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Research Article

Low-Complexity Distributed Multibase Transmission and Scheduling

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This paper addresses the problem of base station coordination and cooperation in wireless networks with multiple base stations. We present a distributed approach to downlink multibase beamforming, which allows for the multiplexing of M user terminals, randomly located in a network with N base stations. In particular, we detail a low-complexity scheduling algorithm, which can be employed with different objective functions, exemplified here by two approaches: (1) maximizing the sum rate of the network; and (2) maximizing the number of users served, given a statistical constraint on the received rate per user. The optimizations are based on locally available information at each base station. Results show that our approaches yield significant gains, when compared to schemes that do not allow cooperation between cells. These gains are obtained without the extensive signaling overhead required in previously known multicell MIMO processing.

1. INTRODUCTION

The scarcity of spectral resources in cellular networks motivates aggressive frequency reuse, an approach that has shown promise of significant capacity gains. In many cases, however, this potential is severely limited by intercell interference [1]. The interference problem may be alleviated in different ways, for example, by exploiting the multiuser diversity [2]. Also, the employment of a system-wide resource distribution is beneficial, through power-allocation and scheduling of the users in the different cells [3].

With many of the existing joint resource allocation and scheduling schemes, the user terminals are still communicating with their preferred base station or access point. However, as a result of the coordination of concurrent transmissions in neighboring cells, the terminals will benefit from reduced interference. A limited form of network multiple input multiple output (MIMO) inspired coordination is presented in [4], where groups of co-located or distributed antennas transmit to a set of users, in a coherent and coordinated manner, with the aim of mitigating intercell interference.

Allowing all the antennas at the network's base stations to act together as *distributed* antennas of a large-scale multiple-antenna array, yet subject to per-base power constraints, is discussed in many recent papers. Such *network coordination* may improve the spectral efficiency of the communication, and reduce the interference from neighboring cells [5].

This form of cell coordination exploits a common signal-processing-based effort, and known multiuser MIMO transmission techniques, such as minimum mean square error, zero-forcing, or dirty paper coding, can be reused over the multibase antenna array [6–8]. In [9], the focus is on joint power control and optimal beamforming, allowing each mobile user to receive cooperative transmissions from all base stations in an active set. Alternatively, the subject of [10] spatial multiplexing over cooperating base stations, with limited, local channel state information.

Theoretical analysis of scheduling or cooperative base station transmission schemes for downlink communication is complicated, in many cases prohibitively so. Still, advances have been made, deriving the capacity-maximizing power allocation for a two-cell system [11], and finding closed-form expressions for (1) the per-cell sum rate of a distributed multicell zero-forcing beamformer [12], and (2) the sum rates using different precoders [13], in both cases for nonfading channels. In [14], the authors consider solutions to optimal transmit beamforming for multiuser downlink with per-antenna power constraints at the base station, so extensions to having distributed antennas are conceivable.

The optimum use of the distributed base antennas leads to a promising research direction. However, two major issues need to be addressed before such techniques can be considered in practical settings. First, the *complexity* of implementing multiuser MIMO solutions for a large number of cells and users is prohibitive. Second, the optimum *antenna combining* requires a large signaling overhead between the base stations of the network, which must exchange information on all the users' channel responses. This is especially problematic in the downlink.

Centralized approaches yield good performance, but remain of interest only for the optimization of very small networks or when dividing the network into clusters of cells. One handicap of clustering, however, lies in the edge effects it creates for users who sit in the neighborhood of two or more clusters, although this can be addressed by dynamic clustering [15].

To avoid the above-presented problems of high complexity and large overhead, in the case of large-scale networks, it is of great interest to derive multibase-aided cooperation techniques, which can be realized in a *distributed* manner and have a reasonable complexity. This is the main topic of this paper, and we explore approaches to distributed pro-cessing, using limited channel state information, for downlink communication in a multiuser, multibase, wireless network.

We investigate some consequences and advantages of such solutions. The key ideas presented here can be summarized as (i) *distributed beamforming* and (ii) *greedy scheduling*. A first part of this work is presented in [16]. The proposed distributed beamforming framework exploits the base antennas so that each scheduled mobile station will receive coherently added versions of the desired signal, possibly from several bases. The scheduling technique attempts to assign users to base stations, one user being served by one or more base stations, and receiving interference from others. More specifically, we present the following contributions.

(1) The first contribution is a practical setup for distributed beamforming, where each base station only needs hybrid channel state information (CSI). By hybrid CSI, we consider instantaneous CSI on locally measured channels and long-term, statistical CSI on nonlocally measured channels. This latter information may be exchanged via a central unit, using a low-rate dedicated channel.

(2) Next, we present low-complexity algorithms for multibase scheduling, where the base stations jointly select users, so as to optimize a chosen objective function, for which we will present the following two variations:

   (i) the network sum capacity, adding up the rates of all the receiving users; and

   (ii) the number of users scheduled, with a statistical per-user rate constraint.

The organization of the rest of this paper is as follows. In Section 2, we present the system model and the distributed beamforming setup. Next, in Section 3, the two different optimization objectives are presented. In Section 4, we detail the user scheduling problem for the centralized case, while Section 5 presents the distributed approaches. Results from numerical simulations are presented in Section 6, and the concluding remarks are contained in Section 7.

Use of notation: in this paper, $\mathbf{A}$, $\mathbf{a}$, and a denotes a matrix, a vector, and a scalar, respectively. For a real-valued function f with domain S, $\arg\max_{x\in S} f(x)$ is the set of elements in S that achieve the global maximum in S. Finally, we define the following three sets of indeces: $\mathcal{N} = \{0, 1, \dots, N-1\}$, $\mathcal{M} = \{0, 1, \dots, M-1\}$, and $\mathcal{N}_t = \{0, 1, \dots, NT_x - 1\}$.

