Performance Enhancement of Multiuser Multi Cell Interference Alignment with Pair Selection

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***Abstract*—Spectral efficiency of a multi user MIMO system can be enhanced using user selection diversity. In this work we exploit the selection diversity to improve the performance of multi user interference alignment based transmit precoding in downlink MIMO multi cell system. We propose three pair selection algorithms which can be categorized based on their feedback requirements and computational complexity. Our algorithms are suboptimal but we show with the help of extensive simulations that they provide considerable gains in the performance of interference alignment based precoding. The algorithms are also compared with a standard pair selection algorithm. The results show that our algorithms outperform the standard selection. We also assess the performance of interference alignment based precoding with pair selection by comparing it with baseline precoding in three different operating regions. The three regions differ with respect to the inter cell interference characteristics in the system. The comparison shows that in the region with high inter cell interference, using our proposed selection algorithms, interference alignment based precoding outperforms the baseline.**

I. Introduction

Interference management in cellular networks is a well known issue which limits the performance of the cellular networks. Interference Alignment (IA) is one of the techniques to manage the interference efficiently by using "$align$" and "$suppression$" strategy. In MIMO systems, using spatial dimension, the IA can be used to design transmit precoding scheme [1]. The IA based precoding provides maximum degrees of freedom for $K-User$ interference channel and it is a capacity-optimal scheme in high SNR regions (see [1] and references therein). In [1] it is applied only to overcome the inter cell interference (ICI) in a coordinated multi cell scenario where each cell is serving a single active user. However, in cellular multi-antenna multi-user (MU-MIMO) systems, we not only deal with the ICI but also the intra-cell (multi-user) interference (MUI). The contributions in [2]–[4] address the issue of MUI along with ICI and the applicability of IA to deal with MUI. In this work, we focus on the IA based transmit precoding given in [5] for downlink MU-MIMO system.

The precoding in [5] is designed by aligning ICI subspace with MUI subspace and it is known as Multi User Inter Cell Interference Alignment (MUICIA). The idea is to use stale ICI information for the alignment. The inspiration of this idea is based on the work presented in [6] and on the characteristics of ICI in the cellular system. With the help of simulations, it has been shown in [5] that the interference subspaces at the receiver in two consecutive transmissions are very close to each other if the channels are varying slowly in time. Hence, the ICI from the last transmission is still useful and can be used to design the transmit precoding for the current transmission. For this purpose, the serving cell requires only the local information i.e. no inter-cell coordination is required. Each user sends the required information only to its serving cell. In contrast to [2], there is no extra signaling required for the determination of alignment plane. Unlike [3] and [4], the precoding in [5] is neither limited to two cells nor it requires the pre-determined vectors for alignment.

It is well known that the user selection diversity provides considerable gains in spectral efficiency of a MU-MIMO system. However, the dimension of selection diversity has not been explored in [5]. Motivated by this fact, we have extended the work in [5] by exploiting this dimension. At first we used a standard multi user selection algorithm [7] to select the users for transmission. The performance of MUICIA precoding is evaluated for increasing number of active users served by the cell. We notice an increase in the performance, however the gains with the standard algorithm are marginal. Therefore, we propose three new algorithms for user selection in a MU-MIMO system. The details of the algorithms are given in Section III. The simulation results show sustainable gains in system spectral efficiency with our algorithms.

In order to evaluate the true effectiveness of MUICIA precoding with user selection, we compare the performance of MUICIA with a state of the art transmit precoding. This precoding is based on the optimization of the ratio of the desired signal (power towards desired user) to the leakage (power towards undesired user) plus noise (SLNR)[8]. It is a balanced transmit precoding scheme as it maintains both signal maximization and interference minimization in the system.

The contribution serves two goals. The first is the proposal of new selection algorithms and their applicability to MUICIA for performance enhancements. The second is to qualitatively analyse the gains of MUICIA over the state of the art which is a necessary step to explore the feasibility of MUICIA in practical systems. The rest of the paper is organized as follows. Section II describes the system under consideration. Section III provides the details on the user selection algorithms. Simulation assumptions and performance analysis are given in Section IV. The major highlights are given in Section V.

$Notations\ and\ Naming$: '$\mathbf{A}$'represents a matrix; '$\mathbf{a}$' is a vector. Superscript H represents the Hermitian.$\|\mathbf{a}\|$ represents the norm of 2nd degree,$\|\mathbf{A}\|_F$ represents the Forbenius norm.

