

Multi-Cell Cooperation for Future Wireless Systems

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1. Introduction

The wireless communications field is experiencing a rapid and steady growth. It is expected that the demand for wireless services will continue to increase in the near and medium term, asking for more capacity and putting more pressure on the usage of radio resources. The conventional cellular architecture considers co-located multiple input multiple output (MIMO) technology, which is a very promising technique to mitigate the channel fading and to increase the cellular system capacity (Foschini & Gans, 1998). On the other hand, orthogonal frequency division multiplexing (OFDM) is a simple technique to mitigate the effects of inter-symbol interference in frequency selective channels (Uppala & Li, 2004), (Bahai et al., 2004). However, the problems inherent to these systems such as shadowing, significant correlation between channels in some environments and intercell interference significantly degrade the capacity gains promised by MIMO techniques (Andrews et al., 2007). Although theoretically attractive, the deployment of MIMO in commercial cellular systems is limited by interference between neighbouring cells, and the entire network is essentially interference-limited (Foschini et al., 2006; Mudumbai et al., 2009).

Conventional approaches to mitigate multi-cell interference, such as static frequency reuse and sectoring, are not efficient for MIMO-OFDM networks as each has important drawbacks (Andrews et al., 2007). Universal frequency reuse (UFR), meaning that all cells/sectors operate on the same frequency channel, is mandatory if we would like to achieve spectrally-efficient communications. However, as it is pointed out in (Foschini et al., 2006), this requires joint optimization of resources in all cells simultaneously to boost system performance and to reduce the radiated power. Such systems have the advantage of macro-diversity that is inherent to the widely spaced antennas and more flexibility to deal with intercell interference, which fundamentally limits the performance of user terminals (UTs) at cell edges (Andrews et al., 2007). Different transmit strategies can be considered, depending on the capacity of the backhaul channel that connects the coordinated base stations. Recently, an enhanced cellular architecture with a high-speed backhaul channel has been proposed and implemented, under the European FUTON project (FUTON, 2011), (Diehm et al., 2010). This project aims at the design of a distributed broadband wireless system (DBWS) by carrying out the development of a radio over fiber (RoF) infrastructure transparently connecting the BSs to a central unit (CU) where centralized joint processing can be performed. Also, multi-cell cooperation is already under study in LTE under the Coordinated

Multipoint (CoMP) concept (3GPP LTE, 2007) that although not included in the current releases, will probably be specified for the future ones.

In recent years, relevant works on multi-cell precoding techniques have been proposed in (Jing et al., 2008), (Somekh et al, 2007), (Boccardi & Huang, 2007), (Zhang et al, 2009), (Marsch & Fettweis, 2009), (Armada et al., 2009), (Kobayashi et al., 2009), (Zhang, 2010), (Bjornson et al., 2010). The multi-cell downlink channel is closely related to the MIMO broadcast channel (BC), where the optimal precoding is achieved by the dirty paper coding (DPC) principle (Costa, 1983). However, the significant amount of processing complexity required by DPC prohibits its implementation in practical multi-cell processing. Some suboptimal multi-cell linear precoding schemes have been discussed in (Jing et al., 2008), where analytical performance expressions for each scheme were derived considering nonfading scenario with random phases. The comparison of the achievable rates by the different proposed cooperative schemes showed a tradeoff between performance improvement and the requirement for BS cooperation, signal processing complexity and channel state information (CSI) knowledge. In (Somekh et al, 2007) the impact of joint multi-cell site processing was discussed through a simple analytically tractable circular multi-cell model. The potential improvement in downlink throughput of cellular systems using limited network coordination to mitigate intercell interference has been discussed in (Boccardi & Huang, 2007), where zero forcing (ZF) and DPC precoding techniques under distributed and centralized architectures have been studied. In (Zhang et al, 2009) a clustered BS coordination is enabled through a multi-cell block diagonalization (BD) scheme to mitigate the effects of interference in multi-cell MIMO systems. Three different power allocation algorithms were proposed with different constraints to maximize the sum rate. A centralized precoder design and power allocation was considered. In (Marsch & Fettweis, 2009), the inner bounds on capacity regions for downlink transmission were derived with or without BS cooperation and under per-antenna power or sum-power constraint. The authors showed that under imperfect CSI, significant gains are achievable by BS cooperation using linear precoding. Furthermore the type of cooperation depends on channel conditions in order to optimize the rate/backhaul tradeoff. Two multi-cell precoding schemes based on the waterfilling technique have been proposed in (Armada et al., 2009). It was shown that these techniques achieve a performance, in terms of weighted sum rate, very close to the optimal. In (Kobayashi et al., 2009), each BS performs ZF locally to remove the channel interference and based on the statistical knowledge of the channels, the CU performs a centralized power allocation that jointly minimizes the outage probability of the UTs. A new BD cooperative multi-cells scheme has been proposed in (Zhang, 2010), to maximize the weighted sum-rate achievable for all the UTs. Multiuser multi-cell precoding with distributed power allocation has been discussed in (Bjornson et al., 2010). It is assumed that each BS has only the knowledge of local CSI and based on that the beamforming vectors used to achieve the outer boundary of the achievable rate region was derived considering both instantaneous and statistical CSI. An overview of the theory for multi-cell cooperation in networks has been presented in (Gesbert et al., 2010).