2. SYSTEM MODEL

We assume a setting with N base stations (BS) and M users or mobile stations (MS), the whole system being engaged in downlink communication. The base stations have T_x transmit antennas each, while, for ease of exposition, the MSs are equipped with a single antenna, $R_x = 1$.

Each base station holds all or part of the same M-length symbol vector, $\mathbf{s} = [s_0, s_1, \dots, s_{M-1}]^T$, where s_m is intended for MS_m, $m \in \mathcal{M}$. The symbols are seen as uncorrelated, $\mathbb{E}[s_m s_k^*] = 0$, for $m \neq k$.

The base stations schedule users and apply precoding in the form of transmit-side matched filtering. To this end, a base station BS_n, $n \in \mathcal{N}$, is required to have perfect, instantaneous CSI on the channels from itself to the M users. This can be done by a preamble using training sequences, enabling the base stations to measure and track the local channels. Note that this assumes a form of symbol-level synchronization between the bases, realizable if the relative distances between the neighboring bases are not too large. Synchronization between widely separated bases is not a requirement, because the larger path loss will in any case limit the need for cooperation between them.

For the nonlocal channels between the $N-1$ base stations BS_l, $l \in \mathcal{N} \setminus n$, and the M users, we assume that BS_n has only long-term, statistical knowledge. Statistical knowledge is equivalent to knowledge of slow-varying macroscopic parameters of the channels, such as distance-based path loss and shadowing effects. See Figure 1 for an illustration of the network, and note that the coefficient $\mathbf{W}_l$ denotes the precoding at BS_l, to be defined.

For the user scheduling, we define a *scheduling graph*, represented by the $N \times M$-sized matrix $\mathbf{G}$:

$$\mathbf{G} = \begin{bmatrix} \mathbf{g}_0 & \mathbf{g}_1 & \cdots & \mathbf{g}_{N-1} \end{bmatrix}^T, \quad (1)$$

with $\mathbf{g}_n$ being the scheduling vector of size $M \times 1$ at BS_n:

$$\mathbf{g}_n = \begin{bmatrix} g_{n0} & g_{n1} & \cdots & g_{n(M-1)} \end{bmatrix}^T, \quad (2)$$

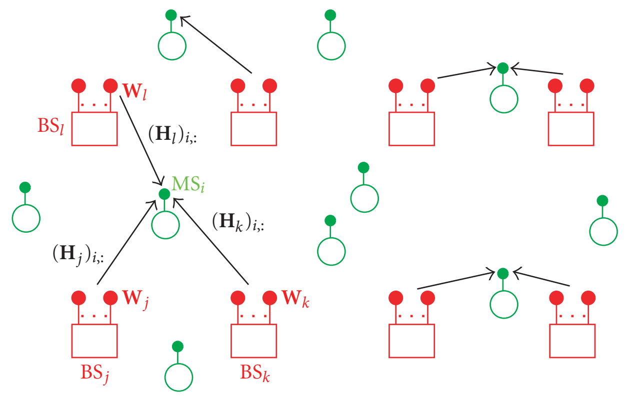

FIGURE 1: System model, showing the base stations as squares in a multicell network, while the mobile stations or users are depicted as circles. Arrows from BS_k to MS_i imply that the MS is scheduled by the base stations, so that BS_k transmits $(\mathbf{W}_k)_i s_i$ to MS_i, over the channel $(\mathbf{H}_k)_{i,:}$. The interference is not shown.

where each coefficient g_{nm} is interpreted as

$$g_{nm} = \begin{cases} 1, & \text{if } \mathrm{BS}_n \text{ transmits to } \mathrm{MS}_m, \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

We schedule *one* user MS_m, $m \in \mathcal{M}$, per base station BS_n, $n \in \mathcal{N}$, at full power, at any given time. More generally, we assume that one user is assigned to each spectral resource slot available per cell (time, frequency, code, etc.). Any MS_m is served by zero, one, or more base stations. For a given BS_n, the optimization is thus limited to choosing the best MS, according to a chosen performance criterion. Thus, this is a pure scheduling problem. Among the possible objective functions, we will present two: (1) the network sum capacity, and (2) a fairness-oriented approach of maximizing the number of users served, with statistical rate constraints. For fairness, we may also rely on user mobility and time-variant channel conditions.

The set of all feasible graphs, under the scheduling constraints above, is denoted by $\mathcal{S}_{\mathbf{G}}$, and includes all $\mathbf{G}$ for which all the vectors $\mathbf{g}_n$, $n \in \mathcal{N}$, contain *a single* nonzero element:

$$\mathcal{S}_{\mathbf{G}} = \{\mathbf{G} = [\mathbf{g}_0 \ \ \mathbf{g}_1 \ \ \cdots \ \ \mathbf{g}_{N-1}]^T : \mathbf{g}_n \in \mathcal{E}_M\}. \quad (4)$$

Here, the set $\mathcal{E}_M = \{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_M\}$ defines the standard basis for the real-vector space $\mathbb{R}^M$, so that $\mathbf{e}_m$ is an $M \times 1$-sized vector with 1 at the mth coordinate, and 0 elsewhere. The cardinality of $\mathcal{S}_{\mathbf{G}}$ is $|\mathcal{S}_{\mathbf{G}}| = M^N$, which mounts to a substantial size as the networks grow.

We combine the user selection with matched filter precoding in the $NT_x \times M$-sized matrix

$$\mathbf{W} = [\mathbf{W}_0 \ \ \mathbf{W}_1 \ \ \cdots \ \ \mathbf{W}_{N-1}]^T, \quad (5)$$

where each $\mathbf{W}_n$, of size $M \times T_x$, is the scheduling and precoding matrix of BS_n. The coefficients of the global precoding matrix $\mathbf{W}$ are $(\mathbf{W})_{n_t m} = w_{n_t m}$, where $n_t \in \mathcal{N}_t$ and $m \in \mathcal{M}$, such that

$$w_{n_t m} = g_{nm} \sqrt{P_t} \frac{h_{mn_t}^*}{|h_{mn_t}|}. \quad (6)$$

Here, h_{mn_t} represents the channel from transmit antenna $n_t \in \mathcal{N}_t$, at BS_n, to the receiving antenna at MS_m, and n is related to n_t as $n = \lfloor n_t/T_x \rfloor$, where $\lfloor \cdot \rfloor$ denotes the floor function. Note that the matched filtering naturally lends itself to distributed implementation.

