Distributed Base Station Cooperation via Block-Diagonalization and Dual-Decomposition

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Abstract—**It has been recently shown that base station cooperation may yield great capacity improvement in downlink multiple antenna cellular networks. However, the proposed solutions assume that there is a central processing unit which coordinates the information exchange and determines the optimal resource allocation of the overall cellular network. Whilst the benefits of base station cooperation are large, computational burden of the central unit can be significant. Thus distributed solutions are desirable. This paper suggests a distributed solution for base station cooperation via block-diagonalization and dual-decomposition to maximize the weighted sum network capacity under per-antenna power constraint. The block-diagonalization pre-coding matrix is determined separately at each base station. It enables the full potential of base station cooperation by determining a trade-off between inter-cell interference mitigation, spatial multiplexing and macro diversity. The power allocation problem is formulated as a network utility maximization (NUM) problem. By looking at its Lagrangian dual problem, the decomposable structure of the optimization problem is revealed. This leads to a distributed and iterative algorithm that converges to the global optimum. The advantage of macro diversity in addition to inter-cell interference mitigation and spatial multiplexing in base station cooperation context is studied and shows superior performance in terms of a higher capacity increase with lower variance.** [1]

I. Introduction

Multiple-input and multiple-output (MIMO) communications is the latest technology to achieve high spectral efficiency in the on-going evolution of cellular networks. The fundamental capacity gain in the MIMO radio link, being proportional to the minimum of the number of transmit and receive antennas, is well understood for an isolated point-to-point link [1]. Recently, it was shown that this capacity scaling law also holds for the interference limited case of a multi-cellular radio system [2] However, since inter-cell interference (ICI) is still the dominant source of performance degradation in the cellular network, removing it will lead to a great performance gain.

Assuming that the base stations in future cellular networks will be connected via a high-speed optical fiber backbone, allows a reliably fast exchanged of information among them. Thus it is possible to coordinate the base antenna transmissions in order to mitigate ICI in the downlink. The objective is that the mobile stations may receive useful signals, as opposed to interferences, from the cooperating base stations. It has been recently shown that base station cooperation may yield great capacity improvement in downlink multiple antenna cellular networks [3] [4] [5] [6]. However, a central processing unit is assumed which coordinates the information exchange and determines the optimal resource allocation of the overall cellular network. Whilst the benefits of base station cooperation are large, computational burden of the central unit can be significant. Thus distributed solutions are desirable.

This paper suggests a distributed solution for base station cooperation via block-diagonalization and dual- decomposition to maximize the weighted sum network capacity under per-antenna power constraint. The per-antenna power constraint is considered, since each antenna has its own power amplifier and is limited individually by the linearity of the amplifier [7]. Each antenna in the cooperation area may be seen as a processor of a distributed computation system connected via a high-speed optical fiber backbone. Each processor iteratively executes a local algorithm and communicates its result to the others until a globally optimal solution is achieved. Since perfect cooperation between base stations is assumed, we can regard spatially separated base stations as one big base station transmitting data to many mobile stations in the cellular network. This results in a broadcast channel with per-antenna power constraint which can be solved distributively via block-diagonalization and dual-decomposition. The remainder of this paper is organized as follows: In Section II we describe our downlink system model. Then, in Section III the method to find the block-diagonalization pre-coding matrix is explained. In Section IV dual-decomposition is used to determine the optimal power allocation distributively. In Section V we describe the used multicell simulation setup and consecutively present the results. Finally, we conclude the paper in Section VI.

II. Downlink System Model

We assume particular orthogonal multiple access (e.g. TDMA or FDMA) within each cell of the radio system, i.e. each cell is loaded with at most one mobile station for each orthogonal dimension and there is no intra-cell interference. Consider a cellular network setup operating in the downlink direction, where there are M base stations, each equipped with t transmit antennas, and N mobile stations, each equipped with r receive antennas. We assume that the total number of transmit antennas in the network is equal or greater than the total number of receive antennas (i.e. $tM \geq rN$), which is the condition required by block-diagonalization [8]. A

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narrow-band flat-fading channel channel is considered and a low mobility environment is assumed, such that the channel remains constant within several frames. Suppose each mobile station can perfectly estimate its channel impulse responses from all base stations. Using a feedback channel, each mobile station transfers its channel knowledge to its serving base station. Assuming the cellular network being connected via a high-speed optical fiber backbone such that information can be broadcasted reliably and fast to all base stations in the cellular network.