In this chapter we design and evaluate linear precoding techniques for multi-cell MIMO-OFDM cooperative systems. Two approaches are considered: centralized with a high-speed backhaul channel, where it is assumed that full CSI and data are available at the CU; and distributed with lower speed backhaul channel, where only some channel information and data are shared by the BSs. The precoder design aims at two goals: allow spatial users separation and optimize the power allocation. The two problems can be decoupled leading

to a two step design: the precoder vectors design and power allocation algorithms. In this chapter we discuss three centralized power allocation algorithms with different complexities and per-BS power constraint: one optimal to minimize the average bit error rate (BER), for which the powers can be obtained numerically by using convex optimization, and two suboptimal. In this latter approach, the powers are computed in two phases. First the powers are derived under total power constraint (TPC). Two criteria are considered, namely minimization of the average BER, which leads to an iterative approach and minimization of the sum of inverse of signal-to-noise ratio for which closed form solution is achieved. Then, the final powers are computed to satisfy the individual per-BS power constraint.

The rest of this chapter is organized as follows: in section 2 the general scenario is described, section 3 discusses centralized multi-cell MIMO OFDM cooperative precoding schemes, while in section 4 distributed multi-cell MIMO OFDM cooperative schemes are proposed, in section 5 the simulation results are presented and discussed. Finally, conclusions are drawn in section 6.

Throughout this chapter, we will use the following notations. Lowercase letters, boldface lowercase letters and boldface uppercase letters are used for scalars, vectors and matrices, respectively. $(\cdot)^H, (\cdot)^T, (\cdot)^*$ represent the conjugate transpose, the transpose and complex conjugate operators, respectively. $E[\cdot]$ represents the expectation operator, \mathbf{I}_N is the identity matrix of size $N \times N$, $\mathcal{CN}(\cdot, \cdot)$ denotes a circular symmetric complex Gaussian vector, $[\mathbf{A}]_{i,j}$ is the (i,j) th element and $[\mathbf{A}]_i$ is the i th column of the matrix \mathbf{A} .