'$\mathbf{I}$' is used for the square identity matrix. '$Tr(\mathbf{A})$' represents the trace of $\mathbf{A}$. A $Site$ comprises three collocated-sectorized antennas. A sector of the site also represents the cell or the transmitter. A mobile user or a receiver is represented by the word User Equipment 'UE'.

II. System Model and Performance Metric

In principle the system we consider here is the same as in [5] but for better understanding we give brief details hereunder. Consider an OFDM based closed loop downlink multiuser MIMO cellular system which consists of I cells each equipped with M transmit antennas serving L active UEs ($L \geq M$). Each UE is equipped with N antennas. Only K out of L UEs are selected simultaneously on the same time-frequency resource for transmission. Each cell transmits r streams to each selected UE. In order to limit the search space, we assume $K = 2$ (pair selection) and single stream transmission for each UE ($r = 1$). Let S_i be the set of users selected by the ith cell. It consists of the indices of the selected pair ($|S_i| = K = 2$).We focus our mathematical analysis for pair selection on a single subcarrier and for a single transmission time, whereas simulation results in Section IV will be given for a wideband OFDM system. The received signal by the UE j when co-scheduled with the UE k by the cell i can be represented by $y_j \in C^{N\times 1}$ and is given by:

$$\mathbf{y}_j = \mathbf{H}_{ji}\mathbf{p}_{ji}x_{ji} + \mathbf{H}_{ji}\mathbf{p}_{ki}x_{ki} + \mathbf{q}_j + \mathbf{n}_j \tag{1}$$

Where, $\mathbf{H}_{ji} \in C^{N\times M}$ is the channel matrix between the ith cell and the corresponding jth UE, we assume a flat fading narrow band channel over a transmission time interval on a subcarrier, (x_{ji}, x_{ki}) are the transmitted symbols by the ith cell, $(\mathbf{p}_{ji}, \mathbf{p}_{ki}) \in C^{M\times 1}$ are the precoding vectors used for transmission by the ith cell, $(\mathbf{H}_{ji}\mathbf{p}_{ki}x_{ki}) \in C^{N\times 1}$ is the MUI term due to the transmission to kth UE by ith cell, $\mathbf{q}_j \in C^{N\times 1}$ is the ICI term due to the transmission of the other $(I-1)$ cells to their corresponding UEs and $\mathbf{n}_j \in C^{N\times 1}$ is the thermal noise term with covariance η^2. We assume unit power transmission by all the cells in the system. The precoding matrices used by the cells are with unit norm. The signal after receive combining is given as

$$y_j^{'} = \mathbf{g}_j^H \mathbf{y}_j$$

where, $\mathbf{g}_j \in C^{N\times 1}$ is the receive vector. We use MMSE based algorithm to calculate the receive vector which can be written as

$$\mathbf{g}_j = (\mathbf{T}_j + \eta^2\mathbf{I})^{-1}\mathbf{H}_{ji}\mathbf{p}_{ji}$$

where, $\mathbf{T}_j \in C^{N\times N}$ represents the Gram sample of the total interference covariance arriving at the jth UE.

For the simulations, the channel realizations used in equation (1) are generated by using a geographical-geometry based stochastic spatial channel model [9]. During the simulation, the output SINR after the receive-processing is evaluated for each allocated time frequency resource sample. This output SINR is then used to calculate the sample Shannon rate. Mean cell rates in bits/s/Hz are evaluated by averaging the rates over all time-frequency resources and cells. We refer to [5] for the expression of output SINR and further details on the performance metric.

III. Selection Algorithms

From now on we consider that each cell selects $K = 2$ UEs to transmit simultaneously on the same OFDM time-frequency resource element. All the cells and UEs are equipped with two antennas ($M = N = 2$). We assume that the perfect channel state information of each UE for the current transmission time interval (TTI) and ICI information from the previous TTI is known to the serving cell through an error free local feedback link. No coordination whatsoever is required between the cells. All algorithms perform exhaustive search except the one based on the condition number of ICI, which performs simple sorting. For a very high number of UEs in a cell the exhaustive search would be prohibitive. However, for a nominal number of active UEs in a cell (10-30 UEs, like in 3GPP based systems [10]) it is still acceptable.