From the definition of $\mathbf{G}$ in (1), it is evident that only *a single* row in each $\mathbf{W}_n$ contains nonzero elements. The transmit power per base station is limited as $\|\mathbf{W}_n\|_F^2 = P_t$ (in Watts), where $\|\cdot\|_F$ is the Frobenius norm.

Now, BS_n transmits $\mathbf{x}_n = \mathbf{W}_n^T \mathbf{s}$ from its T_x antennas. The paths from BS_n to the M receiving MSs are represented by the $M \times T_x$-sized matrix $\mathbf{H}_n$. The total channel matrix $\mathbf{H}$ includes all paths, is of size $M \times NT_x$, and is given as

$$\mathbf{H} = [\mathbf{H}_0 \ \ \mathbf{H}_1 \ \ \cdots \ \ \mathbf{H}_{N-1}]. \quad (7)$$

The coefficient $(\mathbf{H})_{mn_t} = h_{mn_t}$ gives the complex channel gain from transmit antenna $n_t \in \mathcal{N}_t$, at BS_n, $n = \lfloor n_t/T_x \rfloor$ to MS_m, and includes both fast (multipath) fading and more slowly changing effects. The $M \times 1$ received vector at all the mobile stations is

$$\mathbf{y} = \mathbf{H}\mathbf{W}\mathbf{s} + \mathbf{v}, \quad (8)$$

where the $M \times 1$-sized vector $\mathbf{v}$ contains random noise coefficients, following a Gaussian, white distribution, $v_m \sim \mathcal{CN}(0, \sigma_v)$. Each MS_m receives both desired symbols, interfering symbols, and noise:

$$y_m = (\mathbf{H})_{m,:}\mathbf{W}\mathbf{s} + v_m = y_m^d + y_m^i. \quad (9)$$

Here, y_m^d is the desired part of the signal,

$$y_m^d = \sqrt{P_t} \sum_{n_t=0}^{NT_x-1} g_{nm} |h_{mn_t}| s_m, \quad (10)$$

while y_m^i contains the interference and noise,

$$y_m^i = \sqrt{P_t} \sum_{n_t=0}^{NT_x-1} h_{mn_t} \sum_{\substack{k=0 \\ k \neq m}}^{M-1} g_{nk} \frac{h_{kn_t}^*}{|h_{kn_t}|} s_k + v_m. \quad (11)$$

3. SYSTEM OPTIMIZATION

In the following, we present two possible objective functions for use with the distributed beamforming setup. First, in Section 3.1, we focus on the network sum capacity. Section 3.2 presents an alternative; counting the number of mobile stations that are served satisfying a statistical constraint on the received rates.

3.1. The network sum capacity

There is no cooperation or coherent combining between the MSs, so the instantaneous sum capacity of the whole system is simply the sum of the data rates of the M noncooperating MISO receive branches, under ideal single-user decoding assumption [17]:

$$C(\mathbf{G},\mathbf{H}) = \sum_{m=0}^{M-1} C_m(\mathbf{G},\mathbf{H}) = \sum_{m=0}^{M-1} \log_2(1+\mathrm{SINR}_m(\mathbf{G},\mathbf{H})). \quad (12)$$

Here, $C_m(\mathbf{G},\mathbf{H})$ is the data rate at MS_m, and the signal-to-interference-plus-noise ratio (SINR) of user m is $\mathrm{SINR}_m(\mathbf{G},\mathbf{H})$, and depends both on the channel $\mathbf{H}$ and the scheduling graph $\mathbf{G}$. Using the assumptions that $\mathbb{E}[|s_m|^2] = \sigma_s^2$, $\mathbb{E}[s_m s_k^*] = 0$ for $m \neq k$, and that $\mathbb{E}[s_k v_m^*] = 0$ for all possible k and m, we develop the $\mathrm{SINR}_m(\mathbf{G},\mathbf{H})$ as

$$\begin{aligned}
&\mathrm{SINR}_m(\mathbf{G},\mathbf{H}) \\
&= \frac{\mathbb{E}_s[\,|y_m^d|^2]}{\mathbb{E}_{s,v}\left[\,|y_m^i|^2\right]} \\
&= \frac{\mathbb{E}_s[|\sqrt{P_t}\sum_{n_t=0}^{NT_x-1} g_{nm}\,|h_{mn_t}|\,s_m|^2]}{\mathbb{E}_{s,v}\left[|\sqrt{P_t}\sum_{n_t=0}^{NT_x-1} h_{mn_t}\sum_{k=0,k\neq m}^{M-1} g_{nk}(h_{kn_t}^*)/(|h_{kn_t}|)s_k+v_m|^2\right]} \\
&= \frac{(\sqrt{P_t}\sum_{n_t=0}^{NT_x-1} g_{nm}\,|\,h_{mn_t}\,|)^2\sigma_s^2}{\sum_{k=0,k\neq m}^{M-1}|\sqrt{P_t}\sum_{n_t=0}^{NT_x-1} h_{mn_t} g_{nk}(h_{kn_t}^*)/(|\,h_{kn_t}\,|)\,|^2\sigma_s^2+\sigma_v^2}.
\end{aligned} \quad (13)$$

From this, we get

$$C(\mathbf{G},\mathbf{H}) = \sum_{m=0}^{M-1}\log_2\left(1+\frac{(\sqrt{P_t}\sum_{n_t=0}^{NT_x-1} g_{nm}\,|\,h_{mn_t}\,|)^2\sigma_s^2}{[\sum_{k=0,k\neq m}|V|^2\,\sigma_s^2+\sigma_v^2]}\right), \quad (14)$$

where $V = \sqrt{P_t}\sum_{n_t=0}^{NT_x-1} h_{mn_t} g_{nk}(h_{kn_t}^*)/(|h_{kn_t}|)$.