2. Scenario description

Multi-cell architectures that assume a global coordination can eliminate the intercell interference completely. However, in practical cellular scenarios, issues such as the complexity of joint signal processing of all the BSs, the difficulty in acquiring full CSI from all UTs at each BS, and synchronization requirements will make global coordination difficult. Therefore, in this chapter we assume a clustered multi-cell cellular system as shown in Fig. 1, where the BSs are linked to a central unit (e.g., by optical fiber) as proposed in (FUTON, 2010). In such architecture the area covered by the set of cooperating BSs is termed as super-cell. The area defined by all the super-cells that are linked to the same CU is termed as serving area. The BSs corresponding to a super-cell are processed jointly by a joint processing unit (JPU). The number of cooperating BSs per super-cell should not be high for the reasons discussed above. In this chapter, it is assumed that the interference between the super-cells is negligible. In fact as we are replacing the concept of cell by the one of super-cell, this means that there will be some interference among the super-cells especially at the edges. Two approaches can be considered to deal with the inter-super-cell interference. The precoders are designed to remove both intra-super-cell and inter-super-cell interference, but as discussed in (Somekh et al., 2007) this strategy reduces the number of degrees of freedom to efficiently eliminate the intra-super-cell interference. Alternatively, the radio resource management can be jointly performed for a large set of super-cells (the serving area) at the CU, and thus the resource allocation can be done in a way that the UTs of each super-cell edge interfere as little as possible with the users of other super-cells (FUTON, 2010), justifying our assumption to neglect it. This resource allocation problem is however beyond the scope of this chapter. In this latter approach all degrees of freedom can be used to efficiently eliminate the intra-super-cell interference.

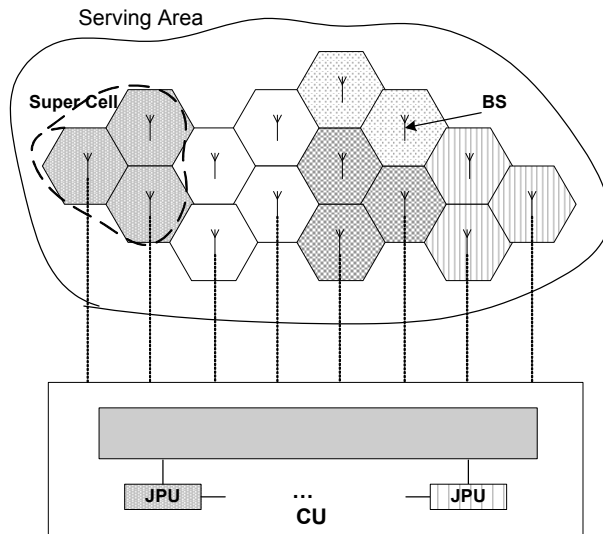


Fig. 1. Enhanced cellular architecture

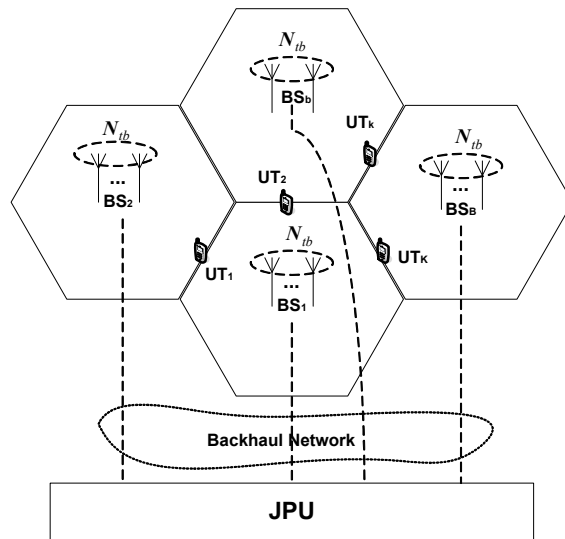


Fig. 2. Multi-cell system overview

We consider a scenario of B BSs comprising a super-cell; each BS is equipped with N_{tb} antennas, transmitting to K UTs as shown in Fig. 2. The total number of transmitting antennas per-super-cell is N_t . User k is equipped with single antenna or an antenna array of N_{r_k} elements and the total number of receiving antennas per-super-cell is N_r , which is equal to the number of users K in case of single antenna UTs. Also, we assume an OFDM based system with N_c parallel frequency flat fading channels.

