A Decentralized Optimization Approach to Backhaul-Constrained Distributed Antenna Systems

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Abstract—**It has been shown that multi-cell co-operations in cellular networks, enabling distributed antenna systems and joint signal processing across cell boundaries, can significantly increase system capacity and fairness. In recent work on this topic, we have proposed an optimization framework and algorithm that applies joint detection in the uplink or joint transmission in the downlink, respectively, to only a selected subset of users. This already yields a large extent of capacity and fairness improvements, while requiring only comparatively small backhaul capacity between co-operating base stations, which is usually the main issue connected to distributed antenna systems. In the following paper, we will introduce a novel concept of partitioning a cellular network and its resources into small subsystems, within which the optimization algorithm can be applied in a decentralized way. While each subsystem requires only very limited system knowledge, and joint detection and transmission is constrained to within subsystems, the performance improvements are still promising and approach those of a centralized optimization scheme in scenarios of strongly constrained backhaul.**

I. INTRODUCTION

It is known that inter-cell interference poses the main capacity limitation in future cellular systems. To overcome this problem, multi-user detection or transmission based interference cancellation across cell borders, often referred to as *distributed antenna systems* (DAS) has been proposed by various authors. Optimistic capacity bounds for large clusters of co-operating cells have been determined for the uplink [1] and downlink [4], [5], and corresponding detection and transmission schemes investigated in e.g. [4], [6], [7].

The main downside of inter-cell co-operation is the vast amount of backhaul required for information exchange between involved base stations. Recently, we have thus introduced an optimization framework [2] and algorithm to improve both the sum capacity and, more significantly, the fairness of a cellular system by applying joint detection only to selected users, constrained by a pre-defined backhaul infrastructure. While our previous work has been based on the idealistic assumption that a central instance in the network has complete system channel knowledge and performs all optimization decisions, we will now introduce a subsystem and resource partitioning scheme that allows to apply the optimization algorithm in a decentralized way. The aim is to enable a best possible extent of interference cancellation within small subsystems that only require strongly localized channel knowledge.

After some notation definitions in section II, we will recall our system model and optimization framework in section III. We will briefly summarize our optimization algorithm in section IV, and then derive a distributed optimization approach through subsystem and resource partitioning in section V. We will then discuss simulation results in section VI and conclude the paper in section VII.

II. NOTATION

The notation we use throughout the paper is as follows. In general, if $\mathbf{X}$ is a matrix, then we refer to the kth *column vector* as $\mathbf{x}_k$, and refer to the matrix elements as $x_{i,j}$, *except* for channel matrices $\mathbf{H}$, where $\mathbf{h}_k$ refers to the *row* or *column* vector corresponding to user k. The operator $\odot$ denotes element-wise multiplication, $\preceq$ denotes element-wise inequality, and operator Δ yields a square matrix with non-zero elements only on the diagonal, either extracted from a given square matrix or generated from a vector. The operator $\mathbf{Y} = \lfloor \mathbf{X} \rfloor$ yields $y_{i,j} = 1$ if $x_{i,j} > 0$, otherwise zero. The expressions $\mathbf{0}_{[i \times j]}$ and $\mathbf{1}_{[i \times j]}$ denote matrices with i rows and j columns, filled with zeros and ones, respectively. $\mathbf{I}_{[i]}$ denotes a size i identity matrix, operators $(\cdot)^T$ and $(\cdot)^H$ denote matrix transpose and Hermitian transpose, respectively.