In the full base station cooperation scheme, each mobile station may receive useful signals from up to tM transmit antennas where M base stations cooperate together to meet specific performance criteria of the network. The received signal for the k-th mobile can be modeled as

$$\mathbf{y}_k = \mathbf{H}_k \mathbf{x} + \mathbf{n}_k, \tag{1}$$

where $\mathbf{y}_k \in \mathcal{C}^{r\times 1}$ is the received signal at user k. The matrix $\mathbf{H}_k = [h^k_{jq}]_{r\times tM}$ is the $r \times tM$ channel transfer matrix with h^k_{jq}, the complex channel gain from the q-th transmit antenna to the j-th receive antenna of user k. Since channel matrix $\mathbf{H}_k$ of user k contains at least M independent links from M spatially separated base stations, by assuming $r < M$, $\mathbf{H}_k$ is likely to yield a full-rank matrix with rank r. $\mathbf{n}_k \in \mathcal{C}^{r\times 1}$ is the vector of additive white Gaussian noise (AWGN) experienced by user k such that its expectation value $E\{\mathbf{n}_k\mathbf{n}_k^H\} = \sigma^2\mathbf{I}_r$. The vector $\mathbf{x} = [x^1, \dots, x^q, \dots, x^{tM}]^T$ is the signal transmitted by all tM antennas, which contains composed signals for all N users, i.e. $\mathbf{x} = \sum_{k=1}^N \mathbf{x}_k$. Hence, the received signal for the k-th mobile can also be expressed as

$$\mathbf{y}_k = \mathbf{H}_k \mathbf{x}_k + \sum_{i=1, i\neq k}^{N} \mathbf{H}_k \mathbf{x}_i + \mathbf{n}_k, \tag{2}$$

where $\sum_{i=1,i\neq k}^N \mathbf{H}_k\mathbf{x}_i$ represents the inter-cell interference experienced by user k.

III. Block-Diagonalization

The block-diagonalization technique [8] makes use of a linear pre-coding matrix to transmit multiple data streams to each user while removing the inter-cell interference at the same time. Note that the inter-stream interference at the same user is still present and will be handled later by a post-processing matrix applied at the mobile station. If $\mathbf{b}_k \in \mathcal{C}^{r\times 1}$ contains the r complex data symbols intended for the k-th user and $\mathbf{W}_k \in \mathcal{C}^{tM\times r}$ is the pre-coding matrix of user k, then the transmitted signal for user k is given by

$$\mathbf{x}_k = \mathbf{W}_k \mathbf{b}_k, \tag{3}$$

where each column of the linear pre-coding matrix $\mathbf{W}_k$, contains the vector $\mathbf{w}_{kj} = [w^1_{kj}, w^2_{kj}, \dots, w^{tM}_{kj}]^T$, which denotes the complex unit norm antenna weight vector (i.e. $||\mathbf{w}_{kj}||^2 = 1$) for j-th symbol stream received by user k. The received signal associated with the linear pre-coding matrices and the data symbols is thus written as

$$\mathbf{y}_k = \mathbf{H}_k\mathbf{W}_k\mathbf{b}_k + \sum_{i=1,i\neq k}^{N} \mathbf{H}_k\mathbf{W}_i\mathbf{b}_i + \mathbf{n}_k \tag{4}$$

Since perfect channel knowledge is assumed at each of the base station transmitters, each base station could separately determine the pre-coding matrix $\mathbf{W}_k$ for the user in its own cell, which should satisfy

$$\mathbf{H}_i\mathbf{W}_k = \mathbf{0} \quad \forall i \neq k \tag{5}$$

If the constraint is satisfied, the inter-cell interference is completely eliminated, since precoding matrix $\mathbf{W}_k$ of user k is orthogonal to the channel seen by other users, $\mathbf{H}_i$. Therefore the received signal for user k after block-diagonalization is

$$\mathbf{y}_k = \mathbf{H}_k\mathbf{W}_k\mathbf{b}_k + \mathbf{n}_k \tag{6}$$

To find $\mathbf{W}_k$, we first define $\tilde{\mathbf{H}}_k$ as the aggregate interference channel observed by the k-th mobile station with matrix dimension $r(N-1)\times tM$

$$\tilde{\mathbf{H}}_k = [\mathbf{H}_1^H \dots \mathbf{H}_{k-1}^H \mathbf{H}_{k+1}^H \dots \mathbf{H}_N^H]^H \tag{7}$$