A. Standard Algorithm: Spatially Orthogonal Users

This method is based on the concept presented in [7]. It finds a pair of users with orthogonal spatial channel structure to avoid MUI and to facilitate the independent streams towards individual users. For this purpose, a metric is defined which estimates the total correlation between all the combinations of users. For any pair of UEs j and k served by the BS i, the metric can be written as:

$$\Omega_{jk} = ||\mathbf{H}_{ji}\mathbf{H}_{ki}^H||_F$$

The objective is to find a set ($S_i = \{j, k\}$) with minimum Ω_{jk} which can be written as:

$$S_i = arg \min_{\{j,k\}\in\{1,2,...L\}} (\Omega_{jk})$$

B. Min-TxColinearity: Minimise Transmit Side Colinearity

This algorithm is a slight modification to the standard algorithm. Similar to [7], our objective is to find a mutually orthogonal pair using the serving channel matrices. However, instead of finding the total correlation between the channels of users, we define a metric based only on the transmit-side correlation. The spatial structure of MIMO channel can be tracked by the transmit-side correlation [11]. We define $\mathbf{R}_j = \mathbf{H}_{ji}^H\mathbf{H}_{ji}$ as the Gram sample of the transmit correlation matrix seen by the UE j. Similarly, for UE k we define $\mathbf{R}_k = \mathbf{H}_{ki}^H\mathbf{H}_{ki}$. Two matrices which exhibit nearly spatial orthogonal structure should have minimum colinearity[12]. The colinearity between $\mathbf{R}_j$ and $\mathbf{R}_k$ is given by:

$$\Pi_{jk} = \frac{|Tr(\mathbf{R}_j\mathbf{R}_k^H)|}{||\mathbf{R}_j||_F||\mathbf{R}_k||_F}$$

We define the objective function to find a pair of users with minimum transmit-side colinearity such that:

$$S_i = arg \min_{\{j,k\}\in\{1,2,...L\}} (\Pi_{jk})$$

The current CSI of the active users is required as feedback for this selection.

C. Max-ICICondNum: Maximise ICI Condition Number

In case of MUICIA precoding, the cell aligns the MUI subspace to the ICI subspace. The degree of alignment will be higher for the UEs which will face non-isotropic ICI, colored ICI. Typically in a cellular system, the ICI is colored when the UE faces strong interference from one or two interfering cells. The presence of strong interferers can be detected with the help of the ratio of maximum to minimum eigenvalue of the ICI covariance matrix [13]. The condition number of the covariance matrix represents this ratio. For this purpose, we consider the condition number of the Gram sample of the ICI covariance matrix. For jth UE it is given by

$$\psi_j = \sqrt{\frac{\lambda_{jmax}}{\lambda_{jmin}}}$$

where, λ_{jmax} and λ_{jmin} are maximum and minimum eigenvalues of the Gram sample of ICI covariance matrix $\mathbf{Q}_j \in C^{N\times N}$. The cell sorts the UEs with respect to their condition numbers and finds the pair by using the following objective function:

$$S_i = arg \max_{\{j,k\}\in\{1,2,...L\}} (\psi_j + \psi_k)$$

Only the condition number of the ICI covariance from the previous transmission is required as feedback.

D. Max-ERate: Maximise Rate Estimated by the Serving Cell

In this algorithm, the selection is based on the transmission rate estimated by the serving cell. For this purpose, the cell i calculates the post receiver SINR for all combinations $\binom{L}{K=2}$ based on the information fed back by the UEs. Let $\{j,k\}$ be one of the possible combination under evaluation by the ith cell. In this case, the symbols $(\mathbf{v}_{ji}, \mathbf{v}_{ki}) \in C^{M\times 1}$ represent the precoding vectors for UE j and UE k respectively. The MUI faced by UE j can be represented by $\tilde{\mathbf{Z}}_{j(k)}$:

$$\tilde{\mathbf{Z}}_{j(k)} = (\mathbf{H}_{ji}\mathbf{v}_{ki})(\mathbf{H}_{ji}\mathbf{v}_{ki})^H \tag{2}$$

We assume that the cell is aware of the receiver algorithm used by the UEs. In practice, this assumption can be realized by defining UE-categories as given in [14]. With the help of estimated MUI from equation (2) and $\mathbf{Q}_j$, the cell computes the receive vector $\mathbf{u}_j \in C^{N\times 1}$ for UE j and is given by the following equation:

$$\mathbf{u}_j = (\tilde{\mathbf{Z}}_{j(k)} + \mathbf{Q}_j + \eta^2\mathbf{I})^{-1}\mathbf{H}_{ji}\mathbf{v}_{ji} \tag{3}$$

