Combined User Selection and MIMO Weight Calculation for AP Cooperation in Dense Wireless Networks

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***Abstract*—This paper addresses the problem of weighted sum rate (WSR) maximization in dense wireless networks with cooperative access points (APs) subject to a per-AP power constraint. We propose a combined optimization procedure that performs both user selection and MIMO weight calculation and scales well as the number of users increases. User selection eliminates some undesirable users, while MIMO weight calculation determines the precoders and combiners for all active nodes. A new performance metric, which takes into account available power, channel quality and orthogonality, and user weights, is used to perform an initial phase of user selection. A WSR maximization algorithm is then executed to optimize MIMO weights of selected users. The proposed algorithm includes additional user selection, i.e. certain users not eliminated in the first phase will be assigned zero-power stream during its execution. Numerical results show that our proposed algorithm achieves about 25% higher aggregate performance than the best existing algorithm while having a substantially lower running time. In fact, the running time is nearly constant as the number of users increases due to the very fast initial user selection phase.**

I. Introduction

In recent years, the performance of wireless devices has steadily improved due to the adoption of advanced physical layer and signal processing techniques. However, the proliferation of both devices and access points (APs) in a limited-spectrum environment has led to lower per-user bandwidth and also increased interference, which further degrades performance. Thus, in dense wireless network settings with multiple APs and a large number of users, per-user performance often is very poor. In this paper, we focus on dense wireless network settings with limited user mobility. Lower mobility tends to be exhibited in enterprise wireless network deployments, for example, as opposed to typical cellular networks where a higher degree of mobility is expected.

To address these performance limitations, access point (AP) cooperation is seen as a promising technique. In general, two levels of downlink cooperation have been discussed in the literature, primarily for cellular networks [1], [2]. One possibility is that the APs obtain channel state information (CSI) of both direct and interfering links. This information allows the APs to coordinate their signaling strategies, such as precoder design and power allocation, to effectively suppress interference across different users. We refer to this approach as *interference coordination* (IC). If the APs are tied together via high-speed links, as the case in most enterprise wireless network deployments, they can share not only the CSI, but also the data signals of the users, which enables a more powerful form of cooperation. In this case, multiple APs can jointly craft their downlink signals to cooperatively serve the users and the interference can be used to enhance performance, not degrade it. We refer to this approach as *cooperative processing* or *full cooperation*.

In the limited mobility scenarios considered herein, most users are stationary for some period of time, which means channel conditions are only slowly time-varying. This allows more computationally expensive algorithms to be used in optimizing the signaling strategies of APs. The specific problem we consider is to maximize the downlink weighted sum rate (WSR) of a dense wireless network with cooperative processing and a per-AP power constraint. We also assume that the number of users is large, as the case of heavily-used dense wireless network deployments. As the number of users increases, the computation time for WSR maximization can quickly become impractical, even when channels are only slowly time-varying. Thus, we also develop a novel method that performs user selection as a pre-processing step to eliminate some users from consideration by the WSR maximization algorithm.

Different methods have been investigated in the literature for multicell networks, e.g. [3]–[6]. In [3], an enhanced block diagonalization (BD) precoding method is proposed to improve the sum rate performance. However, user selection is not considered and so the algorithm cannot handle a large number of users. In [4], two greedy user selection algorithms are proposed for BD precoding. However, performance suffers due to the greedy user selection, which might not produce the best set of users to consider. In [5], two different approaches are considered to optimize the sum-rate performance, where dirty paper precoding (DPC) is assumed within each cell. When dropping the DPC constraint, the second approach becomes equivalent to the solution in [6]. Unfortunately, the computational complexity increases rapidly with the number of users for all methods proposed in [5], [6] making them unsuitable for the problem considered herein. To our knowledge, ours is the first scalable approach that considers a true sum rate maximization problem, i.e. it does not constrain solutions to use zero forcing, block diagonalization, or other approaches where performance is secondary to interference nullification.

To address the WSR maximization problem with cooperative APs, we propose a combined user selection and MIMO weights optimization approach, which determines the active user set and the MIMO precoders and combiners. Our approach has a very low computational complexity, even for a large number of users. A novel user selection algorithm that incorporates multiple decision factors is run as a pre-processing step to eliminate some users from consideration. Then, a modified WSR maximization algorithm optimizes the MIMO precoders and combiners. This modified WSR maximization algorithm can further eliminate users by allocating them zero power and it also determines the number of streams for each active user. Simulation results demonstrate that, with 48 users and 3 APs, our approach increases aggregate performance by 25% compared to the best existing algorithm while running in 1/3 of the time.