We assume $\tilde{\mathbf{H}}_k$ to be full-rank because of independent user locations in different cells, which are sufficiently far apart. Hence, $rank(\tilde{\mathbf{H}}_k) = \min(r(N-1), tM) = r(N-1)$. By sending in the nullspace of $\tilde{\mathbf{H}}_k$, block-diagonalization invests $r(N-1)$ from its tM available spatial dimensions in order to mitigate $r(N-1)$ interference streams from all other users. In this case user k gets full inter-cell interference mitigation gain. Performing the singular value decomposition (SVD) of $\tilde{\mathbf{H}}_k$ yields

$$\tilde{\mathbf{H}}_k = \tilde{\mathbf{U}}_k \begin{bmatrix} \tilde{\mathbf{\Sigma}}_k & \mathbf{0} \end{bmatrix} \begin{bmatrix} \tilde{\mathbf{V}}_k^1 & \tilde{\mathbf{V}}_k^0 \end{bmatrix}^H, \tag{8}$$

then the columns of $\tilde{\mathbf{V}}_k^0$ contains the $tM - r(N-1)$ singular vectors in the nullspace of $\tilde{\mathbf{H}}_k$ and can be interpreted as the remaining spatial dimensions to support spatial multiplexing for user k (cost: r spatial dimensions) and macro diversity. The columns of $\tilde{\mathbf{V}}_k^0$ are candidates for user k's pre-coding matrix $\mathbf{W}_k$ since they will produce zero inter-cell interference. To find an optimal $\mathbf{W}_k$ which is a linear combination of $\tilde{\mathbf{V}}_k^0$, SVD is performed again

$$\mathbf{H}_k\tilde{\mathbf{V}}_k^0 = \mathbf{U}_k \begin{bmatrix} \mathbf{\Sigma}_k & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{V}_k^1 & \mathbf{V}_k^0 \end{bmatrix}^H, \tag{9}$$

where $\mathbf{\Sigma}_k$ is $r\times r$ diagonal matrix containing the singular values of the parallel channels $\lambda_{kj}^{1/2}, \forall j = 1, \dots, r$ and $\mathbf{V}_k^1$ represents the r singular vectors with non-zero singular values. $\mathbf{H}_k^{prj} = \mathbf{H}_k\tilde{\mathbf{V}}_k^0$ with dimension $r\times(tM - r(N-1))$ can be interpreted as the projection of channel $\mathbf{H}_k$ in the nullspace of $\tilde{\mathbf{H}}_k$, where user k can receive parallel streams of data in this subspace without causing inter-cell interference to other users. If $\mathbf{H}_k^{prj}$ has more columns than the number of parallel data streams which can be supported by user k , namely r, the remaining spatial dimensions (i.e. $tM - r(N-1) - r > 0$) will be used for macro diversity. It is known that the squared

Frobenius norm of the projection channel matrix $\mathbf{H}_k^{prj}$ equals the sum of its squared singular values [9]

$$||\mathbf{H}_k^{prj}||_F^2 = \sum_{j=1}^{r} \sum_{l=1}^{tM-r(N-1)} |\mathbf{H}_k^{prj}(jl)|^2 = \sum_{j=1}^{r} \lambda_{kj}, \quad (10)$$

The macro diversity advantage by base station cooperation is obvious in the equation above: If we add 1 extra transmit antenna at each cooperated base station while keeping the number of receive antennas at mobile station constant, the projection channel gets additionally rM power gains through the summation of the powers of each additional path, thus resulting an increase in the sum of its squared singular values.