3.2. Number of served users, under statistical rate constraints

The sum capacity is not the only useful quantitative measure on the performance of a wireless network. A different view could be gained from counting the number of simultaneously served users, given a certain per-user minimum-rate constraint C_R. This can be seen as a quality-of-service (QoS) guarantee for the scheduled users, one way to do QoS-based scheduling is described in [18]. In our case, with access only to hybrid CSI and distributed processing, the final rates are not guaranteed and we refer to the constraints as statistical.

Given a certain scheduling matrix $\mathbf{G}$, a channel realization $\mathbf{H}$, and the rate constraint C_R, we define the set

$$\mathcal{Q}_{\mathbf{G},\mathbf{H},C_R} = \{\mathrm{MS}_m \mid m \in \mathcal{M} \text{ and } C_m(\mathbf{G},\mathbf{H}) \geq C_R\}. \quad (15)$$

The cardinality of this set, denoted $|\mathcal{Q}_{\mathbf{G},\mathbf{H},C_R}|$, is the number of scheduled users whose rates satisfy the constraints. For a given channel realization, there are $|\mathcal{S}_{\mathbf{G}}|$, possibly different, sets $\mathcal{Q}_{\mathbf{G},\mathbf{H},C_R}$. Obviously, it holds that $0 \leq |\mathcal{Q}_{\mathbf{G},\mathbf{H},C_R}| \leq M$.

Only the scheduled mobile stations MS_m, for which $\sum_{n=0}^{N-1} g_{nm} \geq 0$ can possibly contribute to $|\mathcal{Q}_{\mathbf{G},\mathbf{H},C_R}|$, and they only will if their received rates satisfy the constraints. Note that if the rate constraint is too modest, the resulting best scheduling will be one where each base station transmits to a separate MS, as in the conventional, singlebase approach. Therefore, the choice of rate constraints is a crucial one.

Although this scheme does not use power allocation in an attempt to minimize the total power used for transmission, the resulting *power per served MS* is naturally limited by the wish to serve, in a satisfactory manner, as many MS as possible. In Section 6, we study and compare simulation data resulting from use of the two different optimizations approaches described in this and the previous sections.

4. USER SCHEDULING PROBLEM

We seek the scheduling graph $\mathbf{G}$ that optimizes our chosen measures of performance as described in Sections 3.1 and 3.2. The assumption on the scheduling of a single user at each base station is maintained for both approaches.

Given the above presented constraints and assumptions, the optimization problem is expressed as finding the best scheduling graph, such that either (1) the sum capacity $C(\mathbf{G},\mathbf{H})$, or (2) the number of served users with statistical rate constraint is maximized. The latter objective is expected to introduce an element of fairness among the MSs. The scheduling problem can be approached in different ways, first we present a centralized scheduler in Section 4.1, useful for comparison. In Section 5, we propose low-complexity, distributed schedulers.

4.1. Centralized scheduler

The centralized scheduling approach is governed by a central unit, which is required to have full, instantaneous CSI on the whole channel $\mathbf{H}$. The optimization takes the form of an exhaustive search, where the central unit searches the *entire* M^N-sized set of feasible graphs $\mathcal{S}_{\mathbf{G}}$, and picks the one that maximizes the chosen objective function.

For the case of maximum sum capacity, we denote this best scheduling graph by $\mathbf{G}_{\mathrm{SC}}^*$, and write the optimization problem as

$$\mathbf{G}_{\mathrm{SC}}^* = \arg\max_{\mathbf{G}\in\mathcal{S}_{\mathbf{G}}} C(\mathbf{G},\mathbf{H}). \quad (16)$$

For the case when the objective is to maximize the number of users served with an acceptable rate, we find the best graph $\mathbf{G}_{\mathrm{MS}}^*$ as

$$\mathbf{G}_{\mathrm{MS}}^* = \arg\max_{\mathbf{G}\in\mathcal{S}_{\mathbf{G}}} |\,\mathcal{Q}_{\mathbf{G},\mathbf{H},C_R}\,|. \quad (17)$$

If $|Q_{\mathbf{G},\mathbf{H},C_R}| = |Q_{\mathbf{G}',\mathbf{H},C_R}|$, for $G \neq G'$, the chosen graph will be the one that gives the highest sum rate $C(\mathbf{G},\mathbf{H})$.

As mentioned, the cardinality of feasible graph set is $|\mathcal{S}_{\mathbf{G}}| = M^N$, so for a large network, the centralized scheduler is prohibitively complex and time-consuming. Furthermore, this implies a very large amount of feedback information between the MSs and the base stations to be centrally collected by the network, which is not practical for large networks in mobility settings.

Theoretical analysis of these problems are highly nontrivial, but we give two very simple examples to illustrate the case of maximizing the sum capacity.

(1) Interference-limited case

When the noise power is very small compared to the received interference, we neglect it and consider an interference-limited scenario:

$$\lim_{\sigma_v \to 0^+} C(\mathbf{G},\mathbf{H}) = \sum_{m=0}^{M-1} \log_2\left(1 + \frac{\left(\sqrt{P_t}\sum_{n_t=0}^{NT_x-1} g_{nm}\,|\,h_{mn_t}\,|\right)^2}{\sum_{k=0,k\neq m}^{M-1}\,|\,V\,|^2}\right) \tag{18}$$

From this expression, we observe that, with no interference, the sum capacity can theoretically be infinite. That is the case if all the base stations in the network schedule *any single* mobile station, towards which there is at least one nonzero channel.