II. Problem Description

We consider a MIMO network with M cooperative access points (APs), where the m^{th} AP is equipped with $N_{t,m}$ antennas. We assume that there are K users with $N_{r,k}$ antennas for the k^{th} user. Let $N_t = \sum_{m=1}^{M} N_{t,m}$ and $N_r = \sum_{k=1}^{K} N_{r,k}$ be the total numbers of antennas at the AP and receiver side, respectively. The matrix of complex channel gains between the cooperative APs and the antennas of the k^{th} user is denoted by $\boldsymbol{H}_k \in \mathbb{C}^{N_{r,k} \times N_t}$. The data vector $\boldsymbol{x} = \left[\boldsymbol{x}_1^T, \ldots, \boldsymbol{x}_K^T\right]^T$ is jointly precoded by the M APs using the precoding matrix $\boldsymbol{V} = [\boldsymbol{V}_1, \ldots, \boldsymbol{V}_K]$. $\boldsymbol{x}_k \in \mathbb{C}^{N_{r,k}}$ is the transmit signal vector for receiver k, and $\boldsymbol{x}_k$ is assumed to be independently encoded Gaussian codebook symbols with $\mathbb{E}[\boldsymbol{x}_k \boldsymbol{x}_k^\dagger] = \boldsymbol{I}$, where $(\cdot)^\dagger$ is the conjugate transpose of $(\cdot)$. It is assumed that the k^{th} user has $N_{r,k}$ parallel data streams, although some of the streams can have a rate of zero. $\boldsymbol{V}_k \in \mathbb{C}^{N_t \times N_{r,k}}$ is the partition of $\boldsymbol{V}$ applied at the APs to precode the signals of user k.

The received vector at user k is given by

$$\boldsymbol{y}_k = \boldsymbol{H}_k \boldsymbol{V}_k \boldsymbol{x}_k + \sum_{l=1, l \neq k}^{K} \boldsymbol{H}_k \boldsymbol{V}_l \boldsymbol{x}_l + \boldsymbol{n}_k \ , \tag{1}$$

where $\boldsymbol{n}_k$ is the vector of Gaussian noise at the k^{th} user with covariance matrix $\boldsymbol{R}_{n_k}$. The corresponding covariance matrix of the received interference plus noise is given by

$$\boldsymbol{R}_{\bar{k}} = \sum_{l=1, l \neq k}^{K} \boldsymbol{H}_k \boldsymbol{V}_l \boldsymbol{V}_l^\dagger \boldsymbol{H}_k^\dagger + \boldsymbol{R}_{n_k} \ . \tag{2}$$

Assume the received vector $\boldsymbol{y}_k$ is equalized using the linear receive filter $\boldsymbol{U}_k \in \mathbb{C}^{N_{r,k} \times N_{r,k}}$. The received signal of the k^{th} receiver is given by $\hat{\boldsymbol{x}}_k = \boldsymbol{U}_k^\dagger \boldsymbol{y}_k$, which results in the mean-square-error (MSE) covariance matrix of the k^{th} user as

$$\boldsymbol{E}_k = \mathbb{E}\left[(\boldsymbol{U}_k^\dagger \boldsymbol{y}_k - \boldsymbol{x}_k)(\boldsymbol{U}_k^\dagger \boldsymbol{y}_k - \boldsymbol{x}_k)^\dagger\right] \tag{3}$$

and its data rate as

$$R_k = \log \left| \boldsymbol{I} + (\boldsymbol{U}_k^\dagger \boldsymbol{R}_{\bar{k}}^{-1} \boldsymbol{U}_k)(\boldsymbol{U}_k^\dagger \boldsymbol{H}_k \boldsymbol{V}_k \boldsymbol{V}_k^\dagger \boldsymbol{H}_k^\dagger \boldsymbol{U}_k) \right| \ . \tag{4}$$

Our goal is to maximize the weighted downlink sum-rate, which is useful for prioritizing different users and covers different practical applications. For instance, when identical weights are applied for all receivers, the problem becomes sum-rate maximization corresponding to a best effort service. Weighted sum rate maximization can also form the basis for higher-level scheduling algorithms that generate fair schedules with high throughput [7]. Since, in our problem setting, the transmitters are distinct APs that are at different physical locations, the transmit power of each AP should be bounded, which translates into a per-AP power constraint in the WSR maximization problem. This problem can be written as