The pre-coding matrix $\mathbf{W}_k$ for user k subject to zero inter-cell interference is obtained by multiplying $\tilde{\mathbf{V}}_k^0$ with $\mathbf{V}_k^1$ [8]

$$\mathbf{W}_k = \tilde{\mathbf{V}}_k^0 \mathbf{V}_k^1 \quad (11)$$

This $\mathbf{W}_k$ will be informed to all antennas which supply user k. We analyze again the received signal for user k after block-diagonalization

$$\begin{aligned} \mathbf{y}_k &= \mathbf{H}_k \mathbf{W}_k \mathbf{b}_k + \mathbf{n}_k \\ &= \mathbf{H}_k \tilde{\mathbf{V}}_k^0 \mathbf{V}_k^1 \mathbf{b}_k + \mathbf{n}_k \\ &= \mathbf{U}_k \left[\begin{array}{cc} \mathbf{\Sigma}_k & \mathbf{0} \end{array} \right] \left[\begin{array}{cc} \mathbf{V}_k^1 & \mathbf{V}_k^0 \end{array} \right]^H \mathbf{V}_k^1 \mathbf{b}_k + \mathbf{n}_k \\ &= \mathbf{U}_k \mathbf{\Sigma}_k \mathbf{V}_k^{1H} \mathbf{V}_k^1 \mathbf{b}_k + \mathbf{n}_k \\ &= \mathbf{U}_k \mathbf{\Sigma}_k \mathbf{I}_r \mathbf{b}_k + \mathbf{n}_k \\ &= \mathbf{U}_k \left[\begin{array}{ccc} \lambda_{k1}^{1/2}\ b_{k1} & \ldots & \lambda_{kr}^{1/2}\ b_{kr} \end{array} \right]^T + \mathbf{n}_k \end{aligned} \quad (12)$$

The base station where user k is located sends post-processing unitary matrix $\mathbf{U}_k^H$ to mobile station k, so that mobile station k can perform spatial de-multiplexing to separate and decode the individual data streams. Alternatively, $\mathbf{U}_k^H$ can be estimated at each mobile station by transmitting secondary pilots passed already through the effective channel $\mathbf{H}_k \mathbf{W}_k$. Finally, the received signal in mobile station k after post-processing is

$$\tilde{\mathbf{y}}_k = \mathbf{U}_k^H \mathbf{y}_k = \left[\begin{array}{ccc} \lambda_{k1}^{1/2}\ b_{k1} & \ldots & \lambda_{kr}^{1/2}\ b_{kr} \end{array} \right]^T + \tilde{\mathbf{n}}_k \quad (13)$$

The noise vector $\tilde{\mathbf{n}}_k = \mathbf{U}_k^H \mathbf{n}_k$ remains white with covariance $\sigma^2 \mathbf{I}_r$ owing to the unitary transformation. The rate achieved by user k is the sum of rates of its parallel channel: $r_k = \sum_{j=1}^{r} \log_2 \left(1 + \frac{\lambda_{kj}\ P_{kj}}{\sigma^2}\right)$, with power $P_{kj} = E[|b_{kj}|^2]$. The transmit power needed by antenna q to support the symbol b_{kj} by using block-diagonalization is $|w_{kj}^q|^2 P_{kj}$, hence the total transmitted power propagated by antenna q to support the symbols of all users is $\sum_{k=1}^{N} \sum_{j=1}^{r} |w_{kj}^q|^2 P_{kj}$.

IV. Dual-Decomposition

In this section we formulate the power allocation optimization problem while using block-diagonalization pre-coding matrix. It can be seen later that the optimization problem can be solved distributively by using dual-decomposition. Let α_k be the priority weight factor for the k-th user with $\alpha_k \geq 0$, where the user with higher priority should be favored since its rate has a higher weight in the objective function. The problem of finding the optimal user power allocation which maximize the weighted sum network capacity under block-diagonalization subject to per-antenna-power constraint can be formalized as

$$\begin{aligned} max. \quad &: \quad \sum_{k=1}^{N} \sum_{j=1}^{r} \alpha_k \log_2 \left(1 + \frac{\lambda_{kj}\ P_{kj}}{\sigma^2}\right) \\ s.t. \quad &: \quad \sum_{k=1}^{N} \sum_{j=1}^{r} |w_{kj}^q|^2 P_{kj} \leq P_{max} \quad \forall q = \{1, \ldots, tM\} \\ & \quad P_{kj} \geq 0 \quad \forall k = \{1, \ldots, N\} \forall j = \{1, \ldots, r\} \end{aligned} \quad (14)$$