The estimated desired signal power received by UE j can be denoted by δ and using equation (3) it can be written as:

$$\delta = |\mathbf{u}_j^H\mathbf{H}_{ji}\mathbf{v}_{ji}|^2 = \mathbf{u}_j^H(\mathbf{H}_{ji}\mathbf{v}_{ji})(\mathbf{H}_{ji}\mathbf{v}_{ji})^H\mathbf{u}_j \tag{4}$$

Likewise, φ denotes the residual MUI and it can be written as:

$$\varphi = |\mathbf{u}_j^H\mathbf{H}_{ji}\mathbf{v}_{ki}|^2 = \mathbf{u}_j^H(\mathbf{H}_{ji}\mathbf{v}_{ki})(\mathbf{H}_{ji}\mathbf{v}_{ki})^H\mathbf{u}_j \tag{5}$$

Substituting equation (2) in equation (5) we get the following simplified form for the residual MUI term:

$$\varphi = \mathbf{u}_j^H\tilde{\mathbf{Z}}_{j(k)}\mathbf{u}_j \tag{6}$$

Similar to the derivation for residual MUI, the residual ICI is represented by ϑ and it can be estimated using $\mathbf{Q}_j$ as follows:

$$\vartheta = \mathbf{u}_j^H\mathbf{Q}_j\mathbf{u}_j \tag{7}$$

The filtered noise term can be given as:

$$\pi = ||\mathbf{u}_j^H||^2\eta^2 \tag{8}$$

Using the equations (4)-(8), the post receiver SINR for the UE j when paired with the UE k is given by $\beta_{j(k)i}$:

$$\beta_{j(k)i} = \frac{\delta}{\varphi + \vartheta + \pi}$$

Similarly, the cell i can estimate $\beta_{k(j)i}$ for UE k paired with UE j. After the post receiver SINR estimation for all the combinations, the cell uses the following objective function for the pair selection:

$$S_i = arg \max_{\{j,k\}\in\{1,2,...L\}} (\log_2(1+\beta_{j(k)i}) + \log_2(1+\beta_{k(j)i}))$$

IV. Simulation Description and Results

In this section we present the simulation results of the pair selection algorithms described in Section III. We have used the drop based system level simulation methodology as specified by 3GPP in [10]. The realization of all time and frequency selective spatial channels between the cells and the UEs is done according to the channel model given in [9]. Perfect channel estimation and instantaneous error-free feedback of CSI is assumed. Further propagation and antenna related parameters can be referred from [10]. As the focus of this work is to analyse the qualitative impact of different selection algorithms therefore, some of the simulation features like re-transmissions and link adaptation are disabled on purpose. Moreover, the performance metric is evaluated by output SINR using Shannon formula and not according to the mutual information interface (MIESM) given in [10].

One complete simulation cycle consists of several Monte Carlo drops. Each drop consists of certain number of transmission time intervals (TTI). Full buffer traffic and a user speed of 3 km/h is simulated. The total frequency bandwidth is divided into B physical resource blocks (PRB) [10]. Each PRB contains W consecutive subcarriers with a frequency spacing of $15kHz$ (here in $10MHz$ including band gap: 576 subcarriers, $B = 50, W = 12$).With the user speed of 3 km/h, we have slow time variant and nearly frequency flat channels within a single PRB. However, we have frequency diversity due to high number of PRBs with in a TTI. We have the possibility of B different pair selections within a TTI if the number of active users is very high.

The UEs are dropped in the coverage area according to the given downlink wide band average SINR (σ in dB). This input SINR depends upon the average receive signal level from the serving cell, upon the average receive signal from all

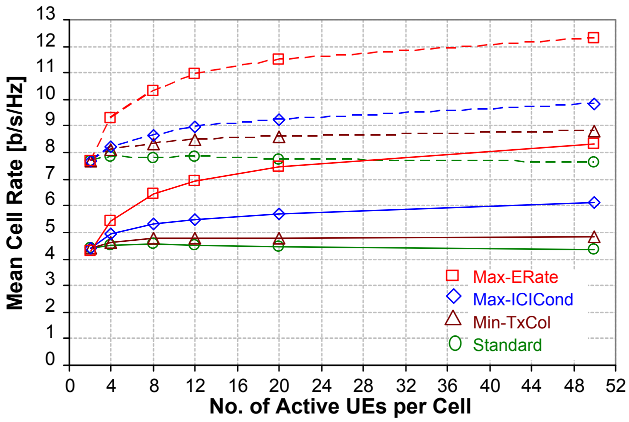

Fig. 1. Performance of MUICIA precoding with different pair selection algorithms in ICI limited ($\sigma = 0dB$; Smoothed lines) and MUI limited ($\sigma = 14dB$; Dashed lines) regions.