$$\begin{aligned} \max_{\substack{\{\boldsymbol{V}_k\}_{k\in\mathcal{U}} \\ \{\boldsymbol{U}_k\}_{k\in\mathcal{U}}}} \quad & \sum_{k\in\mathcal{U}} \omega_k R_k \\ s.t. \quad & \sum_{k\in\mathcal{U}} Tr(\boldsymbol{\Gamma}_m \boldsymbol{V}_k \boldsymbol{V}_k^\dagger) \leq P_m, m = 1, \ldots, M \ , \end{aligned} \tag{5}$$

where the user set is denoted by $\mathcal{U} = \{1, \ldots, K\}$ and a diagonal matrix $\boldsymbol{\Gamma}_m \in \mathbb{R}^{N_t \times N_t}$ is introduced for each AP, in order to select the partition of precoding matrix $\boldsymbol{V}$ applied at AP m. Thus, $\boldsymbol{\Gamma}_m$ contains ones on the diagonal elements corresponding to the antennas of AP m and zeros elsewhere. ω_k is the weight for the k^{th} user and P_m is the maximum transmit power of AP m.

III. Combined User Selection and MIMO Weights Calculation

In our targeted high-density environment, the number of users is relatively large, meaning that only a subset of users can be served simultaneously in one time slot. The algorithm proposed in [8] for interfering MIMO channels, which can jointly optimize the user selection (i.e., allocating zero power to deactivate users) and MIMO weights, could be extended to solve the formulated WSR maximization problem with the added per-AP power constraint. However, the computational complexity of this modified algorithm increases rapidly as the number of users increases. Other algorithms address the problem by completely separating the user selection and precoder design [4], [9]. In those greedy incremental user selection algorithms, however, a previously selected user might become redundant when new users are added and this limits the performance of the final solution.

To overcome the problems in existing work, we propose a combined user selection and MIMO weights optimization algorithm. First, a fast pre-user selection procedure is performed to approximate a "good" subset of users by selecting K_0 users out of K users based on the performance metric, i.e. maximizing the potential WSR. Then, the MIMO precoders and combiners of the selected users are optimized, where the proposed algorithm can further refine the user selection and stream allocation by removing redundant users and deactivating streams with zero power, if necessary to improve the final WSR.

1. Let $\mathcal{U}_r = \{1, \ldots, K\}$ and $\mathcal{U}_s = \emptyset$
   $k^* = \text{argmax}_{k \in \mathcal{U}_r} w_k \log \left| \boldsymbol{I} + P_k \bar{\boldsymbol{H}}_k \bar{\boldsymbol{H}}_k^H / N_r \right|$
2. Update $\mathcal{U}_s = \{k^*\}$ and $\mathcal{U}_r = \mathcal{U}_r - \{k^*\}$
3. *If* $(|U_s| < K_0)$
4. Calculate the priority metric $f(\boldsymbol{H}_k, \boldsymbol{H}_{sel})$ for $\forall k \in \mathcal{U}_r$ using (6).
5. $k^* = \text{argmax}_{k \in \mathcal{U}_r} \; f(\boldsymbol{H}_k, \boldsymbol{H}_{sel})$
6. Quit if $f(\boldsymbol{H}_{k^*}, \boldsymbol{H}_{sel}) < 0$; Else go to step 2
7. *Else* Quit

Fig. 1: Pre-user selection pseudocode

1. Initialization: $\boldsymbol{V}_k = \boldsymbol{V}_k^0$ for all $k \in \mathcal{U}_s$;
2. Repeat
3. Compute $\boldsymbol{U}_k$ using (8) for all $k \in \mathcal{U}_s$ for given $\boldsymbol{V}_k$'s;
4. Compute $\boldsymbol{W}_k$ using (9) for given $\boldsymbol{V}_k$'s and $\boldsymbol{U}_k$'s;
5. Update $\boldsymbol{V}_k$'s by solving problem (7);
6. until $\left| \sum_{k \in \mathcal{U}_s} \omega_k R_k^{(n)} - \sum_{k \in \mathcal{U}_s} \omega_k R_k^{(n-1)} \right| \leq \epsilon$.

Fig. 2: Alternating optimization for WSR maximization

A. Pre-user selection

The objective of the user selection procedure is to select $K_0 < K$ users, that will potentially contribute to high-WSR performance. With a targeted K_0, it is costly to enumerate and evaluate $\begin{pmatrix} K \\ K_0 \end{pmatrix}$ possible user groups. In this section, we propose an incremental selection algorithm to determine a high-performance user group.

In dense wireless networks, the inter-user interference is generally substantial. To improve the WSR performance, important factors should be taken into account for user selection procedure: (1) mutual orthogonality of selected users' channels, (2) the channel quality of selected users, (3) the user weights $w_k's$ and (4) the available power. Our proposed efficient user selection algorithm that incorporates all of these factors is shown in Figure 1.

