A Low Complexity Distributed Multibase Transmission Scheme for Improving the Sum Capacity of Wireless Networks

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***Abstract*— This paper addresses the problem of base station coordination in multicell wireless networks. We present a distributed approach to downlink multibase beamforming as well as a low complexity, near-optimal, scheduling algorithm allowing the multiplexing of M user terminals randomly located in a network with N base stations. The algorithms rely on the maximization of the sum rate of the network, based on locally available information at each base station. Results show that our approach yields significant gains in the system capacity when compared to schemes not allowing cooperation between cells, without requiring the extensive signaling overhead involved in optimal multicell MIMO processing.**

I. Introduction

Aggressive frequency reuse in multicell systems has shown promise of significant capacity gains. In many cases, however, this potential is severely limited by intercell interference [1]. We may alleviate the interference problem by employing a system-wide resource distribution, through power-allocation and scheduling of the users in the different cells [2].

In such schemes, user terminals are still communicating with their preferred base station (or access point), but benefiting from reduced interference created by concurrent transmissions in neighboring cells.

For enhanced performance, this form of resource allocation-based cooperation between cells, may be augmented with a signal processing-based cooperation. In this scenario, the antennas at all base stations in the network are seen as *distributed* antennas of a large-scale MIMO array, yet subject to per-base power constraints. In this view, 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 [3].

Certain approaches of this nature are considered in e.g. [4] and [5], and also with a more theoretical approach in [6] and [7]. The optimum use of the distributed base antennas that can be found, indicates a promising research avenue. Yet, it brings two major issues in practical settings: First, the complexity of implementing multiuser MIMO solutions for a large number of cells and users is prohibitive. Second, optimum antenna combining requires a large signaling overhead between the bases of the network, which must exchange information on all the users' channel responses. This type of approach remains of interest for the optimization of very small networks or clusters of cells. The disadvantage of clustering, however, lies in the edge effects it creates for users who sit in the neighborhood of two or more clusters.

To avoid these problems, in the case of larger scale networks, deriving multibase MIMO-aided cooperation techniques, which can be realized in a *distributed* manner and have a reasonable complexity, is of great interest.

In this paper, we investigate such solutions. The key ideas presented here can be summarized as (i) *distributed beamforming* and (ii) *greedy scheduling*. The proposed distributed beamforming framework exploits the base antennas so that coherently added signals are received at each of the mobiles, possibly from several bases. The scheduling technique aims at assigning users to base stations, one MS being served by one or more BS, from which distributed beamforming will be performed.

More specifically, we present the following contributions:

- A 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 non-locally measured channels.
- A low complexity algorithm for multibase scheduling, where the base stations jointly select users, so as to maximize the sum capacity of the network.

The organization of this paper is as follows: In Section II we present the system model. Next, in Section III the optimization problem and possible approaches are given. Results from numerical simulations are presented in Section V, and the concluding remarks are contained in Section VI.

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II. System model

We assume a setting with N base stations (BS) and M mobile stations (MS), the whole system being engaged in downlink communication. For ease of exposition, all the BSs and MSs are equipped with a single antenna. Each base station holds an M-length symbol vector, $\boldsymbol{s} = [s_0,\, s_1,\, \cdots,\, s_{M-1}]^T$, where s_m is intended for MS_m, $m \in \{0, 1, \ldots, M-1\}$. 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 is required to have perfect CSI on the channels from itself to the M users. This can be done by a preamble using training sequences. 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 cooperation between such cells.

For the channels between the other $N-1$ base stations and the M users, we assume BS_n to have 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 and shadowing effect. See Fig. 1 for an illustration of the network, and note that the coefficient w_{li} denote 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 $\boldsymbol{G}$:

$$\boldsymbol{G} = [\boldsymbol{g}_0\, \boldsymbol{g}_1\, \ldots\, \boldsymbol{g}_{N-1}]^T, \text{ with } \boldsymbol{g}_n = [g_{n0},\, g_{n1},\, \ldots\, , g_{n(M-1)}]^T,$$

where each coefficient g_{nm} is interpreted as

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

We schedule *one* user MS_m, $m \in \{0, 1, \ldots, M-1\}$, per base station BS_n, $n \in \{0, 1, \ldots, N-1\}$, at full power, at any given time. More generally, we assume that one user is assigned to each spectral resource slot available at each 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 receiver, according to a chosen performance criterion, so this is a pure scheduling problem. There is no attempt at fairness by requiring all users to be served, for this, we rely on user mobility and time-variant channel conditions.