III. SYSTEM AND OPTIMIZATION FRAMEWORK

We observe a cellular system with a total of K users equally distributed over M cells (i.e. M base stations), where each base station has N_a receive or transmit antennas, in uplink or downlink, respectively, and each terminal has 1 receive/transmit antenna. The total number of base station antennas is $N_A = MN_a$. As in most existing systems, three-fold sectorization is employed, i.e. three base stations serving one sector each are always grouped into one site, yielding a total of S sites. By default, users will be communicating solely with their *home* base station, where maximum ratio combining or beamforming is applied in uplink and downlink, respectively. Additionally, the system can select certain users in adjacent cells for joint transmission or joint detection across cell-borders (i.e. *virtual MIMO* operations). For a suitable selection of such users, we have introduced an optimization framework in [2], [3] that enables the calculation of the user capacities and the required backhaul between sites as a function of resource allocation, a selection of certain users for virtual MIMO operations, and power allocation.

For resource allocation, we have introduced the concept of a *group* in [2] as a set of users in different cells sharing the same resources (e.g. OFDMA sub-carriers, codes etc.). We assume that all users within the same cell are assigned to orthogonal resources, so that there is no *intra*-cell interference, and *inter*-cell interference can be shaped according to our needs. We will see later that it can be beneficial to assign users near the same cell edges to the same resources, in order to create strong interference that can be cancelled efficiently through virtual MIMO. We describe resource allocation through matrix

$$\mathbf{G} \in \{0,1\}^{[K \times K]} \text{ e.g. } \mathbf{G} = \begin{bmatrix} \mathbf{1} & \mathbf{1} & \mathbf{1} & \cdots & 0 & 0 \\ \mathbf{1} & \mathbf{1} & \mathbf{1} & \cdots & 0 & 0 \\ \mathbf{1} & \mathbf{1} & \mathbf{1} & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & \mathbf{1} & \mathbf{1} \\ 0 & 0 & 0 & \cdots & \mathbf{1} & \mathbf{1} \end{bmatrix}, \tag{1}$$

in this example grouping the first three and last two users onto the same resources, respectively. Obviously, grouping follows the law of transcivity and reflexivity, hence $\mathbf{G}' = \mathbf{G}$ and $\forall i, j : \mathbf{g}_i^T \mathbf{g}_j \in \{0, \mathbf{g}_i^T \mathbf{g}_i\}$ must hold. The selection of users for virtual MIMO techniques is given by matrix

$$\mathbf{V} \in \mathbb{N}_0^{+[N_A \times K]} \text{ e.g. } \mathbf{V} = \begin{bmatrix} 16 & 0 & 16 & \cdots & 0 & 0 \\ 0 & 0 & 0 & \cdots & 8 & 8 \\ 0 & 0 & 0 & \cdots & 8 & 8 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 10 & 0 & 10 & \cdots & 0 & 0 \\ 0 & 0 & 0 & \cdots & 16 & 16 \end{bmatrix} \tag{2}$$

where each entry $v_{a,k} > 0$ states that base station antenna a is actively involved in the communication with user k, the actual value stating the quantization bits used if the received or transmitted signals are relayed over the backhaul. For all users involved in a common virtual MIMO operation, we assume the set of base station antennas and quantization bits to be equal, fulfilling $\forall i, j : \mathbf{g}_i^T \mathbf{g}_j > 0 \rightarrow \mathbf{v}_i^T \mathbf{v}_j \in \{0, \mathbf{v}_i^T \mathbf{v}_i\}$. In [2], [3], we derived the user capacities $\mathbf{c} = [c_1, ..., c_K]^T$ in uplink and downlink as stated in equations (10) and (11), where $\mathbf{H} \in \mathbb{C}^{[N_A \times K]}$ or $\mathbf{H} \in \mathbb{C}^{[K \times N_A]}$ is the system channel matrix for uplink or downlink, respectively, $\mathbf{n} \in \mathbb{C}^{[K \times 1]}$ is the thermal noise power connected to each user. The fact that channel matrix $\mathbf{H}$ is itself a function of resource allocation $\mathbf{G}$ is omitted for notational brevity, and can be fully neglected if resource allocation is performed prior to any optimization steps based on $\mathbf{H}$. We assume that a linear MMSE filter is used for joint detection of selected users in the uplink, and a Wiener filter with a per-base-station power constraint is used in the downlink. An expression for the downlink filter matrices $\mathbf{W}$ is given in [3]. The variable $\mathbf{p} \in \mathbb{R}_0^{+[K \times 1]}$ refers to the transmit power assigned to each user, which is constrained to