The algorithm starts by selecting the user with highest interference-free weighted data rate. Let $\boldsymbol{Q}_k$ be the row basis of $\bar{\boldsymbol{H}}_k$, where $\bar{\boldsymbol{H}}_k = \boldsymbol{R}_{n_k}^{-1/2} \boldsymbol{H}_k$. The selected user set is denoted by $\mathcal{U}_s$ and the remaining user set is denoted by $\mathcal{U}_r$. The number of users in $\mathcal{U}_s$ is given by $|\mathcal{U}_s|$. The priority metric is defined as follows:

$$
\begin{aligned}
f(\boldsymbol{H}_k, \boldsymbol{H}_{sel}) = \quad & w_k \log_2 (1 + \frac{P_t / N_r}{|\mathcal{U}_s| + 1} ||\boldsymbol{H}_{e,k}||_F^2) \\
& + \sum_{i \in \mathcal{U}_s} w_i \log_2 (1 + \frac{P_t / N_r}{|\mathcal{U}_s| + 1} ||\bar{\boldsymbol{H}}_i \boldsymbol{H}_{e,k}^{\perp}||_F^2) \\
& - \sum_{i \in \mathcal{U}_s} w_i \log_2 (1 + \frac{P_t}{N_r |U_s|} ||\bar{\boldsymbol{H}}_i||_F^2),
\end{aligned}
\tag{6}
$$

where $\boldsymbol{H}_{sel} = \left[\bar{\boldsymbol{H}}_i \right]_{i \in \mathcal{U}_s}$, $\boldsymbol{H}_{e,k} = \bar{\boldsymbol{H}}_k \times null(\boldsymbol{H}_{sel})$ and $\boldsymbol{H}_{e,k}^{\perp} = \boldsymbol{I} - \boldsymbol{Q}_k \boldsymbol{Q}_k^{\dagger}$. $|| \cdot ||_F$ denotes the Frobenius norm. $P_t = \sum_{m=1}^{M} P_m$ is the total transmit power of the cooperative APs. The first term in (6) evaluates the WSR contribution of user k when its precoder lies in the null space of the selected users' channel matrices. In the second term, the channels of previously selected users are projected to the null space of user k's equivalent channel. The selection priority metric implicitly reflects how much WSRM performance gain is contributed by user k. Then, the user with highest priority metric will be selected in each round. However, the maximum value of the priority metric could be less than 0, indicating that adding a new user may even hurt the overall performance. In this case, the user selection will terminate before K_0 users are selected.

Note that the parameter K_0 in the user selection algorithm can be tuned to achieve different tradeoffs between the aggregate performance and computational complexity. Smaller K_0 will eliminate more users at this stage and the achievable WSR will degrade as the price of lower computational complexity for MIMO weights computation. With larger K_0, fewer users will be excluded by the user selection procedure and the loss of WSR performance will be smaller.

B. MIMO precoder and combiner calculation

Once the pre-user selection is complete, the precoders and combiners of selected users are determined by solving the WSR maximization problem for the remaining users. The targeted WSR maximization problem in (5) needs to be modified by replacing the user set $\mathcal{U}$ with $\mathcal{U}_s$. However, the WSR maximization problem is a non-convex problem, which is difficult to solve based on the Karush-Kuhn-Tucker (KKT) conditions for the formulated problem.

Therefore, we consider a more tractable approach to solve the problem. Consider the weighted MSE minimization problem as follows,

$$
\begin{aligned}
\min_{\{\boldsymbol{V}_k\}_{k \in \mathcal{U}_s}} \quad & \sum_{k \in \mathcal{U}_s} Tr(\boldsymbol{W}_k \boldsymbol{E}_k) \\
s.t. \quad & \sum_{k \in \mathcal{U}_s} Tr(\boldsymbol{\Gamma}_m \boldsymbol{V}_k \boldsymbol{V}_k^{\dagger}) \leq P_m, m = 1, \ldots, M.
\end{aligned}
\tag{7}
$$

Based on [6], it can be proved that the gradient of WSR maximization and the gradient of weighted sum MSE minimization are equal if the information lossless MMSE receiver is applied as

$$
\boldsymbol{U}_k = (\boldsymbol{H}_k \boldsymbol{V}_k \boldsymbol{V}_k^{\dagger} \boldsymbol{H}_k^{\dagger} + \boldsymbol{R}_{\bar{k}})^{-1} \boldsymbol{H}_k \boldsymbol{V}_k \tag{8}
$$

and the MSE weights satisfy

$$
\boldsymbol{W}_k = \omega_k (\boldsymbol{I} + \boldsymbol{B}_k^{\dagger} \boldsymbol{V}_k^{\dagger} \boldsymbol{H}_k^{\dagger} \boldsymbol{R}_{\bar{k}}^{-1} \boldsymbol{H}_k \boldsymbol{V}_k \boldsymbol{B}_k), \tag{9}
$$

where $\boldsymbol{B}_k$ is an arbitrary unitary matrix. The $\boldsymbol{R}_{\bar{k}}$ in (2) is updated by letting $\boldsymbol{V}_i = \boldsymbol{0}$ for $i \notin \mathcal{U}_s$.