3. Centralized multi-cell based system

We consider a multi-cell system based on the scenario defined in previous section where the BSs are transparently linked by optical fiber to a central unit. Thanks to the high speed backhaul, we can assume that all the information of all BSs, i.e., full CSI and data, belonging to the same super-cell are available at the JPU. Thus, to remove the multi-cell multiuser interference we can use a similar linear precoding algorithm designed for single cell based systems. The major difference between multi-cell and single cell systems is that the power constraints have to be considered on a per-BS basis instead. The proposed schemes are considered in two phases: singular value decomposition SVD based precoding and power allocation.

3.1 System model

To build up the mathematical model we consider that user $k, k=1, \dots, K$ can receive up to N_{r_k} data symbols on subcarrier $l, l=1, \dots, N_c$ i.e., $\mathbf{x}_{k,l} = [x_{k,1,l} \ \dots \ x_{k,N_{r_k},l}]^T$ and the global symbol vector, comprising all user symbol vectors, is $\mathbf{x}_l = [\mathbf{x}_{1,l}^T \ \dots \ \mathbf{x}_{K,l}^T]^T$ of size $N_r \times 1$.

The data symbol of user k on subcarrier l , is processed by the transmit precoder $\mathbf{W}_{k,l} \in \mathbb{C}^{N_t \times N_{r_k}}$ in JPU, before being transmitted over BSs antennas. These individual precoders together form the global transmit precoder matrix on subcarrier l , $\mathbf{W}_l = [\mathbf{W}_{1,l} \ \dots \ \mathbf{W}_{K,l}]$ of size $N_t \times N_r$. Let the downlink transmit power over the N_t distributed transmit antennas for user k and data symbol $i, i=1, \dots, N_{r_k}$ on subcarrier l , be $p_{k,i,l}$, with $\mathbf{p}_{k,l} = [p_{k,1,l} \ \dots \ p_{k,N_{r_k},l}]$ and the global power matrix $\mathbf{P}_l = \text{diag}\{\{\mathbf{p}_{1,l} \ \dots \ \mathbf{p}_{K,l}\}\}$ is of size $N_r \times N_r$.

Under the assumption of linear precoding, the signal transmitted by the JPU on subcarrier l is given by $\mathbf{z}_l = \mathbf{W}_l \mathbf{P}_l^{1/2} \mathbf{x}_l$ and the global received signal vector on subcarrier l can be expressed by,

$$\mathbf{y}_l = \mathbf{H}_l \mathbf{W}_l \mathbf{P}_l^{1/2} \mathbf{x}_l + \mathbf{n}_l \quad (1)$$

where $\mathbf{H}_l = [\mathbf{H}_{1,l}^T \ \dots \ \mathbf{H}_{K,l}^T]^T$ of size $N_r \times N_t$ is the global frequency flat fading MIMO channel on subcarrier l . The channel of user k is represented by

$\mathbf{H}_{k,l} = [\mathbf{H}_{1,k,l} \ \dots \ \mathbf{H}_{b,k,l} \ \dots \ \mathbf{H}_{B,k,l}]$ of size $N_{r_k} \times N_t$, and $\mathbf{H}_{b,k,l}$ of size $N_{r_k} \times N_{t_b}$ represents the channel between user k and BS $b, b=1, \dots, B$ on subcarrier l . The channel $\mathbf{H}_{b,k,l}$ can be decomposed as the product of the fast fading $\mathbf{H}_{b,k,l}^c$ and slow fading $\sqrt{\rho_{b,k}}$ components, i.e., $\mathbf{H}_{b,k,l} = \mathbf{H}_{b,k,l}^c \sqrt{\rho_{b,k}}$, where $\rho_{b,k}$ represents the long-term power gain between BS b and user k and $\mathbf{H}_{b,k,l}^c$ contains the fast fading coefficients with $\mathcal{CN}(0,1)$

entries. $\mathbf{n}_l = [\mathbf{n}_{1,l}^T \ \dots \ \mathbf{n}_{K,l}^T]^T$ represents the global additive white Gaussian noise (AWGN)

vector and $\mathbf{n}_{k,l} = [n_{k,1,l} \ \dots \ n_{k,N_{r_k},l}]^T$ is the noise at the user k terminal on subcarrier l with zero mean and power σ^2 , i.e., $\mathbb{E}[\mathbf{n}_{k,l} \mathbf{n}_{k,l}^H] = \sigma^2 \mathbf{I}_{N_{r_k}}$.