(2) Static channels

Now, assume that all the channels are static and equal to unity, $h_{mn} = 1$, $\{m,n\} \in \{\mathcal{M},\mathcal{N}\}$. For the ease of exposition, we assume that the BSs are single-antenna $T_x = 1$, and define $\delta = \sigma_v^2/(P_t\sigma_s^2)$. Now, (14) simplifies to

$$C(\mathbf{G},\mathbf{H}_1) = \sum_{m=0}^{M-1} \log_2\left(1 + \frac{\left(\sum_{n=0}^{N-1} g_{nm}\right)^2}{\sum_{k=0,k\neq m}^{M-1}\left(\sum_{n=0}^{N-1} g_{nk}\right)^2 + \delta}\right). \tag{19}$$

We give three example cases, assuming that there are as many MSs as BSs in the network $M = N$: when (1) all the BSs schedule a single MS, (2) all MSs are scheduled by a separate BS, and (3) half of the BSs schedule one MS and the rest schedule a second MS. The corresponding sum rates are

$$\begin{aligned} C_1 &= \log_2\left(1 + \frac{N^2}{\delta}\right), \\ C_2 &= M\log_2\left(1 + \frac{1}{N-1+\delta}\right), \\ C_3 &= 2\log_2\left(1 + \frac{(N/2)^2}{(N/2)^2+\delta}\right). \end{aligned} \tag{20}$$

Using $N \geq 2$ and a sensible range $0 < \delta \leq 1$, it is obvious from these examples that the best rate is achieved in C_1, where all BSs schedule a single MS. In fact, from a sum-rate point of view in this case, scheduling any single MS is the best choice, which makes intuitive sense given the slope of the log function.

Even when the channels have different, distance-based path loss, which is closer to reality and should diminish the interference problem between far-away nodes, the network very quickly becomes interference-limited, and scheduling more than a few users is suboptimal.

5. DISTRIBUTED SOLUTIONS

The concept of the centralized scheduler is simple, as the scheduling graph $\mathbf{G}$ is constructed in a central unit, and then each base station only needs to be told which MS to schedule. However, the exponential complexity increases and the need for full, centralized, instantaneous CSI motivates the search for low-complexity solutions with acceptable performance.

In the following, we give some distributed user scheduling approaches. One approach to derive distributed algorithms is to break channel information into two sets, characterized as being local or nonlocal information. These sets of information are treated differently and dubbed together as *hybrid CSI*. Here, the term is used to describe the fact that BS_n, $n \in \mathcal{N}$, has full, instantaneous CSI on its local channels, defined as the T_xM channels linking BS_n to all the M users, and represented by $\mathbf{H}_n$. On the remaining $M(N-1)T_x$ channels, BS_n has only long-term, statistical CSI, by which, for this scenario, we specifically refer to the path loss and the shadow fading.

In Section 5.1, we describe a spatially distributed multibase scheduler of relatively low complexity and where only hybrid CSI is needed. For comparison, we also give a fully distributed scheduler, as well as a conventional singlebase scheduler, in Sections 5.2 and 5.3, respectively. Note that these comparisons are tailored neither to maximize the capacity nor the number of scheduled MSs, they simply illustrate alternative scheduling approaches.

5.1. Iterative, distributed scheduling

We present an iterative scheme, in which the base stations successively make greedy scheduling decisions and update the common scheduling graph $\mathbf{G}$. They all optimize the same objective function, thus benefiting from intercell cooperation, but have access only to hybrid CSI.

This approach demands that *statistical channel state information* is distributed to all the base stations prior to optimization, and that the updated scheduling graph is always known to the base stations. In comparison with the centralized scheme, the feedback load is significantly reduced.

The system starts from an initial graph $\mathbf{G}_0$, known to all the base stations. Next, in a predetermined, nonoptimized order, all the BS_n, $n \in \mathcal{N}$, are allowed to update the scheduling graph once, including its own best scheduling vector $\mathbf{g}_n^*$ in $\mathbf{G}_n$ to form $\mathbf{G}_{n+1}$. The distributed scheduling is performed based on the choice of objective function and with access to hybrid CSI.

We summarize the scheduling procedure for both choices of optimization functions, the maximum sum rate and the maximum number of served users, the latter with a statistical constraint on the user rate.

For ease of exposition, we define the matrix

$$\widetilde{\mathbf{G}}_n = \left[\mathbf{g}_0 \ \cdots \ \mathbf{g}_{n-1} \ \widetilde{\mathbf{g}}_n \ \mathbf{g}_{n+1} \ \cdots \ \mathbf{g}_{N-1}\right]^T, \tag{21}$$

where $\mathbf{G}_n = \left[\mathbf{g}_0 \ \cdots \ \mathbf{g}_{n-1} \ \mathbf{g}_n \ \mathbf{g}_{n+1} \ \cdots \ \mathbf{g}_{N-1}\right]^T$, in other words, $\mathbf{g}_n$ in row n of $\mathbf{G}_n$ is exchanged with $\widetilde{\mathbf{g}}_n$.

(1) *Maximum network downlink sum capacity*

Initilize $\mathbf{G}_0$.

for $n = 0 : N-1$

$$\mathbf{g}^*_{n,\text{SC}} = \arg\max_{\tilde{\mathbf{g}}_n \in \mathcal{E}_M} \mathbb{E}_{\tilde{\mathbf{H}}_n}\{C(\tilde{\mathbf{G}}_n, \mathbf{H})\};$$
$$\mathbf{G}_{n+1} = [\mathbf{g}_0 \ \cdots \ \mathbf{g}_{n-1} \ \mathbf{g}^*_{n,\text{SC}} \ \mathbf{g}_{n+1} \ \cdots \ \mathbf{g}_{N-1}]^T; \quad (22)$$

end

$\mathbf{G} = \mathbf{G}_N$.