Based on the equivalence relation between WSR maximization and weighted sum MSE minimization, an iterative algorithm can be derived to find a local WSR-optimum, as summarized in Figure 2.

The algorithm alternatively updates the precoders $\boldsymbol{V}_k$'s, MSE weights $\boldsymbol{W}_k$'s and MMSE combiner $\boldsymbol{U}_k$'s, which solves a weighted sum MSE minimization problem in each iteration. As analyzed in [6], the algorithm will converge to a local WSR-optimum. Moreover, to simplify the receiver complexity, diagonal MSE matrices can be achieved by choosing proper unitary matrices $\boldsymbol{B}_k$. Hence, we use a modified precoding matrix $\tilde{\boldsymbol{V}}_k = \boldsymbol{V}_k\boldsymbol{B}_k$ to make the MSE matrices diagonal without changing the data rates. Here, $\boldsymbol{B}_k$ is given by the following eigenvalue decomposition,

$$\boldsymbol{B}_k\boldsymbol{\Lambda}_k\boldsymbol{B}_k^\dagger = \boldsymbol{V}_k^\dagger\boldsymbol{H}_k^\dagger\boldsymbol{R}_{\bar{k}}^{-1}\boldsymbol{H}_k\boldsymbol{V}_k \tag{10}$$

where $\boldsymbol{\Lambda}_k \in \mathbb{R}^{N_{r,k}\times N_{r,k}}$ is a diagonal matrix containing the eigenvalues of $\boldsymbol{V}_k^\dagger\boldsymbol{H}_k^\dagger\boldsymbol{R}_{\bar{k}}^{-1}\boldsymbol{H}_k\boldsymbol{V}_k$ ordered in decreasing order. It leads to a diagonal MSE matrix for the k^{th} receiver as

$$\boldsymbol{E}_k = (\boldsymbol{I}+\boldsymbol{\Lambda}_k)^{-1}. \tag{11}$$

While the weighted sum MSE minimization problem can be solved by extending the algorithms in [6] and [10] to the formulated problem with per-AP power constraint, the solutions provided by these iterative algorithms lack the ability to quickly deactivate links. Specifically, the solutions in [6] and [10] cannot decouple the precoder of the k^{th} user and its combiner, which can only gradually reduce the power allocated to some links as the algorithm iterates, eventually deactivating links but only after many iterations.

In order to further refine the selected users and determine the active streams of each user efficiently, we propose a different algorithm to solve the weighted sum MSE minimization problem. First, the Lagrangian of the weighted sum MSE minimization problem is given by

$$L = \sum_{k\in\mathcal{U}_s} Tr(\boldsymbol{W}_k\boldsymbol{E}_k) + \sum_{m=1}^{M}\mu_m(Tr(\boldsymbol{\Gamma}_m\boldsymbol{V}\boldsymbol{V}^\dagger) - P_m), \tag{12}$$

where $\mu_m \geq 0$ for $m = 1,\dots,M$ are the Lagrange multipliers. The dual problem is given by

$$\max_{\boldsymbol{\mu}} \quad q(\boldsymbol{\mu}) \quad s.t. \mu_m \geq 0, \text{for } m = 1,\dots,M, \tag{13}$$

where $\boldsymbol{\mu} = (\mu_1,\dots,\mu_M)^T$ and $q(\boldsymbol{\mu}) = \min_{\boldsymbol{V}} \ L(\boldsymbol{V},\boldsymbol{\mu})$ is the Lagrangian dual function. The dual problem can be solved iteratively, where in each iteration the precoder matrix $\boldsymbol{V}$ can be solved by using the KKT conditions for a fixed set of Lagrange multipliers, and the master problem is solved to find the Lagrange multipliers.