The signal transmitted by the BS b on subcarrier l can be written as $\mathbf{z}_{b,l} = \mathbf{W}_{b,l} \mathbf{P}_l^{1/2} \mathbf{x}_l$, where $\mathbf{W}_{b,l}$ of size $N_{t_b} \times N_r$ represents the global precoder at BS b on subcarrier l . The average transmit power of BS b is then given by,

$$\mathbb{E}[\|\mathbf{z}_b\|^2] = \sum_{k=1}^K \sum_{i=1}^{N_r} \sum_{l=1}^{N_c} p_{k,i,l} [\mathbf{W}_{b,k,l}^H \mathbf{W}_{b,k,l}]_{i,i} \quad (2)$$

where \mathbf{z}_b is the signal transmitted over the N_c subcarriers and $\mathbf{W}_{b,k,l}$ of size $N_{t_b} \times N_{r_k}$ represents the precoder of user k on subcarrier l at BS b .

3.2 Centralized precoder vectors

In this section, we consider the SVD based precoding algorithm similar to the one proposed in (Yu et al., 2004). We assume that $N_t \geq N_r$. Briefly, we define $\tilde{\mathbf{H}}_{k,l}$ as the following $(N_r - N_{r_k}) \times N_t$ matrix,

$$\tilde{\mathbf{H}}_{k,l} = [\mathbf{H}_{1,l} \dots \mathbf{H}_{k-1,l}, \mathbf{H}_{k+1,l} \dots \mathbf{H}_{K,l}]^T \quad (3)$$

If we denote rank of $\tilde{\mathbf{H}}_{k,l}$ as $\tilde{L}_{k,l}$ then the null space of $\tilde{\mathbf{H}}_{k,l}$ has dimension of $N_t - \tilde{L}_{k,l} \geq N_{r_k}$. The SVD of $\tilde{\mathbf{H}}_{k,l}$ is partitioned as follows,

$$\tilde{\mathbf{H}}_{k,l} = \tilde{\mathbf{U}}_{k,l} \tilde{\mathbf{D}}_{k,l} [\tilde{\mathbf{V}}_{k,l}^{(0)} \tilde{\mathbf{V}}_{k,l}^{(1)}]^H \quad (4)$$

where $\tilde{\mathbf{V}}_{k,l}^{(0)}$ holds the $N_t - \tilde{L}_{k,l}$ singular vectors in the null space of $\tilde{\mathbf{H}}_{k,l}$. The columns of $\tilde{\mathbf{V}}_{k,l}^{(0)}$ are candidate for user k precoding matrix $\mathbf{W}_{k,l}$, causing zero gain at the other users, hence result in an effective SU-MIMO system. Since $\tilde{\mathbf{V}}_{k,l}^{(0)}$ potentially holds more precoders than the number of data streams user k can support, an optimal linear combination of these vectors must be found to build matrix $\mathbf{W}_{k,l}$, which can have at most N_{r_k} columns. To do this, the following SVD is formed,

$$\mathbf{H}_{k,l} \tilde{\mathbf{V}}_{k,l}^{(0)} = \mathbf{U}_{k,l} \mathbf{D}_{k,l} [\mathbf{V}_{k,l}^{(0)} \mathbf{V}_{k,l}^{(1)}]^H \quad (5)$$

where $\mathbf{D}_{k,l}$ is $L_{k,l} \times L_{k,l}$ and $\mathbf{V}_{k,l}^{(1)}$ represents the $L_{k,l}$ singular vectors with non-zero singular values. The $L_{k,l} \leq N_{r_k}$ columns of the product $\tilde{\mathbf{V}}_{k,l}^{(0)} \mathbf{V}_{k,l}^{(1)}$ represent precoders that further improve the performance subject to producing zero inter-user interference. The transmit precoder matrix will thus have the following form,

$$\bar{\mathbf{W}}_l = [\tilde{\mathbf{V}}_{1,l}^{(0)} \mathbf{V}_{1,l}^{(1)} \quad \dots \quad \tilde{\mathbf{V}}_{K,l}^{(0)} \mathbf{V}_{K,l}^{(1)}] \mathbf{P}_l^{1/2} = \mathbf{W}_l \mathbf{P}_l^{1/2} \quad (6)$$