$$\mathbf{p} \preceq P_{max}^{[MT]}, \quad \text{or} \quad \mathbf{M}_U \Delta(\mathbf{U}\mathbf{1}_{[K \times 1]})^{-1} \mathbf{U}\mathbf{p} \preceq P_{max}^{[BS]} \cdot \mathbf{1}_{[M \times 1]} \tag{3}$$

for uplink and downlink, respectively, where $\mathbf{M}_U \in \{0,1\}^{[M \times K]}$ maps users onto base stations, and $P_{max}^{[MT]}$ and $P_{max}^{[BS]}$ are the maximum transmit powers of each mobile terminal or base station, respectively. $\mathbf{u}_k$ refers to matrix

$$\mathbf{U} \in \{0,1\}^{[K \times K]} = \left\lfloor \mathbf{G} \odot \left(\mathbf{V}^T \mathbf{V}\right) \right\rfloor \tag{4}$$

where each $u_{k_1,k_2} > 0$ states that users k_1 and k_2 are involved in the same virtual MIMO operation, and ξ_k is the relative quantization noise power (w.r.t. the average receive or transmit power at each base station antenna), given by

$$\xi_k \in \mathbb{R}^{+[N_A \times 1]} = \left[\frac{1}{2^{v_{1,k}-2}}, \frac{1}{2^{v_{2,k}-2}}, ..., \frac{1}{2^{v_{N_A,k}-2}} \right]^T \tag{5}$$

In [2], [3], we have also derived the following expressions for the backhaul $\mathbf{B} \in \mathbb{N}_0^{+[S \times S]}$ between different sites, where $b_{i,j}$ states the backhaul required from site i to site j.

$$\mathbf{B}^{[UL]} = \rho \cdot \sum_{k=1}^{K} \frac{\left[\mathbf{0}_{[S \times s_k - 1]} \quad \mathbf{M}_S \mathbf{v}_k \quad \mathbf{0}_{[S \times S - s_k]} \right]}{\mathbf{u}_k^T \mathbf{1}_{[K \times 1]}}, \tag{6}$$

$$\mathbf{B}^{[DL]} \preceq \rho \cdot \sum_{k=1}^{K} c_k \left[\mathbf{0}_{[S \times s_k - 1]} \quad \lfloor \mathbf{M}_S \mathbf{v}_k \rfloor \quad \mathbf{0}_{[S \times S - s_k]} \right]^T \tag{7}$$

where ρ is the effective per-user bandwidth in symbols per second, $\mathbf{M}_S \in \{0,1\}^{[S \times N_A]}$ maps base station antennas to sites, and $\mathbf{s} = [s_1 ... s_K]$ states each user's *master site*, i.e. the central site performing the joint pre- or post-processing, if the user is selected for virtual MIMO. In such cases, we assume that in the uplink, the backhaul relays received and quantized baseband signals from involved base stations to master sites, whereas in the downlink, uncoded user data is distributed from the master sites to all involved base stations, which then perform transmit pre-processing redundantly. This has proven beneficial for a strongly constrained backhaul in [3]. We can only upper-bound the downlink backhaul in (7), as the uncoded user traffic depends on various other aspects (modulation and coding schemes etc.) not investigated here. Any choice of parameters $(\mathbf{V}, \mathbf{s})$ must fulfill the backhaul constraint

$$\mathbf{B} \preceq \mathbf{D} \tag{8}$$

where $\mathbf{D} \in \mathbb{N}_0^{+[S \times S]}$ denotes the available extent of backhaul infrastucture (in bit/s/link) between sites.