Based on the KKT conditions, the gradient of L with respect to $\boldsymbol{V}_k^\dagger$ should be zero, which yields the following equation

$$\begin{aligned}\boldsymbol{H}_k^\dagger\boldsymbol{U}_k\boldsymbol{W}_k &= \boldsymbol{H}_k^\dagger\boldsymbol{U}_k\boldsymbol{W}_k\boldsymbol{U}_k^\dagger\boldsymbol{H}_k\boldsymbol{V}_k + \\ &\sum_{l\in\mathcal{U}_s,l\neq k}\boldsymbol{H}_l^\dagger\boldsymbol{U}_l\boldsymbol{W}_l\boldsymbol{U}_l^\dagger\boldsymbol{H}_l\boldsymbol{V}_k + \sum_{m=1}^{M}\mu_m\boldsymbol{\Gamma}_m\boldsymbol{V}_k.\end{aligned} \tag{14}$$

The above equation can only provide the precoder $\boldsymbol{V}_k$ as a function of its combiner $\boldsymbol{U}_k$. To overcome this problem, we solve the precoder using (14) and (8). Let us first perform the following compact singular value decomposition (SVD),

$$\boldsymbol{R}_{\bar{k}}^{-1/2}\boldsymbol{H}_k\boldsymbol{\Pi}_{\bar{k}}^{-1/2} = \boldsymbol{F}_k\boldsymbol{D}_k\boldsymbol{G}_k^\dagger, \tag{15}$$

where

$$\boldsymbol{\Pi}_{\bar{k}} = \sum_{l=\in\mathcal{U}_s,l\neq k}\boldsymbol{H}_l^\dagger\boldsymbol{U}_l\boldsymbol{W}_l\boldsymbol{U}_l^\dagger\boldsymbol{H}_l + \sum_{m=1}^{M}\mu_m\boldsymbol{\Gamma}_m; \tag{16}$$

and $\boldsymbol{D}_k \in \mathbb{R}^{N_{r,k}\times N_{r,k}}$ is a diagonal matrix containing the singular values of $\boldsymbol{R}_{\bar{k}}^{-1/2}\boldsymbol{H}_k\boldsymbol{\Pi}_{\bar{k}}^{-1/2}$ ordered in decreasing order; $\boldsymbol{F}_k \in \mathbb{C}^{N_{r,k}\times N_{r,k}}$ and $\boldsymbol{G}_k \in \mathbb{C}^{N_t\times N_{r,k}}$ are the corresponding left and right singular vectors of $\boldsymbol{R}_{\bar{k}}^{-1/2}\boldsymbol{H}_k\boldsymbol{\Pi}_{\bar{k}}^{-1/2}$.

Based on [11] and [8], the precoder has the following structure for given μ_m's,

$$\boldsymbol{V}_k = \boldsymbol{\Pi}_{\bar{k}}^{-1/2}\boldsymbol{G}_k\boldsymbol{\Psi}_k, \tag{17}$$

where $\boldsymbol{\Psi}_k$ is an $N_{r,k}\times N_{r,k}$ diagonal matrix with non-negative elements on the diagonal, given by

$$\boldsymbol{\Psi}_k = \left(\boldsymbol{W}_k^{1/2}\boldsymbol{D}_k^{-1} - \boldsymbol{D}_k^{-2}\right)_+^{1/2}, \tag{18}$$

and $(\cdot)_+$ is the matrix $(\cdot)$ with the negative elements replaced with zeros. Here, the $(\cdot)_+$ operation in component $\boldsymbol{\Psi}_k$ can potentially turn off some streams by allocating zero power.

Different from the solution in [6] and [10], the power allocated to each stream for the k^{th} user given by (17) is determined by the received interference plus noise, the interference to other receivers, and the available power. It implies that the decision on whether to activate or deactivate the streams is based on the current state of the network, instead of on whether the stream was active or inactive previously.

To find the Lagrange multiplier μ_m, the ellipsoid method or sub-gradient method can be used. The solution given by the proposed WSR maximization algorithm can set the active streams with a small number of iterations. Therefore, it can quickly remove redundant users with inactive precoders and eliminate their effects on other users.

C. Joint algorithm for WSR maximization

Due to the properties of the proposed WSR maximization algorithm, it can also be implemented without the pre-user selection procedure. In this case, the user selection is jointly determined with the MIMO weights, where a user is active when its precoder is active with non-zero power.

Especially when the number of users is relatively small, the proposed WSR maximization algorithm can be performed to solve (5) directly, which will not generate much higher computational complexity than the combined algorithm.

IV. Simulation Results

In this section, simulation results that evaluate the performance of our proposed scheme are reported. For all simulations, we assume a quasi-static Rayleigh flat-fading channel, which is considered constant for the duration of a burst that appears randomly in time. The path-loss exponent is set to 3 and the noise power is -80 dBm. We consider that the APs are located in a line with an interval of X meters. We uniformly distribute k_m users around the m^{th} AP within a radius of Y meters. The total number of users is given by $\sum_{m=1}^{M} k_m = K$. Unless otherwise specified, we consider 3 APs, each with four antennas, and two antennas for each user.