(2) *Maximum number of users served*

Initialize $\mathbf{G}_0$.

for $n = 0 : N-1$

$$\mathcal{G}_{\text{MS}} = \arg\max_{\tilde{\mathbf{g}}_n \in \mathcal{E}_M} \mathbb{E}_{\tilde{\mathbf{H}}_n}\{|\mathcal{Q}_{\tilde{\mathbf{G}}_n,\mathbf{H},C_R}|\};$$
$$\mathbf{g}^*_{n,\text{MS}} = \arg\max_{\tilde{\mathbf{g}}_n \in \mathcal{G}_{\text{MS}}} \mathbb{E}_{\tilde{\mathbf{H}}_n}\{C(\tilde{\mathbf{G}}_n, \mathbf{H})\}; \quad (23)$$
$$\mathbf{G}_{n+1} = [\mathbf{g}_0 \ \cdots \ \mathbf{g}_{n-1} \ \mathbf{g}^*_{n,\text{MS}} \ \mathbf{g}_{n+1} \ \cdots \ \mathbf{g}_{N-1}]^T;$$

end

$\mathbf{G} = \mathbf{G}_N$.

Here, the double use of arg max signifies that when several g_n give the same $|\mathcal{Q}_{\tilde{\mathbf{G}}_n,\mathbf{H},C_R}|$, we select the one yielding the maximum sum rate, based on the available CSI.

In both approaches, $\mathbf{G}_{n+1}$ is found in the same way as $\tilde{\mathbf{G}}_n$, where $\mathbf{g}_l$, $l \neq n$, are taken from $\mathbf{G}_n$, which contains all previously updated scheduling choices. Also, $\mathbb{E}_{\tilde{\mathbf{H}}_n}$ denotes taking the expected value with respect to all channels in

$$\tilde{\mathbf{H}}_n = [\mathbf{H}_0, \ \mathbf{H}_1, \ \cdots \ \mathbf{H}_{n-1}, \ \mathbf{H}_{n+1}, \ \cdots \ \mathbf{H}_{N-1}]. \quad (24)$$

This matrix contains all the channel coefficients of the full-channel $\mathbf{H}$, except $\mathbf{H}_n$. As $\mathbf{H}_n$, the local channel matrix from BS_n to all MSs, is instantaneously known at BS_n, there is no need to average over it, while BS_n only has long-term statistical information on the rest of the channel; $\tilde{\mathbf{H}}_n$.

In the above iterative procedure, for both objective functions, the scheduling graph is updated once for each of the N base stations. After traversing all the base stations, the last version of $\mathbf{G}$ is the final scheduling matrix. This calls for a central unit to hold and distribute the intermediate $\mathbf{G}_n$, but the exchange of information to and from the users is moderate.

5.2. Fully distributed user scheduling

This comparison is fully distributed and noncooperative, so no central unit is required for coordination. Each BS_n schedules the MS_m with the maximum receive signal-to-noise ratio (SNR), with no regard for the interference. In other words, BS_n finds its own best scheduling vector $\mathbf{g}^*_n$, such that

$$\mathbf{g}^*_n = \arg\max_{\mathbf{g}_n \in \mathcal{E}_M} \text{SNR}(\mathbf{g}_n, \mathbf{H}_n), \quad (25)$$

where $\text{SNR}(\mathbf{g}_n, \mathbf{H}_n)$ is defined as

$$\text{SNR}(\mathbf{g}_n, \mathbf{H}_n) = \frac{|\sqrt{P_t}\, \mathbf{g}_n \overline{\mathbf{H}}_n|^2 \sigma_s^2}{\sigma_v^2}, \quad (26)$$

where $\overline{\mathbf{H}}_n$ denotes a matrix with entries $(\overline{\mathbf{H}}_n)_{mn} = |(\mathbf{H}_n)_{mn}|$. This represents the receive SNR in MS_m, the single MS scheduled by BS_n, for which $g_{nm} = 1$. From a network point of view, one mobile station may be selected by multiple base stations, in which case it receives a coherently added sum of the desired signal, beamformed from all the antennas of these base stations.

This method has low complexity and only local information is used, while statistical external information is not needed. One disadvantage is the limited amount of cell cooperation; the base stations are not aware of each other, and this will in turn limit network performance.

5.3. Conventional single base station assignment

Finally, we formalize a conventional singlebase approach for this scenario, in the sense that a receiving MS can only be scheduled by a single base station. A central unit goes through the N available base stations, and allows each base station to choose a previously unscheduled MS, if there are any left. The central unit holds and updates the scheduling graph, ensuring that one MS is scheduled by one base station only. For BS_n, the user is selected by maximizing the receive SNR:

$$\mathbf{g}^*_n = \arg\max_{\mathbf{g}_n \in \mathcal{S}_e} \text{SNR}(\mathbf{g}_n, \mathbf{H}_n), \quad (27)$$

where $\mathcal{S}_e$ is a subset of the full $\mathbb{R}^M$ standard basis $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_M\}$, representing those users not already scheduled by a base station. Each BS only needs local CSI.

The central unit exploits the available information by optimizing the scheduling order, at all times coupling the BS-MS pair that has maximum expected SNR, among those remaining. When there are no more base stations or users left to connect, the scheduling graph is finished.

Note that the last two scheduling approaches, in Sections 5.2 and 5.3, are not linked to the two objective functions used in this paper, as presented in Section 3.

6. NUMERICAL RESULTS

Next, we present some results of Mont Carlo simulations for the above-described schedulers, for both optimization objectives, as described in Sections 3.1 and 3.2. The focus is on how the low-complexity, iterative, and distributed scheduling approach in Section 5.1 performs when compared to the centralized, the fully distributed, and the conventional schemes; see Sections 4.1, 5.2, and 5.3, respectively.