IV. OPTIMIZATION PROBLEM AND ALGORITHM

We are thus facing the large optimization problem

$$[\hat{\mathbf{G}}, \hat{\mathbf{V}}, \hat{\mathbf{s}}, \hat{\mathbf{p}}] = \underset{\mathbf{G},\mathbf{V},\mathbf{s},\mathbf{p}}{\text{argmax}} \quad W\left[\mathbf{c}(\mathbf{G}, \mathbf{V}, \mathbf{s}, \mathbf{p})\right] \Big|_{\mathbf{D}} \tag{9}$$

for a given backhaul infrastructure $\mathbf{D}$ and power constraints as in (3). W is any function that yields an overall performance metric based on the user capacities. In our case we want to improve system fairness, and thus design W so that it returns the average capacity of the 5 percent of weakest users. As the dimensionality of the optimization problem and discreteness of input parameters $\mathbf{G}, \mathbf{V}, \mathbf{s}$ prohibits any brute force search or convex optimization approach, we stated an algorithm in [2] that serializes the problem in order to yield a reasonable result at low complexity. The algorithm can be summarized as

$$\begin{aligned} c_k^{[UL]} = \log_2 \Bigg(\Bigg[\Bigg(& \Delta\left(\mathbf{p}\mathbf{u}_k^T\right)^{\frac{1}{2}} \mathbf{H}^H [\underbrace{\Delta\left(\mathbf{H}\Delta(\mathbf{p}[\mathbf{g}_k^T - \mathbf{u}_k^T])\mathbf{H}^H\right)}_{\text{Interference from other users in group}} + \dots \\ & + \underbrace{\Delta(\mathbf{H}\Delta(\mathbf{p}\mathbf{g}_k^T)\mathbf{H}^H + \Delta(\mathbf{n}))\Delta(\xi_k)}_{\text{Quantization noise}} + \Delta(\mathbf{n})]^{-1}\mathbf{H}\Delta\left(\mathbf{p}\mathbf{u}_k^T\right)^{\frac{1}{2}} + \mathbf{I}_{[K]} \Bigg)^{-1} \Bigg]_{k,k} \Bigg) \end{aligned} \tag{10}$$

$$c_k^{[DL]} = \log_2 \left(1 + \frac{\overbrace{p_k \cdot \left|\mathbf{h}_k[\mathbf{W}_{(k)}]_k\right|^2}^{\text{Desired signal power}}}{\underbrace{\mathbf{h}_k\mathbf{W}_{(k)}\Delta([\mathbf{U} - \mathbf{I}_{[K]}]_k\mathbf{p}^T)\mathbf{W}_{(k)}^H\mathbf{h}_k^H}_{\text{Interference from users within joint transmission}} + \underbrace{\mathbf{h}_k\lfloor\mathbf{V}\rfloor\Delta(\lfloor\mathbf{V}\rfloor^T\lfloor\mathbf{V}\rfloor)^{-1}\Delta([\mathbf{G} - \mathbf{U}]_k\mathbf{p}^T)\mathbf{h}_k^H}_{\text{Interference from other users within group}} + n_k} \right) \tag{11}$$

- Determine parameter $\mathbf{p}$ by using a standard or no power control in uplink and downlink, respectively
- Determine a simple resource allocation by ranking the users within one cell according to their isolation (i.e. a higher value if the user is in the cell center, and lower if the user is close to a cell border and thus subject to or creating inter-cell interference), and assigning users with a similar extent of isolation to the same resources
- Now loop through the users (weak users first) and successively add more (and larger) virtual MIMO operations to the users until the available backhaul is exhausted
- If desired, the transmit power $\mathbf{p}$ could now be adjusted to additionally improve system fairness

Please refer to [2] for details on the algorithm.

V. SUBSYSTEM AND RESOURCE PARTITIONING

In previous work [2], [3], we have always assumed one central instance within the network to have entire channel knowledge of all users and base stations, centrally performing all decisions w.r.t. our stated optimization problem. This is of course practically infeasible, and we thus want to derive how the optimization can also be performed through distributed decision makers with strongly localized channel knowledge.