The set of feasible graphs, $\mathcal{S}_{\boldsymbol{G}}$, includes all $\boldsymbol{G}$ for which each $\boldsymbol{g}_n$, $n \in \{0, 1, \ldots, N-1\}$, $\boldsymbol{g}_n^T$ being the n-th row vector of $\boldsymbol{G}$, contains *a single* non-zero element:

$$\mathcal{S}_{\boldsymbol{G}} = \Big\{ \boldsymbol{G} \;:\; \boldsymbol{g}_n \in \{\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_M\} \Big\}\,, \tag{2}$$

where $\boldsymbol{e}_m$ is an $M \times 1$-sized vector with 1 at the m-th coordinate, and 0 elsewhere, so the set $\{\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_M\}$ defines the standard basis for $\mathbb{R}^M$.

We combine this user selection and the matched filter pre-coding in $\boldsymbol{W} = \big[\boldsymbol{w}_0\;\boldsymbol{w}_1\;\;\ldots\;\;\boldsymbol{w}_{N-1}\big]^T$, a matrix of size $N \times M$.

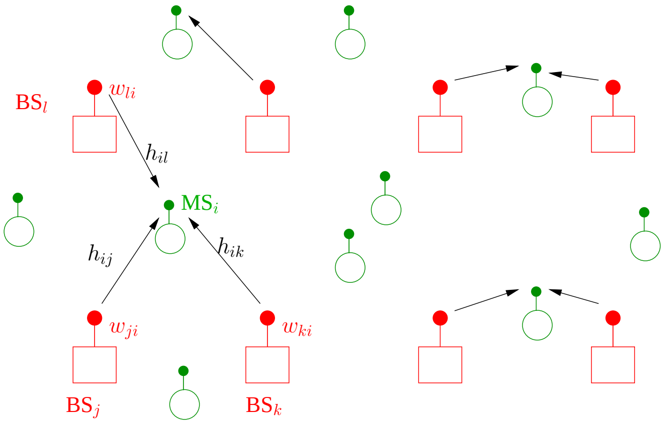

Fig. 1. System model, showing the base stations as squares in a multicell network, while the users are depicted as circles. Arrows from BS_k to MS_i implies that MS_i is scheduled by BS_k, the interference is not shown.

Each $\boldsymbol{w}_n = [w_{n0}\; w_{n1}\;\; \ldots\;\; w_{n(M-1)}]^T$ is the scheduling and precoding vector of BS_n, where the coefficient

$$w_{nm} = g_{nm} \sqrt{P_t}\, \frac{h_{mn}^*}{|h_{mn}|}\,, \tag{3}$$

is used by BS_n for s_m, the symbol intended for MS_m. Here, h_{mn} is the complex channel gain between BS_n and MS_m, including both fast (multipath) fading and more slowly-changing effects. The transmit power per BS is limited as $|\boldsymbol{w}_n|^2 = P_t$ (in Watts) and BS_n transmits $x_n = \boldsymbol{w}_n^T \boldsymbol{s}$. The $M \times 1$ vector of received symbols at all the MSs is

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{W}\boldsymbol{s} + \boldsymbol{v}\,, \tag{4}$$

where $\boldsymbol{H}$ is the $M \times N$-sized total channel matrix, with entries $(\boldsymbol{H})_{mn} = h_{mn}$. The $M \times 1$ vector $\boldsymbol{v}$ contains random noise coefficients, following a Gaussian, white distribution, $v_m \sim (0, \sigma_v)$. Each MS_m may receive both desired symbols, interfering symbols, and is also affected by noise:

$$y_m = (\boldsymbol{H})_{m,:}\boldsymbol{W}\boldsymbol{s} + v_m = y_m^d + y_m^i\,, \tag{5}$$

where the desired part of the signal is

$$y_m^d = \sqrt{P_t} \sum_{n=0}^{N-1} g_{nm} |h_{mn}| s_m\,, \tag{6}$$

while the interference and noise are contained in

$$y_m^i = \sqrt{P_t} \sum_{n=0}^{N-1} h_{mn} \sum_{\substack{k=0\\k\neq m}}^{M-1} g_{nk} \frac{h_{kn}^*}{|h_{kn}|} s_k + v_m\,. \tag{7}$$