The base stations are placed in a grid, as seen in Figure 1, with a minimum distance d between neighbors. The positions of the mobile users are quasistatic, generated following a random and uniform spatial distribution over the entire network area.

Table 1: Simulation parameters.

Parameter	Value
Shadow fading mean μ_χ	0
Shadow fading standard dev. σ_χ	10 dB
Transmit power P	1 Watt
Transmit antenna gain G_t	16 dB
Receive antenna gain G_r	6 dB
Antenna heights $\{h_b, h_r\}$	$\{30, 1\}$ m
Carrier frequency f_c	1800 MHz
Smallest distance d between BSs	0.5 km
Number of antennas $\{T_x, R_x\}$	$\{1, 1\}$
Random MS locations N_{MS}	50
Channel realizations N_{chan}	200
Rate constraint, $C_m(\mathbf{G}, \mathbf{H})$	4 b/s/Hz for all SNR

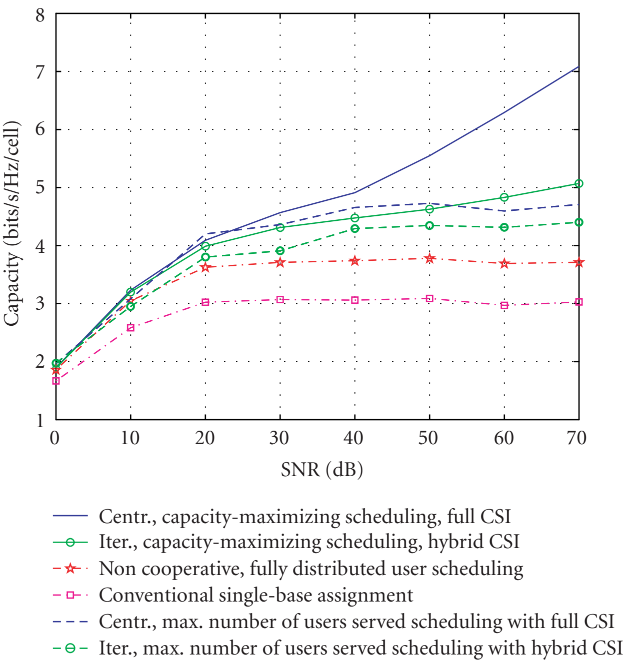

Figure 2: Sum capacity per cell versus edge-of-cell SNR for $N = M = 4$. Note that the iterative, capacity-maximizing scheduling approaches lie between that of the centralized schemes and the interference-limited performance of the fully distributed and the conventional schedulers. Note also that the attempt to maximize the number of scheduled users with acceptable rate limits the sum capacity. The statistical rate constraint was $C_R = 4$ b/s/Hz.

The channel from antenna $n_t \in \mathcal{N}_t$, located at BS_n, $n = \lfloor n_t/T_x \rfloor$, to MS_m is $h_{mn_t} = \gamma_{mn_t} h'_{mn_t}$, where h'_{mn_t} represents the complex random, Rayleigh distributed fast fading, $h'_{mn_t} \sim \mathcal{CN}(0, 1)$. The constant and slow-varying transmission effects are contained in γ_{mn_t}. In dB scale, we write

$$\gamma_{mn_t,\text{dB}} = G_{t,\text{dB}} - \rho_{mn_t,\text{dB}} + \chi_{mn_t,\text{dB}} + G_{r,\text{dB}}, \qquad (28)$$

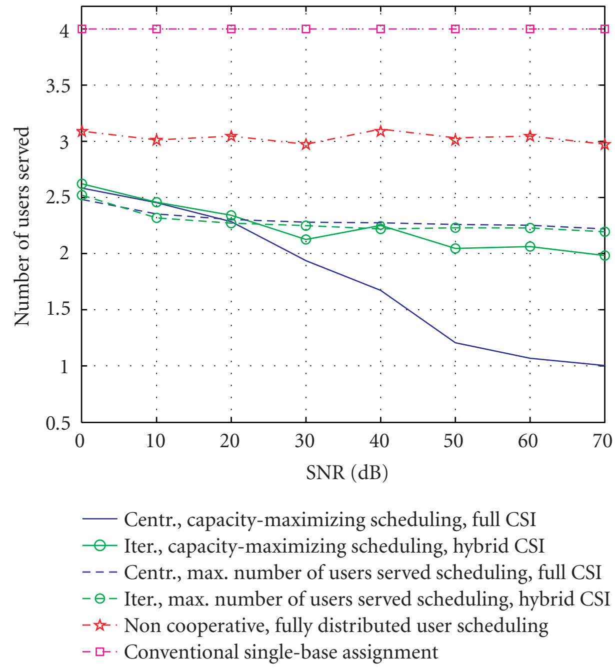

Figure 3: Number of MS served versus edge-of-cell SNR for $N = M = 4$. Note that the iterative, and the centralized $|\mathcal{Q}_{\mathbf{G},\mathbf{H},C_R}|$-maximizing approaches both schedule a relatively constant number of users, while the centralized and iterative capacity-maximizing approaches schedule fewer users as the SNR increases. The conventional approach schedules N users, regardless of the conditions. The statistical rate constraint was $C_R = 4$ b/s/Hz.

where $G_{t,\text{dB}}$ and $G_{r,\text{dB}}$ are the transmit and receive antenna gains, and $\rho_{mn,\text{dB}}$ is the path loss, generated using the COST 231 model [19]. The distributed, long-term (shadow) fading $\chi_{mn,\text{dB}}$ is modeled as random, log-normal $\chi_{mn_t,\text{dB}} \sim \mathcal{N}(\mu_\chi, \sigma_\chi)$. Useful parameters are detailed in Table 1.

All the simulations were run by averaging the resulting sum capacity over a total of N_{MS} random MS locations and N_{chan} realizations of the instantaneously known channel coefficients. The expectation operator $\mathbb{E}_{\tilde{\mathbf{H}}_n}$, of (22) and (23), implies further averaging for each of the N_{chan} channel realizations.