We define that a decision maker only has the channel knowledge connected to a subset of users and base station antennas, which we refer to as a *subsystem*, such that local optimizations are constrained to virtual MIMO operations within this subset of antennas. Obviously, a major problem is that it is generally not possible for a user to be served by a virtual MIMO operation across subsystems, unless

- an exchange of channel information between subsystems is enabled, and a mechanism exists for multiple decision makers to agree on virtual MIMO across subsystems
- *and / or* subsystems are defined such that they overlap, which again requires a mechanism for multiple decision makers to agree on how to handle users in common

Both solutions would require a large extent of additional backhaul for negotiations between subsystems, and therefore do not appear attractive. Instead, we suggest to define subsystems in conjunction with a smart, yet simple resource partitioning scheme, such that no virtual MIMO beyond subsystems is required. Specifically, we want to assure that the majority of users are assigned to subsystems such that their major interferers are also in the same subsystem and can be combatted efficiently through virtual MIMO.

A useful input towards the design of subsystems is figure 1, which shows the main two interfering cells for any location in the central cell 1, based on the hexagonal cell setup and Okumura-Hata pathloss model in [1]. This indicates *towards where* a terminal creates interference in the uplink, and *from where* it receives major interference in the downlink. As the interference pattern is the same in all cells, we can see that by grouping all users in e.g. cells 1, 2 and 3 close to the point where the three cells meet into one subsystem, we can assure that for these users the two strongest interferers can potentially be cancelled - if they are assigned to the same block of resources and enough backhaul is available. We can similarly proceed for all users in cell 1, except those for which the main interference comes from cells 3 and 6. Here, we have an *assymetrical* interference situation, i.e. we will not be able to find a user within cell 6 whose strongest interference comes from cells 1 and 3. To guarantee the cancellation of the two strongest interferers for all users involved, we would here have to establish a subsystem spanning at least 5 cells. However, exactly the mentioned users in cell 1 are very close to their own base station, and will thus usually have an acceptable SINR without any interference cancellation at all.

We now propose a subsystem and resource partitioning scheme based on our previous observations. We split each cell into 5 almost equally-sized areas according to the interference pattern from 1, by merging the two areas closest and furthest away from the base station (i.e. in cell 1 the areas mainly interfered by cells *3; 6* and *2; 7*). The resources are also split into 5 equally-sized blocks, and assigned to users according to their location, as illustrated in figure 2. Within one block of resources, we apply the same technique as in [2], i.e.

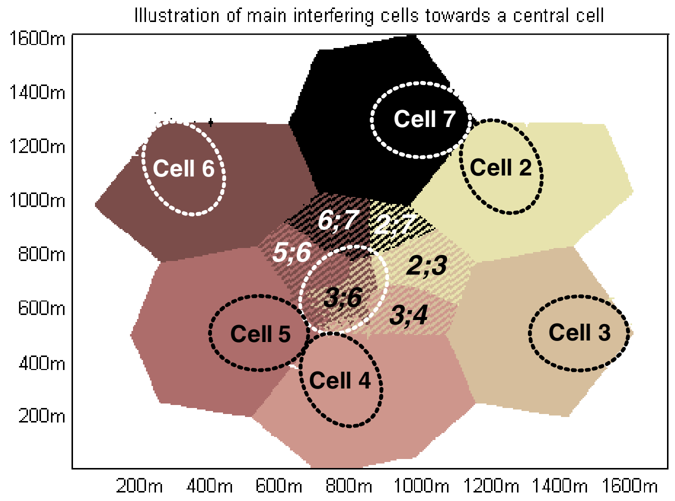

Fig. 1. Illustration of the adjacent cells towards which a user in the central cell causes the most interference in the uplink (or from which he receives the most interference in the downlink)