The signal-to-interference-plus-noise ratio (SINR) of user m is denoted $\text{SINR}_m(\boldsymbol{G}, \boldsymbol{H})$, as it depends both on the channel $\boldsymbol{H}$ and the scheduling graph $\boldsymbol{G}$. 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 $\text{SINR}_m(\boldsymbol{G},\boldsymbol{H})$ as:

$$\begin{aligned}\text{SINR}_m(\boldsymbol{G},\boldsymbol{H}) &= \frac{\mathbb{E}_s[|y_m^d|^2]}{\mathbb{E}_{s,v}[|y_m^i|^2]}\\ &= \frac{\mathbb{E}_s\left[|\sqrt{P_t}\sum\limits_{n=0}^{N-1} g_{nm}|h_{mn}|s_m|^2\right]}{\mathbb{E}_{s,v}\left[|\sqrt{P_t}\sum\limits_{n=0}^{N-1} h_{mn}\sum\limits_{\substack{k=0\\k\neq m}}^{M-1} g_{nk}\frac{h_{kn}^*}{|h_{kn}|}s_k + v_m|^2\right]}\\ &= \frac{\left(\sqrt{P_t}\sum\limits_{n=0}^{N-1} g_{nm}|h_{mn}|\right)^2\sigma_s^2}{\sum\limits_{\substack{k=0\\k\neq m}}^{M-1}\left|\sqrt{P_t}\sum\limits_{n=0}^{N-1} h_{mn}g_{nk}\frac{h_{kn}^*}{|h_{kn}|}\right|^2\sigma_s^2+\sigma_v^2}\,. \end{aligned} \tag{8}$$

III. User scheduling problem

We seek the scheduling graph $\boldsymbol{G}$ that optimizes our chosen measure of performance; the network downlink sum capacity.

There is no cooperation or coherent combining between the MSs, so the instantaneous capacity of the whole system is simply the sum of the data rates of the M non-cooperating MISO receive branches.

$$\begin{aligned}C(\boldsymbol{G},\boldsymbol{H}) &= \sum_{m=0}^{M-1} C_m(\boldsymbol{G},\boldsymbol{H})\\ &= \sum_{m=0}^{M-1}\log_2(1+\text{SINR}_m(\boldsymbol{G},\boldsymbol{H}))\,,\end{aligned} \tag{9}$$

where $C_m(\boldsymbol{G},\boldsymbol{H})$ is the data rate at MS_m. From (8), we get

$$\begin{aligned}C(\boldsymbol{G},\boldsymbol{H}) = \sum_{m=0}^{M-1}\log_2\Bigg(1+\Big(\sqrt{P_t}\sum_{n=0}^{N-1}g_{nm}|h_{mn}|\Big)^2\sigma_s^2\Bigg/\\ \Big[\sum_{\substack{k=0\\k\neq m}}^{M-1}\Big|\sqrt{P_t}\sum_{n=0}^{N-1}h_{mn}g_{nk}\frac{h_{kn}^*}{|h_{kn}|}\Big|^2\sigma_s^2+\sigma_v^2\Big]\Bigg).\end{aligned} \tag{10}$$

Given the above presented constraints and assumptions, the optimization problem is expressed as finding the best scheduling matrix, such that the sum capacity $C(\boldsymbol{G},\boldsymbol{H})$ is maximized. This problem can be approached in different ways, first we present a centralized scheduler in Subsection III-A, useful for comparison. In Section IV, we propose low-complexity distributed schedulers.

A. Centralized Scheduler

The centralized scheduling approach requires full, instantaneous CSI on the whole channel, and is performed by a central unit, in the form of an exhaustive search. The central unit iterates through the *entire* set of feasible graphs $\mathcal{S}_{\boldsymbol{G}}$, and picks the one that maximizes the sum capacity, denoted $\boldsymbol{G}^*$.

$$\boldsymbol{G}^* = \arg\max_{\boldsymbol{G}\in\mathcal{S}_{\boldsymbol{G}}} C(\boldsymbol{G},\boldsymbol{H})\,. \tag{11}$$

The cardinality of feasible graphs set is $|\mathcal{S}_{\boldsymbol{G}}| = M^N$, 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 bases, to be centrally collected by the network, which is not practical for large networks in mobility settings.