A. WSR and computational complexity performance

First, we study the WSR performance with our proposed algorithms. The presented results are averaged over 1000 channel realizations. Both the proposed combined algorithm with orthogonality-based user selection and the joint algorithm without user selection are evaluated. We also compare our approaches to the WMMSE method [6], DPC [12], and the BD algorithm [4]. Since there is no existing work on the DPC with per-AP power constraint, we use the DPC algorithm with sum power constraint to serve as the upper bound of the actual DPC.

Fig. 3 shows the WSR and computation time of different algorithms as a function of the number of users. The upper bound is provided by the DPC scheme with sum power constraint. The c-algorithm for BD precoding scheme in [4] is extended to the WSR maximization problem. Comparing the combined algorithm with pre-user selection with $K_0 = 8$ to the joint algorithm, the performance loss due to the pre-user selection is less than 5%, while the computation time is significantly reduced and becomes almost independent of the number of users. Our proposed algorithm with pre-user selection achieves about 25% higher WSR than WMMSE and 40% higher than BD precoding scheme. Moreover, the c-algorithm-based BD precoding requires the highest computation time of all approaches, taking more time than even our proposed WSR maximization algorithm *without* user selection.

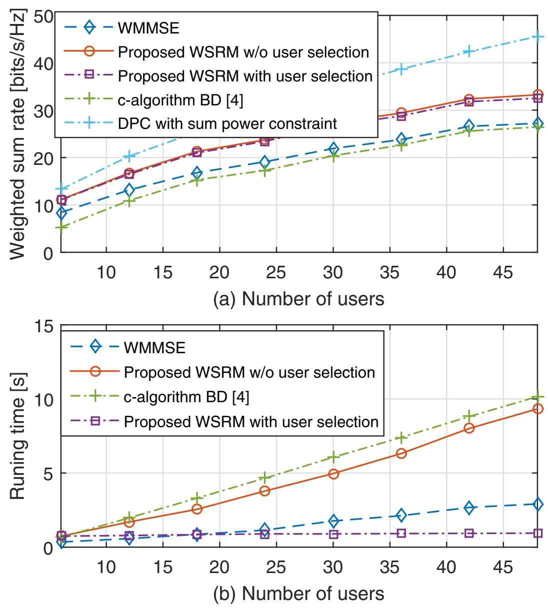

Fig. 3: WSR and running time as a function of the number of users.

Fig. 4 shows the WSR as a function of the circle radius Y. The number of users is 30 and the inter-AP spacing is 30 m. Smaller radius suggests that the users are more densely distributed around each AP, indicating high received SNR. Thus, the WSR achieved by these algorithms increases as the radius decreases. The gap between the upper bound (DPC) and our proposed algorithm is less than 10%, and is caused by both the nonlinear precoding technique and the relaxed power constraint. WMMSE performs worse at low SNR values than with high SNR, while both of our proposed algorithms achieve about 25% higher WSR than that of WMMSE. When the radius is small enough, the BD algorithm performs close to our proposed algorithms, outperforming the WMMSE algorithm.

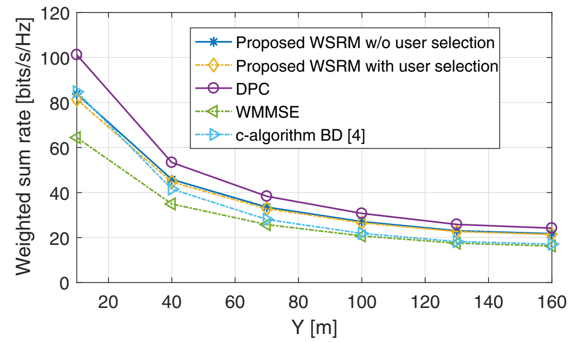

Fig. 4: WSR as a function of the radius Y.

To demonstrate the performance gain from full cooperation, the WSRs at different levels of cooperation are illustrated in Fig. 5. Besides the considered full cooperation, we evaluate three other cases, namely interference coordination (IC), non-cooperation across APs, and orthogonal channels for APs. The WSR is plotted as a function of the AP separation in Fig. 5, while the circle radius Y is fixed to 50 m. The aggregate performance of different levels of cooperation will converge to the same point with a sufficiently large X. More closely distributed APs result in higher WSR for the full cooperation case, while producing lower WSR for IC and non-cooperative cases. This is because decreasing the AP separation increases the interference, which negatively impacts the IC and non-cooperation solutions, while these interfering channels are turned into useful channels with full cooperation.