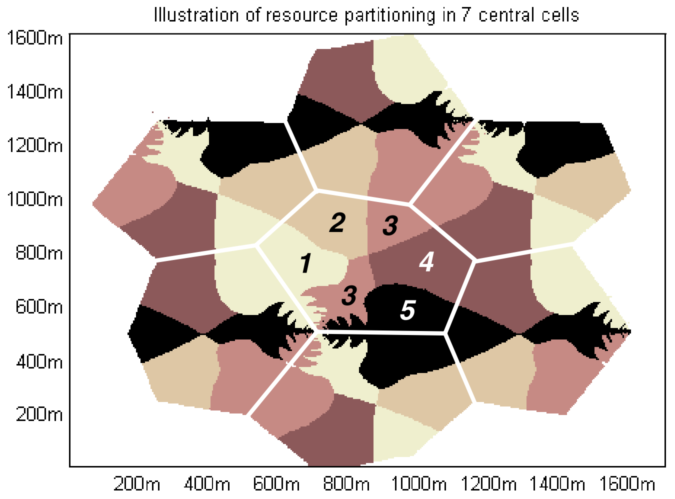

Fig. 2. Assignment of blocks of resources to users according to their location in the network. This resource allocation enables to efficiently cancel the strongest two interferers of the majority of users in the system

we rank and group the users according to their isolation. Now we can run the optimization algorithm from [2] within each subsystem, assuming that a simple global scheduler lets adjacent subsystems take turns in optimizing and thus receive a fair share of the available backhaul. The only overhead communication that needs to take place between subsystems is a continuous update on the remaining backhaul capacity.

VI. Simulation Results

We have simulated a hexagonal cell setup of 19 sites with three cells each as in [1], and an OFDMA system with separate 5MHz bandwidth for uplink and downlink, respectively, corresponding to [8]. We assume 2 receive and transmit antennas per base station, and that sites are connected in a bidirectional mesh with a common link capacity δ. We can thus state

$$d_{i,j} = \begin{cases} \delta & \text{if sites } \quad i,j \quad \text{adjacent} \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

A total of 50 users are randomly distributed within each cell, and each user obtains an equal effective bandwidth of $\rho = 84000$ data symbols per second. We generally compute average capacities over 10 realizations of matrix $\mathbf{H}$ based on Okumura-Hata plus i.i.d small-scale Rayleigh fading. For the new subsystem and resource partitioning scheme from section V, the optimization algorithm from [2] is used in 22 subsystems around the central site, where each subsystem contains 30 users equally taken from three involved cells. For the uplink, 8-bit quantization of signals received and relayed between sites, and 16-bit quantization of locally processed signals is chosen, i.e. $\mathbf{V} \in \{0, 8, 16\}^{[N_A \times K]}$. The plots show the performance of the users within the central site only.

Figure 3 shows the average capacity of all users and that of the 5% weakest users as a function of δ, i.e. the available backhaul per link, for uplink and downlink. We compare the performance of a centralized optimization approach as in [2], [3], with and without the novel resource partitioning, to a decentralized optimization within subsystems. We can see that the novel resource partitioning as such already improves the weak user's capacity in centrally-optimized cases, as interference can be combatted through more efficient virtual MIMO operations. This corresponds to an observation in [6] that joint detection is most efficient if the path losses between involved users and base stations are similar. The downside is that in low-backhaul regimes many users will be facing especially strong interference that is not cancelled. This effect is more severe in the downlink, where no power control is applied, and where resource partitioning is thus only beneficial beyond a backhaul capacity of about 120 Mbit/s/link. For the decentralized case, the performance already reaches a plateau for a small extent of backhaul, as the subsystem partitioning only enables the cancellation of maximum two interferers per user, and any larger extent of available backhaul remains unused.