IV. Distributed Solutions

The concept of the centralized scheduler is simple, as each BS only needs to be told which MS to schedule. However, the exponential complexity increase and the need for full, instantaneous CSI in a central unit motivates the search for low-complexity solutions with acceptable performance.

In the following, we give some user scheduling approaches of a more distributed nature. One approach to derive distributed algorithms is to break channel information into two sets, characterized as being local or non-local 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 has full, instantaneous CSI on its local channels, defined as the M channels linking BS_n to all the users, $\boldsymbol{h}_n = [h_{0n},\, h_{1n},\, \ldots\, h_{(M-1)n}]^T$. On the remaining $M(N-1)$ 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 IV-B, we describe a spatially distributed multi-base scheduler, of relatively low complexity and where only hybrid CSI is needed. For comparisons, we also give a fully distributed, greedy scheduler and a conventional singlebase scheduler, in Sections IV-A and IV-C, respectively.

A. Greedy User Scheduling

The first scheme is greedy and fully distributed, no central unit is required for coordination. Each BS_n, $n\in\{0,1,\ldots,N-1\}$ 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 $\boldsymbol{g}_n^*$, such that:

$$\boldsymbol{g}_n^* = \arg\max_{\boldsymbol{g}_n\in\{\boldsymbol{e}_1,\boldsymbol{e}_2,\ldots,\boldsymbol{e}_M\}} \text{SNR}(\boldsymbol{g}_n,\boldsymbol{h}_n)\,, \tag{12}$$

where $\text{SNR}(\boldsymbol{g}_n,\boldsymbol{h}_n)$ is defined as

$$\text{SNR}(\boldsymbol{g}_n,\boldsymbol{h}_n) = \frac{\mathbb{E}_s\left[\left|\sqrt{P_t}\sum\limits_{m=0}^{M-1} g_{nm}|h_{mn}|s_m\right|^2\right]}{\sigma_v^2}\,. \tag{13}$$

Please note that the sum in the above nominator has a single non-zero term. From a network point of view, one receiving user may be selected by multiple base stations, in which case it receives a coherently added sum of the desired signal, beamformed from these BSs.

The advantages of this method are the very low complexity and the fact that only local information is used, while statistical external information is not needed. In that sense, this scheme is fully distributed. One disadvantage is the limited amount of cell cooperation, which will in turn limit network performance.

B. Iterative Capacity-Maximizing Scheduling

Next, we present an iterative scheme, in which the base stations successively update the scheduling graph $\boldsymbol{G}$. In this case, all cells will share a common objective of maximizing the sum capacity, thus benefiting from inter-cell cooperation. The price to pay in comparison with the scheme above, is the need to exchange statistical information throughout the network, as well as keeping the scheduling graph updated. The system starts from an initial graph $\boldsymbol{G}_0$, known to all the BSs. Next, in a pre-determined, non-optimized order, each BS$_n$ determines its best corresponding vector $\boldsymbol{g}_n^*$ in $\boldsymbol{G}$, such that:

$$\boldsymbol{g}_n^* = \arg \max_{\boldsymbol{g}_n \in \{\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_M\}} \mathbb{E}_{\tilde{\boldsymbol{H}}_n} \big\{ C(\boldsymbol{G}, \boldsymbol{H}) \big\} \,, \tag{14}$$

where $\mathbb{E}_{\tilde{\boldsymbol{H}}_n}$, denotes taking the expected value with respect to all channels in

$$\tilde{\boldsymbol{H}}_n = [\boldsymbol{h}_0, \, \boldsymbol{h}_1, \, \ldots \, \boldsymbol{h}_{n-1}, \, \boldsymbol{h}_{n+1}, \, \ldots \, \boldsymbol{h}_{N-1}] \,, \tag{15}$$

which is a matrix containing all the column vectors of the full channel $\boldsymbol{H}$, except $\boldsymbol{h}_n$, the channel from BS$_n$ to all MSs. As $\boldsymbol{h}_n$ is instantaneously known at BS$_n$, no averaging is needed. This reflects that BS$_n$ only has local, instantaneous channel state information, while it has long-term statistical information on the rest of the channel; $\tilde{\boldsymbol{H}}_n$.