Simulations have been run for different scenarios, where performance is measured by both the network sum capacity of (14) per cell, with unit bits/second/Herz/cell, and by the number of mobile stations served, in different figures.

First, we simulated a rather small network, with only 4 transmitting base stations and 4 receiving, mobile users, $N = M = 4$. For simplicity, the base stations are assumed equipped with a single antenna, as are the receiving users, $T_x = R_x = 1$. In Figure 2, the curves show how the network sum capacity develops with an increasing edge-of-cell SNR (reference value for single-user at distance d_{ref}). The centralized scheduler of Section 4.1 and the iterative scheduler of Section 5.1 are both represented with two curves, one for each objective function, as shown in the figure legend. The remaining two curves are obtained by using the

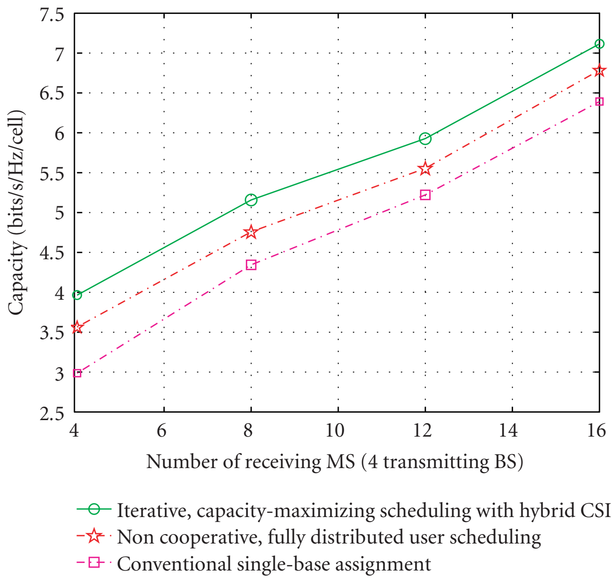

Figure 4: Sum capacity per cell versus number of receiving MSs, for edge-of-cell SNR of 20 dB and $N = 4$ base stations. Note that the iterative, capacity-maximizing scheduling outperforms both the fully distributed and the conventional scheduling approaches.

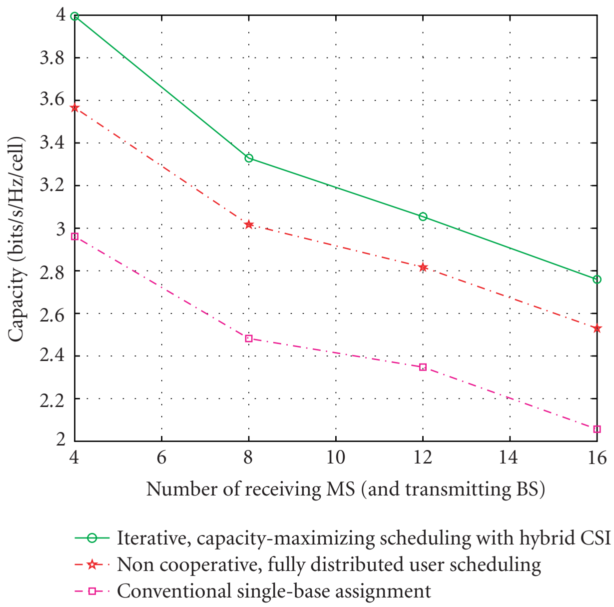

Figure 5: Sum capacity per cell versus number of receiving MSs and base stations ($N = M$), for edge-of-cell SNR of 20 dB. Note that the iterative, capacity-maximizing scheduling outperforms both the fully distributed and the conventional scheduling approaches.

schemes described in Sections 5.2 and 5.3, in downward order.

Next, in Figure 3, we show the number of users scheduled, for the same schemes as in the previous figure. When comparing the results of Figures 2 and 3, we observe that the choice of objective function indeed has an impact; when attempting to maximize $|\mathcal{Q}_{\mathbf{G},\mathbf{H},C_R}|$, the network sum capacity will suffer. This also applies for the corresponding case of maximizing the sum capacity, in which case the number of MS served will decrease with increased SNR.

Focusing purely on the sum capacity of the network, we also fix the SNR to 20 dB and explore the network sum capacity when increasing the number of receiving users $M = \{4, 8, 12, 16\}$, while keeping a constant $N = 4$ base stations. The results are shown in Figure 4. In this case, as the M increases beyond N, note that only N of these users will be served at any given time. No simulation results for maximizing $|\mathcal{Q}_{\mathbf{G},\mathbf{H},C_R}|$ were included here.

Finally, in Figure 5, we present the simulation results when increasing the number of receiving users and base stations, $M = N = \{4, 8, 12, 16\}$. We observe that the sum capacity per cell is decreasing when increasing M and N together, and imagine one explanation for this being the increased levels of interference resulting from more base stations transmitting. In Figures 4 and 5, only three curves are plotted, as the centralized scheme of Section 4.1 is very time-consuming for larger networks. No simulation results for maximizing $|\mathcal{Q}_{\mathbf{G},\mathbf{H},C_R}|$ were included here.

7. CONCLUSIONS

In this paper, we have presented approaches for base station coordination and cooperation in multibase, multiuser wireless networks. First, a framework for distributed, downlink beamforming was given, where each participating base station only needs access to hybrid channel state information, including instantaneous CSI on locally measured channels. Next, we have detailed some scheduling schemes to use with this framework, which may be tailored to different optimization needs; such as the maximization of the network sum capacity or the maximization of the number of MSs that can be scheduled while enjoying a certain rate. For both cases, the low-complexity approach of distributed, iterative, scheduling represents a middle course between the interference-limited fully distributed and conventional schemes, and the prohibitively complex centralized algorithm.

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