Besides this modest plateau behavior, however, the results in figure 4 indicate that the local optimization scheme almost approaches the performance of a centralized scheme for strongly limited backhaul. For the uplink in figure 4(a), we compare the performance of a conventional scheme (maximum ratio combining, scrambling to mitigate inter-cell interference) to schemes applying joint detection to selected users under different backhaul constraints, and for centralized or decentralized optimization algorithms. We can see that the latter two perform similarly for 10 or 20 Mbit/s/link backhaul, except for the 40% of weak users, which perform worse in the decentralized scheme. The same can be observed in the downlink in figure 4(b), where we have added conventional schemes based on either Alamouti or beamforming from the two transmit antennas of one base station to each user. Here we can observe a few very weak users for the decentralized optimization scheme, which appear to be exactly the users with an assymetrical interference situation as stated before.

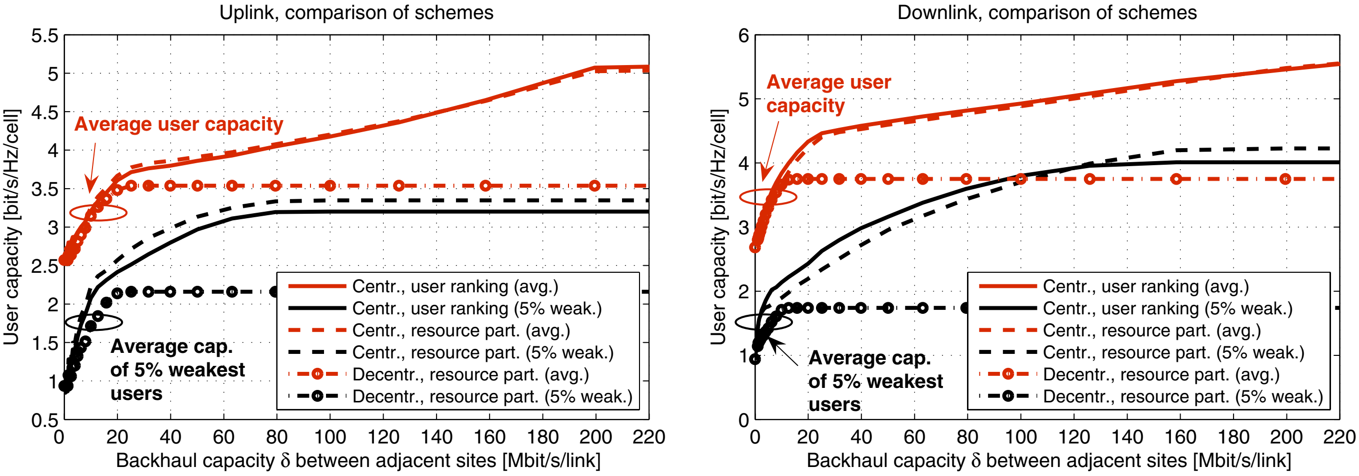

Fig. 3. The average capacity of all users in the central site and that of the 5% weakest users as a function of backhaul capacity per link