In the above iterative procedure, the global scheduling graph $\boldsymbol{G}$ is updated once for each of the N base stations. This calls for a central unit to hold and distribute the current $\boldsymbol{G}$, but the exchange of information to and from the users is moderate.

C. Conventional Singlebase 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 BS. A central unit goes through the N available base stations, and allows each BS to choose a previously unscheduled MS, if there are any left. This approach is based on the same hybrid CSI as in the previous sections. The central unit holds and updates the scheduling graph, ensuring that one MS is scheduled by one BS only. For BS$_n$, the user is selected by maximizing the receive SNR.

$$\boldsymbol{g}_n^* = \arg \max_{\boldsymbol{g}_n \in \mathcal{S}_e} \text{SNR}(\boldsymbol{g}_n, \boldsymbol{h}_n) \,, \tag{16}$$

where $\mathcal{S}_e$ is a subset of the full $\mathbb{R}^M$ standard basis $\{\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_M\}$, representing those users not already scheduled by a BS.

The central unit exploits the available information to a maximum by optimizing the order in which the receiving users are scheduled to the base stations, at all times coupling the BS-MS pair that maximum expected SNR, among the remaining, not previously scheduled, BSs and MSs.

V. Numerical Results

Next, we present some results of Monte-Carlo simulations for the above described schedulers, focusing on how the low-complexity, capacity-maximizing approach in Section IV-B performs when compared to the centralized, the greedy and the conventional schemes.

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

TABLE I
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	6 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
Random MS locations N_{MS}	50
Channel realizations N_{chan}	200

The channel from BS$_n$ to MS$_m$ is $h_{mn} = \gamma_{mn} \, h'_{mn}$, where h'_{mn} represents the complex random, Rayleigh distributed fast fading, $h'_{mn} \sim \mathcal{CN}(0, 1)$. The constant and slow-varying transmission effects are contained in γ_{mn}. In dB scale, we write

$$\gamma_{mn,\text{dB}} = G_{t,\text{dB}} - \rho_{mn,\text{dB}} + \chi_{mn,\text{dB}} + G_{r,\text{dB}} \,, \tag{17}$$

where $G_{t,\text{dB}}$ and $G_{r,\text{dB}}$ are the transmit and receive antenna gains, and ρ_{mn} is the path loss, generated using the COST 231 model [8]. The distributed, long-term (shadow) fading $\chi_{mn,\text{dB}}$ is modeled as random, log-normal, $\chi_{mn,\text{dB}} \sim \mathcal{N}(\mu_\chi, \sigma_\chi)$. Useful parameters are detailed in Table I.

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 $\mathbb{E}_{\tilde{\boldsymbol{H}}_j}$, of (14), implies further averaging for each of the N_{chan} channel realizations.

Simulations have been run for three different scenarios, where performance is measured by the network sum capacity of (10) per cell, with unit bits/second/Herz/cell.

First, we tested a rather small network, with only 4 transmitting base stations and 4 receiving users, $N = M = 4$. In Fig. 2, the curves show how the network sum capacity develops with an increasing edge-of-cell target SNR (reference value for single-user at distance d_{ref}). The top curve represents the centralized scheduler of Section III-A, while the other three result from using the schemes described in Sections IV-B, IV-A and IV-C, in downward order.

Second, we fixed the target SNR to 20 dB and explored 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 Fig. 3. In this case, as the M increases beyond N, note that only N of these users will be served at any given time.

Finally, in Fig. 4, 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 see an explanation for this in the increased levels of interference resulting from more BSs transmitting. In Figs. 3 and 4, only three curves are plotted, as the centralized scheme of Section III-A is very time-consuming in larger networks.

