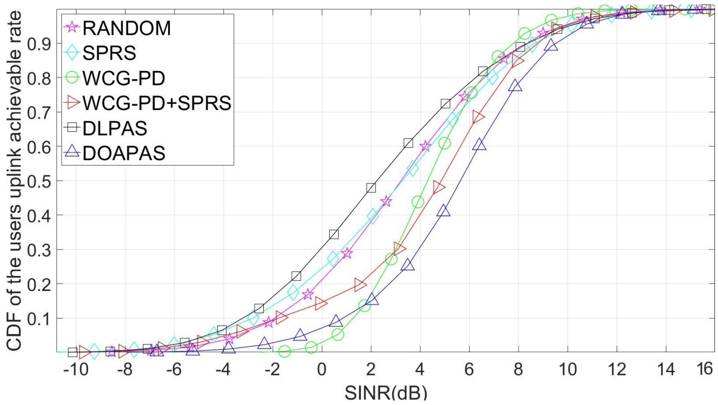

Fig. 2. Comparison of all assignment algorithms' CDF of the users uplink achievable rate (bps) vs. SINR for 15 pilots.

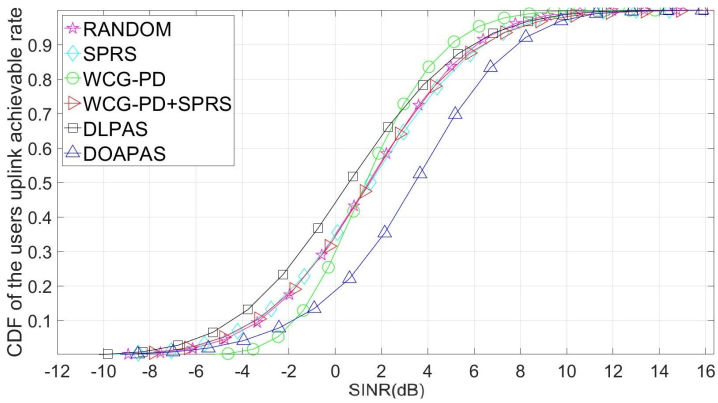

Fig. 3. Comparison of all assignment algorithms' CDF of the users uplink achievable rate (bps) vs. SINR for 10 pilots.

Figs. 4 and 5 clearly prove that the proposed scheme shows better performance by providing a higher achievable rate than other schemes for the same transmission power. The gap between the performances of algorithms is becoming wider when the transmission power is getting higher.

The motivation of a dynamic optimization based algorithm for SINR in this paper is not to use all channel vectors for all users which is a huge size $512\times19\times10\times19$ of the matrix for all users to all antennas. Furthermore, elements of this 4-D huge matrix are complex numbers so it means that $512\times19\times10\times19\times64$ bits ($\sim$120Mb) are required to keep all coefficients of channel vectors (**h**) for only one simulation. In the scope of this study, 200K simulations are run to ensure the confidence of repeatability. If the whole channel vectors were recorded, it would have required $512\times19\times10\times19\times64\times200$K bits which is nearly 24 TB. On the other hand, the proposed model requires only $\sim$1 GB of memory for Beta and corresponding pilot values as input data for 200K simulations. Thus, pilot contamination is reduced to minimum levels with less complexity and memory requirements with the proposed method.

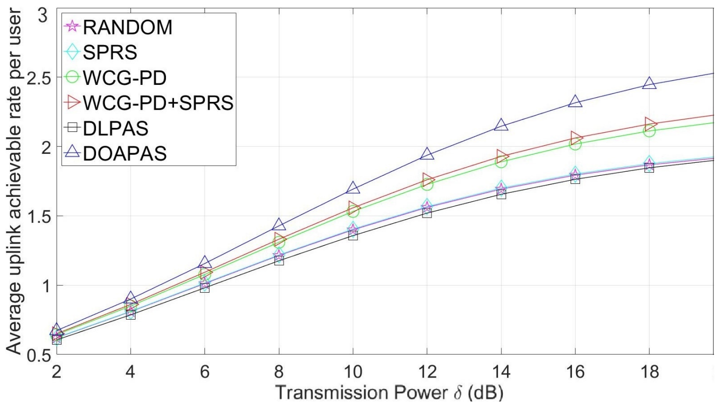

Fig. 4. Comparison of all assignment algorithms' average uplink achievable rate per user (bps/Hz) vs. transmission power for 15 pilots.

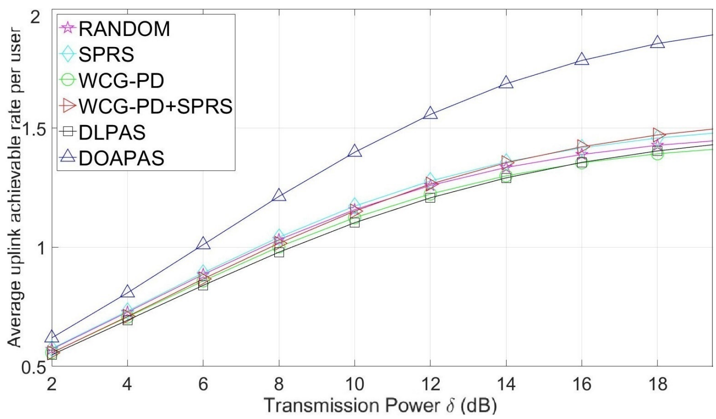

Fig. 5. Comparison of all assignment algorithms' average uplink achievable rate per user (bps/Hz) vs. transmission power for 10 pilots.

5. CONCLUSION AND FUTURE WORK

This study provides a novel, highly effective optimization for pilot assignment schemes to reduce pilot contamination. The capacity optimization algorithm finds the optimal change in the pilot assignments. In the capacity optimization part, each cell is optimized based on the number of dynamically changing pilots' usage regarding neighboring cells. The simulation results show that this approach outperforms several of the most recent classical methods in [11] and popular deep learning-based pilot assignment approach [13]. In fact, this improvement is more clear for the critically limited number of pilot sequences. In future work, the optimization part of this study is being modeled using one of the Reinforcement Learning techniques.

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