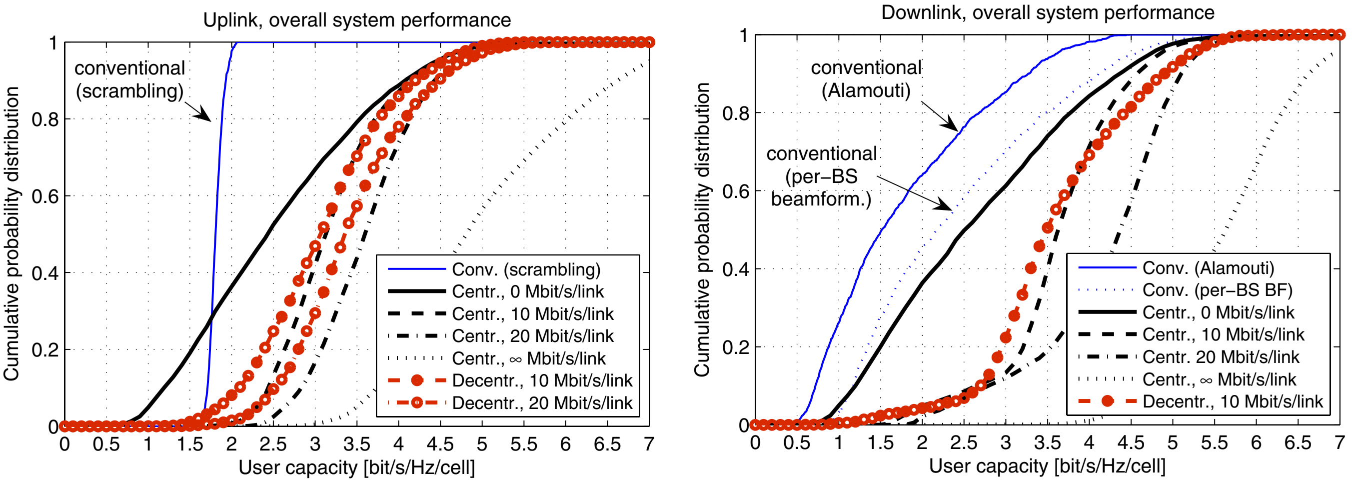

Fig. 4. CDFs of user capacity for conventional and centralized or decentralized virtual MIMO schemes under different backhaul constraints

VII. CONCLUSIONS

In this paper, we have described a methodology of dividing a cellular network into small subsystems, within which decentralized optimization algorithms for selective joint detection or joint transmission can be applied. A simple, user location based resource partitioning scheme shapes inter-cell interference in a way that such virtual MIMO techniques within subsystems can efficiently cancel the two strongest interferers for the majority of users. For limited backhaul scenarios, the novel scheme approaches the capacity and fairness improvements of a centralized optimization scheme with global channel knowledge, while only requiring limited channel knowledge in each subsystem. Though our resource partitioning scheme is derived from a specific cell setup and pathloss model in this paper, we suggest that our methodology can be applied to any kind of interference pattern, and is thus an interesting option for future mobile communication systems, where efficient interference cancellation at low complexity is desired.

REFERENCES

[1] P. Marsch, S. Khattak, and G. Fettweis, *A Framework for Determining Realistic Capacity Bounds for Distributed Antenna Systems*, in Proceedings of the IEEE Inform. Theory Workshop (ITW'06), China, Oct. 2006

[2] P. Marsch and G. Fettweis, *A Framework for Optimizing the Uplink Performance of Distributed Antenna Systems under a Constrained Backhaul*, in Proc. of the Int. Conf. on Comm. (ICC'07), Glasgow, June 2007

[3] P. Marsch and G. Fettweis, *A Framework for Optimizing the Downlink Performance of Distributed Antenna Systems under a Constrained Backhaul*, in Proc. of the 13th Europ. Wirel. Conf. (EW'07), Paris, April 2007

[4] R. Böhnke, V. Kühn and K.D. Kammeyer, *Fast Sum Rate Maximization for the Downlink of MIMO-OFDM Systems*, Canadian Workshop on Information Theory (CWIT 2005), Canada, June 2005

[5] M. K. Karakayali, G. J. Foschini, R. A. Valenzuela, and R. D. Yates, *On the Maximum Common Rate Achievable in a Coordinated Network*, in Proceedings of IEEE International Conference on Communications (ICC'06), Turkey, June 2006

[6] S. Khattak, W. Rave, G. Fettweis, *Multiuser turbo detection in a distributed antenna system*, 15th IST Wireless and Mobile Communications summit, Greece, June 2006

[7] M. Schubert and H. Boche, *Solution of the multiuser downlink beamforming problem with individual SINR constraints*, IEEE Trans. Veh. Technol., vol. 53, no. 1, pp. 1828, Jan. 2004.

[8] 3GPP TR 25.814-150, *Physical layer aspect for evolved UTRA*, May 2006