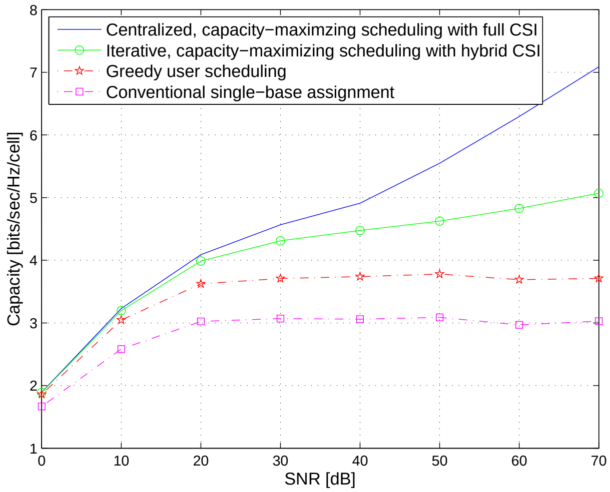

Fig. 2. Sum capacity per cell versus edge-of-cell target SNR for $N = M = 4$, averaged over N_{MS} random MS location sets and N_{chan} channel realizations. Note that the iterative, capacity-maximizing scheduling approach lies between that of the centralized scheme and the interference-limited performance of the greedy and the conventional schedulers.

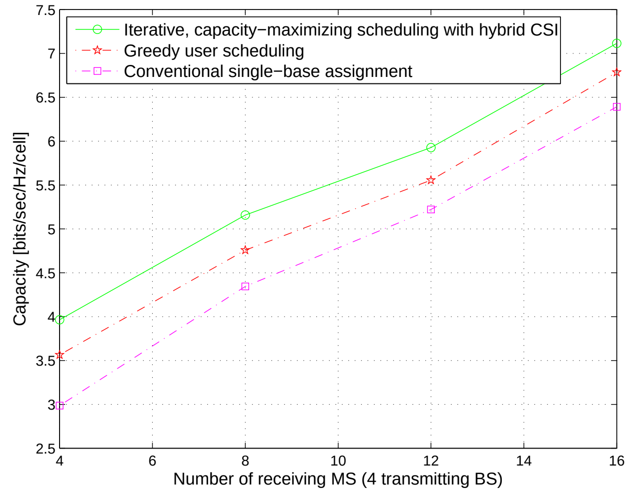

Fig. 3. Sum capacity per cell versus number of receiving MSs, for edge-of-cell target SNR of 20 dB and $N = 4$ BSs, averaged over N_{MS} random MS location sets and N_{chan} channel realizations. Note that the iterative, capacity-maximizing scheduling outperforms both the greedy and the conventional scheduling approaches.

VI. Conclusion

In this paper, we have presented approaches to base station coordination in multicell, multiuser wireless networks. First, a framework for distributed, downlink beamforming was given, where each partaking BS 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, all aimed at maximizing the sum capacity of the network. In particular, the low-complexity approach for iterative, capacity-maximizing scheduling represents a middle course between the interference-limited greedy and conventional schemes, and the prohibitively complex centralized algorithm.

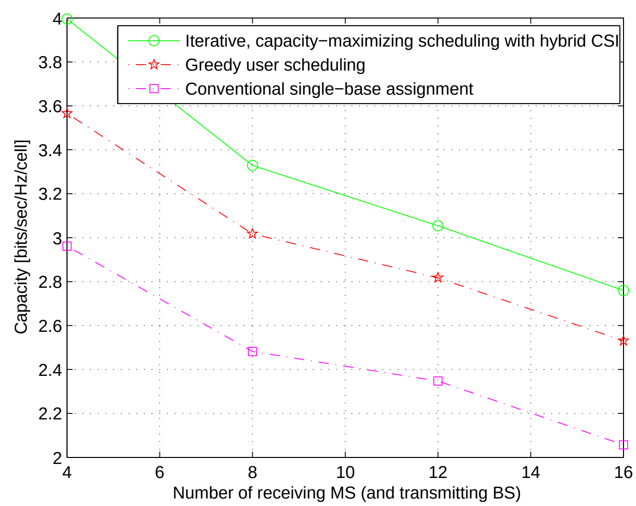

Fig. 4. Sum capacity per cell versus number of receiving MSs and BSs ($N = M$), for edge-of-cell target SNR of 20 dB, averaged over N_{MS} random MS location sets and N_{chan} channel realizations. Note that the iterative, capacity-maximizing scheduling outperforms both the greedy and the conventional scheduling approaches.

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