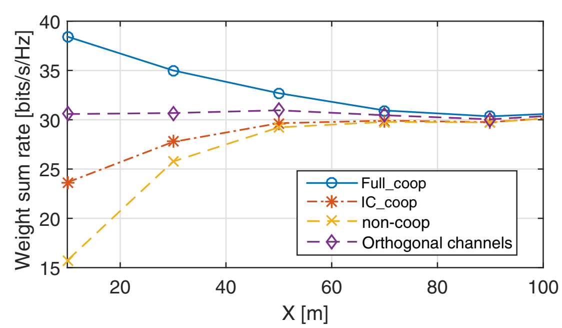

Fig. 5: WSR performance of different MU-MIMO networks. $Y = 50$.

We also evaluate the WSR as a function of the number of APs in Fig. 6, where the number of users is fixed to 20. All APs and receivers are randomly located within a circle of radius 100 m. We also include the performance with non-overlapping time slot assignment for APs, so that only one AP can serve all users at a given time slot. As more APs are deployed in the area, more power is provided to improve the average received SINR, which leads to higher WSR for both full cooperation and IC, while assigning non-overlapping time slots to APs will not change the WSR. Note that, as the interference gets more severe, the performance gap between full cooperation and IC becomes greater because of full cooperation's ability to utilize the interfering channels across different APs. The results also show that wireless performance with full cooperation scales linearly with the number of APs increasing from 2 to 10.

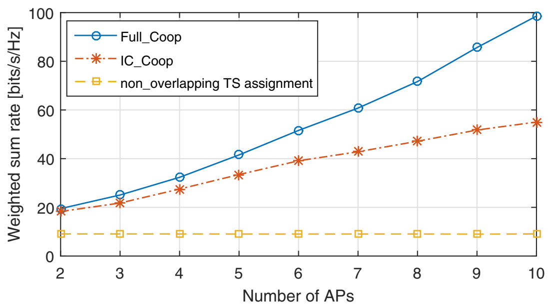

Fig. 6: WSR as a function of the number of APs.

B. Convergence properties

We also investigate the convergence performance by comparing our proposed WSR maximization algorithm with the WMMSE algorithm in [6]. We set the same starting point for both algorithms and two random trials of experiments are performed for $K = 8$ and $K = 18$. Fig. 7(a) shows the WSR as a function of the number of iterations. Although the convergence speed varies for different channel realizations, the results indicate that our proposed approach converges much faster than the WMMSE method with respect to the number of iterations. This occurs because the WMMSE method gradually reduces the power of some streams, requiring many iterations to deactivate streams, while our algorithm is able to completely deactivate some poor links in a single iteration. To validate the property of our proposed algorithm of deactivating streams efficiently, the number of active streams is plotted as a function of the number of iterations in Fig. 7(b). Streams with non-zero power are deemed as active streams. For different number of users, our proposed WSRM algorithm quickly reduces the number of active streams to the supportable number and becomes stable in less than 10 iterations, while the WMMSE needs more than 1000 iterations to completely deactivate the unnecessary streams. These results validate that the proposed WSR maximization algorithm can eliminate redundant users and determine the active streams efficiently.

V. Conclusion

An approach to maximize performance in dense wireless networks with limited mobility and AP cooperation was presented and evaluated. The proposed approach was shown to outperform previous approaches to the problem while having significantly lower running time for a moderate to large number of users. Future work will consider incorporating the approach into a scheduling framework in order to provide both high performance and fairness across users.

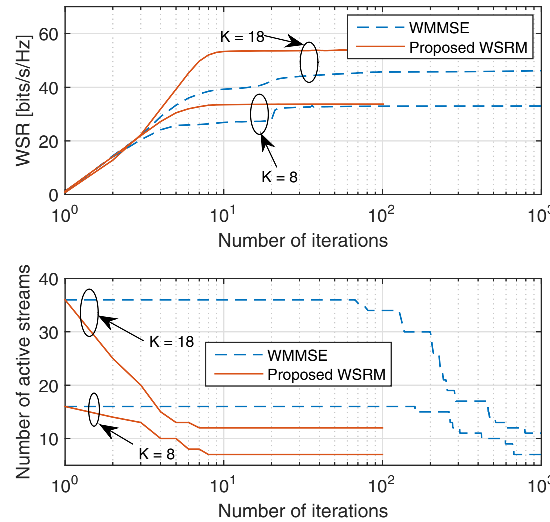

Fig. 7: Convergence rate. (a) WSR as a function of the number of iterations. (b) Number of active streams as a function of the number of iterations.

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