Caused by the linear constraints of the optimization problem in conjunction with a concave objective function $f_o(\mathbf{P}) = \sum_{k=1}^{N} \sum_{j=1}^{r} \alpha_k \log_2 \left(1 + \frac{\lambda_{kj}\ P_{kj}}{\sigma^2}\right)$, we end up with a convex optimization problem [10]. Our optimization problem can be formulated as a network utility maximization (NUM) optimization problem

$$\begin{aligned} max. \quad &: \quad \sum_{k=1}^{N} \sum_{j=1}^{r} U_{kj}(P_{kj}) \\ s.t. \quad &: \quad \sum_{k=1}^{N} \sum_{j=1}^{r} |w_{kj}^q|^2 P_{kj} \leq P_{max} \quad \forall q = \{1, \ldots, tM\} \\ & \quad P_{kj} \geq 0 \quad \forall k = \{1, \ldots, N\} \forall j = \{1, \ldots, r\}, \end{aligned} \quad (15)$$

with $U_{kj}(P_{kj}) = \alpha_k \log_2 \left(1 + \frac{\lambda_{kj}\ P_{kj}}{\sigma^2}\right)$ being the utility function. It has the following properties: twice-differentiable, increasing, and strictly concave. Although the objective function is separable in P_{kj}, the allocated power P_{kj} is coupled through the shared transmit antennas. By looking at its Lagrangian dual problem, our NUM problem will reveal its decomposable structures, which is the key to a distributed and iterative algorithm that converges to the global optimum. The basic idea of dual-decomposition is to decompose the original large problem into distributively solvable sub-problems which are then coordinated by a high-level master problem via pricing [11]. Form the Lagrangian of (15), we obtain

$$\begin{aligned} L(P_{kj}, \mu_q) &= \sum_{k=1}^{N} \sum_{j=1}^{r} U_{kj}(P_{kj}) + \\ & \quad \sum_{q=1}^{tM} \mu_q \left(P_{max} - \sum_{k=1}^{N} \sum_{j=1}^{r} |w_{kj}^q|^2 P_{kj} \right) \\ &= \sum_{k=1}^{N} \sum_{j=1}^{r} \left[U_{kj}(P_{kj}) - \left(\sum_{q=1}^{tM} \mu_q |w_{kj}^q|^2 \right) P_{kj} \right] \\ & \quad + \sum_{q=1}^{tM} \mu_q P_{max} \\ &= \sum_{k=1}^{N} \sum_{j=1}^{r} L_{kj}(P_{kj}, \mu^{kj}) + \sum_{q=1}^{tM} \mu_q P_{max}, \end{aligned} \quad (16)$$

where $\mu_q \geq 0$ is the dual variable and can be interpreted as the price for a unit of transmission power from antenna q. The

k-th base station where user k is located is informed about this price μ_q by antenna q and then computes the total price $\mu^{kj} = \sum_{q=1}^{tM} \mu_q |w_{kj}^q|^2$, where the sum is taken over all antennas that supply the j-th stream of the k-th user. The base station assigned to the k-th user determines the optimal power P_{kj}^* that maximizes the benefit: $L_{kj}(P_{kj}, \mu^{kj}) = U_{kj}(P_{kj}) - \mu^{kj} P_{kj}$, i.e. utility minus the transmission cost to supply the j-th stream of the k-th user with power P_{kj}. Thus we have the sub-optimizaton problem, which should be solved by the k-th base station for each stream j

$$\begin{aligned} max. \quad &: \quad U_{kj}(P_{kj}) - \mu^{kj} P_{kj} \\ s.t. \quad &: \quad P_{kj} \geq 0 \end{aligned} \tag{17}$$