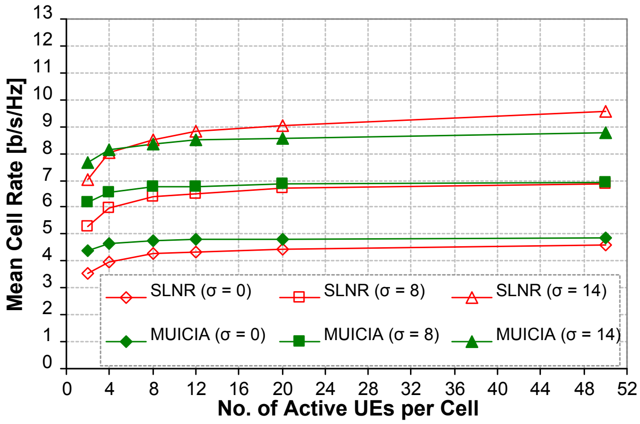

Fig. 2. Comparison of the performance of MUICIA with SLNR using $Min - TxColinearity$ as selection algorithm when $\sigma = \{0, 8, 14\}dB$.

other cells and upon the thermal noise. It is also commonly known as zser-geometry. This parameter controls the position of the UEs in a cell coverage area. Typical values of σ lie between -5 to 17 dB for a freqeuncy reuse-1 cellular system. Lower values of σ indicate that the UEs are close to the cell border and facing a high inter cell interference, representing ICI-limited region. Although MUI exists in the region but just to emphasize the strong influence of ICI at cell border we explicitly term the region as ICI-limited. Similarly, higher values of σ represent MUI-limited region i.e. the UEs are very close to the cell center. Middle order values of σ represent a region where both ICI and MUI have significant influence on the performance of the system. We find it necessary to define the operating regions of the system with respect to the strengh of inter cell interference because in the absence of strong inter cell interference, the interference alignment based transmit precoding may suffer the loss in the performance[15].

The results in Figures 1-4 are the outcome of the 3-cells scenario modelled by a site with co-located 3-sectorized antennas where each sector corresponds to a cell. This is given as

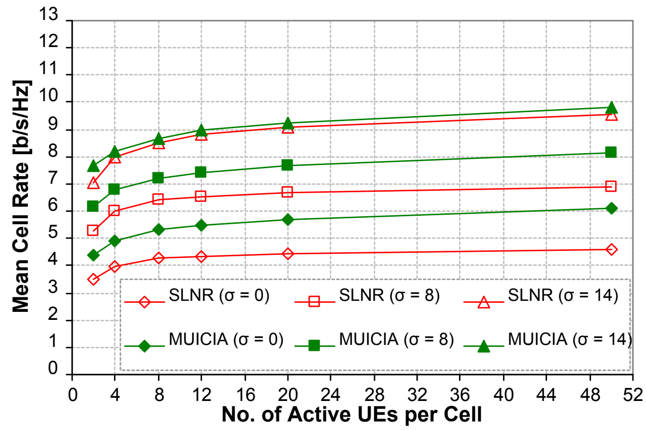

Fig. 3. Comparison of the performance of MUICIA using $Max - ICICondNum$ with SLNR using $Min - TxColinearity$ when $\sigma = \{0, 8, 14\}dB$.

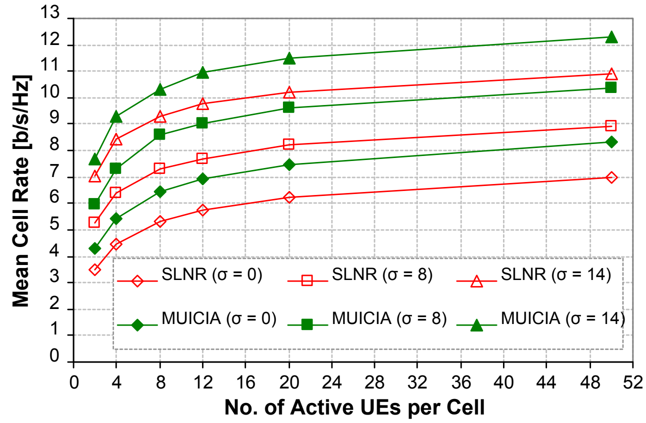

Fig. 4. Comparison of the performance of MUICIA with SLNR using $Max - ERate$ as selection algorithm when $\sigma = \{0, 8, 14\}dB$.