The solution of this sub-optimization problem for a given μ^{kj} is

$$P_{kj}^*(\mu^{kj}) = \arg \max_{P_{kj} \geq 0} \left[U_{kj}(P_{kj}) - \mu^{kj} P_{kj} \right], \tag{18}$$

which has a unique solution due to the strict concavity of $U_{kj}(P_{kj})$. The sub-optimization problem in (17) is maximum, if

$$\begin{aligned} \frac{d \left[U_{kj}(P_{kj}) - \mu^{kj} P_{kj} \right]}{dP_{kj}} &= 0 \\ P_{kj}^* = \left[\frac{\alpha_k}{\mu^{kj} ln2} - \frac{\sigma^2}{\lambda_{kj}} \right]^+, \end{aligned} \tag{19}$$

where $[z]^+ = \max\{z, 0\}$ denotes the projection onto the non-negative orthant. Note that more power is allocated for higher priority factor α_k, bigger singular value $\lambda_{kj}^{1/2}$ and cheaper transmission price μ^{kj}. This individually optimal power allocation $P_{kj}^*(\mu^{kj})$ may not be globally optimal for a general price vector $\mu = [\mu_1, \ldots, \mu_q, \ldots, \mu_{tM}]^T$. The master dual-problem controls the price vector μ, so that it iteratively approaches a price vector μ^* that achieved both individual and global optimality

$$\begin{aligned} min. \quad &: \quad g(\mu) = \sum_{k=1}^{N} \sum_{j=1}^{r} g_{kj}(\mu^{kj}) + \sum_{q=1}^{tM} \mu_q P_{max} \\ s.t. \quad &: \quad \mu \geq 0, \end{aligned} \tag{20}$$

where $g_{kj}(\mu^{kj}) = L_{kj}(P_{kj}^*(\mu^{kj}), \mu^{kj})$ is the dual function. Since the solution in (19) is unique, it follows that the dual function $g(\mu)$ is differentiable and the following gradient method, which has a distributive nature, can be used for each transmit antenna q to solve the master dual-problem

$$\begin{aligned} &\mu_q(n+1) = \\ &\left[\mu_q(n) - \gamma \left(P_{max} - \sum_{k=1}^{N} \sum_{j=1}^{r} |w_{kj}^q|^2 P_{kj}^*(\mu^{kj}(n)) \right) \right]^+ \\ &\forall q = 1, \ldots, tM, \end{aligned} \tag{21}$$

where n is the iteration index and $\gamma > 0$ is a sufficiently small positive step-size [12]. Equation (21) has an economic interpretation of supply and demand [13]. If the demand $\sum_{k=1}^{N} \sum_{j=1}^{r} |w_{kj}^q|^2 P_{kj}^*$ for transmission power from all mobile stations at antenna q is below the power that the antenna can supply , namely P_{max}, then the price for a unit transmission power at the next iteration $\mu_q(n+1)$ will decrease. Otherwise if the demand exceeds the supply, then the price for a unit transmission power at the next iteration $\mu_q(n+1)$ will rise, which will in turn decrease the demand. Thus as $n \to \infty$, the demand and supply will converge to the equilibrium price for all antennas, namely μ^*. Since our primal problem is convex and satisfies the Slater condition, thus the duality gap (i.e. $f_o(\mathbf{P}) - g(\mu)$) is zero [10], where the primal variable found at the equilibrium price $\mathbf{P}(\mu^*)$ is indeed the global optimal power allocation $\mathbf{P}^* = [P_{11}^*, \ldots, P_{kj}^*, \ldots, P_{Nr}^*]^T$.

TABLE I
SIMULATION ASSUMPTIONS.

channel model	3GPP SCME[2]
scenario	urban-macro
additional modifications	scenario-mix[3]
f_c	2 GHz
intersite distance	500 m
number of base station	37
base station height	32 m
number of mobile station	37
mobile station height	2 m

V. MULTICELL SIMULATION RESULTS

The simulation assumptions are given in the Table I. Applied is the 3GPP SCME channel model resulting in frequency flat MIMO channels with omni-directional base station antennas. Since each mobile station may experience different channel conditions from different base stations, e.g. line of sight (LOS) or non line of sight (NLOS), we suggest to use a so-called scenario-mix [15]. This scenario mix models the interference statistics more realistically, and leads to higher average cell capacities compared to the widely used assumption having same propagation conditions from all base stations.