a baseline scenario by 3GPP [10]. Figure 1 presents the performance improvements in cell spectral efficiency using MUICIA transmit precoding with different selection algorithms over the increasing number of active users in ICI-limited ($\sigma = 0dB$) and MUI-limited ($\sigma = 14dB$) regions. There are many important effects in this figure, but we focus on some highlights here. Notice that all our proposed algorithms provide considerable gains in the performance as compared to the standard selection algorithm. The $Max - ICICondNum$ which is an orthodox method, outperforms classical orthogonality based selection $Min - TxColinearty$ in both cases of σ. This is because $Max - ICICondNum$ increases the alignment gain for MUICIA and suppression gain at the receiver by selecting active UEs experiencing strong ICI. Moreover, the gains of $Max - ICICondNum$ are higher in ICI-limited region due to the highly coloured (strongly directed) interference in ICI-limited region. It shows that if multiple antenna UEs are available in the system with advanced receiver algorithms, $Max - ICICondNum$ can be used for pair selection. The selection with $Max - ERate$ outperforms all other algorithms and it provides relatively better performance in MUI-limited region. It shows that with UE-category information and with slow time variant channels, transmission rate estimation can be done with high accuracy at the serving cell which helps to select maximum rate UEs.

Now, we intend to compare the performance of MUICIA and the baseline SLNR using $Min - TxColinearty$ user selection. In Figure 2, we see that $\sigma = 0dB$ i.e. ICI-limited region, SLNR suffers the performance loss due to strong ICI. At $\sigma = 8dB$, SLNR is still ouperformed by MUCIA, however for very high number of UEs, the two precodings are very close in the performance. In MUI-limited region i.e. $\sigma = 14dB$, we see a cross over in the performance already at 4 active UEs. It shows that if we have $Min - TxColinearty$ as selection algorithm then the performance comparison of the two precoding schemes depends upon the ICI and the number of active UEs. Moreover, we notice that the percentage of gain in the performance of SLNR is higher using $Min-TxColinearty$ as selection algorithm. This is because, orthogonality based selection supports SLNR based precoding. Therefore, for fair comparison, we present the performance of MUICIA with $Max - ICICondNum$ and SLNR with $Min - TxColinearty$ in Figure 3. Here we find different conclusions than Figure 2. The MUICIA outperforms SLNR in ICI-limited region with $\sigma = 0dB$ as well as with $\sigma = 8dB$ where both ICI and MUI are influential. At $\sigma = 14dB$ i.e. MUI-limited region, gains of MUICIA are very marginal.

Further to the comparison, Figure 4 shows the results when both precodings are using $Max - ERate$ based selection in 3-cells scenario. With this selection, MUICIA outperforms SLNR with very high gains for all the number of UEs as well as for all interference regions. If the issues of computational complexity and feedback are overcome, then IA with $Max - ERate$ is a better choice than SLNR.

V. Conclusion and Future Work

In this work we have achieved two objectives. The first is to improve the performance of IA based precoding in a MU-MIMO system using pair selection. With the help of extensive simulations we have shown that our proposed selection algorithms bring considerable gains to the performance of MUICIA. In general, in MU-MIMO system, selection of spatially separable users enhances the performance of the transmission scheme. However, we found out that in case the transmission scheme is based on interference alignment, $Max - ICICondNum$ is the better choice. Additionally, this is more beneficial as it is based only on simple sorting process to search the users and it requires very small feedback. For a high number of active users, the $Max - ERate$ is computationally complex but it provides enormous gains in system performance. The complexity of $Max - ERate$ can be reduced by employing greedy search based approaches. The second objective is to assess the performance of MUICIA by comparing it with a baseline precoding SLNR. The results have shown that MUICIA outperforms SLNR for high and average inter cell interference regions. This provides a strong statement for further research to transform the gains of interference alignment in a larger cellular scenario. However, we must also accept that these results represent realistic scenario but with ideal assumptions and further research should consider the real world aspects like limited feedback and channel estimation errors. Moreover, another important issue is the user fairness which was not the target of this study but it should also be considered in future works.

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