As a performance metric, we considered the maximization of the sum network capacity that could be achieved by solving the optimization problem. We set the priority factor to be equal for all users, i.e. $\alpha_k = 1, \forall k$. The power constraint at each base station is 15 dBm, which will be divided equally to $t \in \{1, 2, 3, 4\}$ transmit antennas to realize per-antenna power constraint while ensuring fair comparison between different transceiver setups. In Fig. 1 (left), we compare the cumulative distribution function (CDF) of the average network capacity achieved by the single-input single-output (SISO), the multiple-input single-output (MISO) and the multiple-input multiple-output (MIMO) system with full base station cooperation. We assert that by completely eliminating the inter-cell interference, the increase of capacity from SISO to MIMO 2x2 and MIMO 4x4 is relative proportional to the

[2]Spatial Channel Model Extended [14].

[3]Each cell may have different channel conditions, e.g. LOS or NLOS [15].

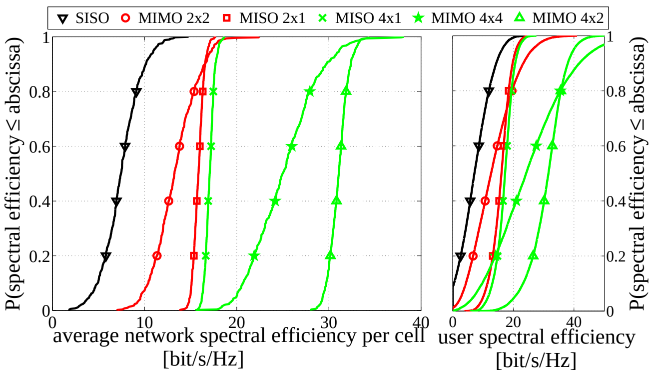

Fig. 1. Comparison of the average network capacity (left) and the overall user capacity (right) in a fully coordinated SISO, MISO and MIMO system.

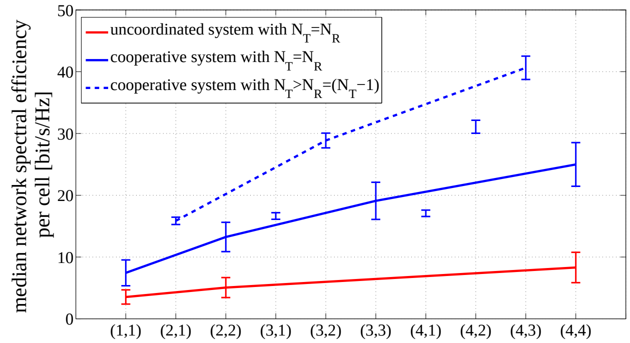

Fig. 2. Comparison of achievable median network capacity with (blue) and without (red) base station cooperation for different transceiver setups.

number of antennas. However, the variance of the CDF by these symmetric transceiver setups (i.e. $r = t$) is large, since there is no spatial dimension left to exploit macro diversity. If the number of transmit antennas at the base station is larger than required to mitigate the inter-cell interference, the macro diversity gain can be exploited yielding a much steeper capacity distribution and thus ensuring a more robust MIMO communication. Determining a good trade-off between macro diversity and spatial multiplexing will increase the average spectral efficiency as well. For example in case of the MIMO 4x2 system the average spectral efficiency is clearly increased while its variance is considerably reduced compared to the symmetric MIMO 4x4 system. In Fig. 1 (right), we compare the CDF of the user capacity. We observe that excess of transmit antennas at the base stations enhances user fairness. In Fig. 2, we compare the median network capacity with and without base station cooperation for different transceiver setups. Without base station cooperation, the inter-cell interference is partly removed by using interference rejection combining (IRC) at the mobile station [16]. By removing the inter-cell interference, base station cooperation with symmetric transceiver setups achieves higher increase in capacity compared to the system without cooperation. Even higher capacity increase with lower variance could be achieved by allowing 1 excess transmit antenna at each cooperated base station (i.e. t = r + 1) to utilize the substantial macro diversity gain.

VI. Conclusions

In this paper, we suggest an algorithm for distributed base station cooperation by using two concatenated techniques. Block-diagonalization is used to eliminate the inter-cell interference and to exploit spatial multiplexing and macro diversity. Subsequent dual-decomposition is used to determine the optimal power allocation distributively. The advantage of macro diversity in addition to inter-cell interference mitigation and spatial multiplexing in base station cooperation context is studied and shows superior performance in terms of a higher capacity increase with lower variance.

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