The global precoder matrix with power allocation, $\bar{\mathbf{W}}_l = [\mathbf{W}_{1,l} \quad \dots \quad \mathbf{W}_{K,l}] \mathbf{P}_l^{1/2}$ as computed above, block-diagonalizes the global equivalent channel \mathbf{H}_l , i.e., $\mathbf{H}_l \bar{\mathbf{W}}_l = \text{diag}\{\{\mathbf{H}_{e,1,l}, \dots, \mathbf{H}_{e,K,l}\}\}$ and the interference is completely removed considering perfect CSI.

Let us define $\mathbf{H}_{e,k,l} = \mathbf{H}_{k,l} \bar{\mathbf{W}}_{k,l} = \mathbf{H}_{k,l} \mathbf{W}_{k,l} \mathbf{P}_{k,l}^{1/2}$ of size $N_{r_k} \times N_{r_k}$ as the equivalent enhanced channel for user k on subcarrier l , where $\mathbf{P}_{k,l} = \text{diag}\{\mathbf{p}_{k,l}\}$ is of size $N_{r_k} \times N_{r_k}$. Rewriting equation (1) for this user, we have,

$$\mathbf{y}_{k,l} = \mathbf{H}_{e,k,l} \mathbf{x}_{k,l} + \mathbf{n}_{k,l} \quad (7)$$

To estimate $\mathbf{x}_{k,l}$, user k processes $\mathbf{y}_{k,l}$ by doing maximal ratio combining (MRC), and the soft decision variable $\hat{\mathbf{x}}_{k,l}$ is given by

$$\hat{\mathbf{x}}_{k,l} = \mathbf{H}_{e,k,l}^H \mathbf{y}_{k,l} = \mathbf{H}_{e,k,l}^H \mathbf{H}_{e,k,l} \mathbf{x}_{k,l} + \mathbf{H}_{e,k,l}^H \mathbf{n}_{k,l} \quad (8)$$

It should be mentioned that channel $\mathbf{H}_{e,k,l}$ can be easily estimated at UT k . It can be shown that,

$$\mathbf{H}_{e,k,l}^H \mathbf{H}_{e,k,l} = \text{diag} \left\{ \left[p_{k,1,l} \lambda_{k,1,l}, \dots, p_{k,N_r,k,l} \lambda_{k,N_r,k,l} \right] \right\} \quad (9)$$

where $\sqrt{\lambda_{k,i,l}}$ is the i th singular value of matrix $\mathbf{H}_{k,l} \mathbf{W}_{k,l}$. From equations (8) and (9) is easy to see that the instantaneous SNR of data symbol i of user k on subcarrier l can be written as

$$\text{SNR}_{k,i,l} = \frac{p_{k,i,l} \lambda_{k,i,l}}{\sigma^2} \quad (10)$$

From (10), assuming a M-ary QAM constellations, the instantaneous probability of error of data symbol i of user k on subcarrier l is given by (Proakis, 1995),

$$P_{e,k,i,l} = \psi Q \left(\sqrt{\beta \text{SNR}_{k,i,l}} \right) \quad (11)$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt$, $\beta = 3 / (M-1)$ and $\psi = (4 / \log_2 M) (1 - 1/\sqrt{M})$.

3.3 Power allocation strategies

Once the multi-cell multiuser interference removed, the power loading elements of \mathbf{P}_l can be computed in order to minimize or maximize some metrics. Most of the proposed power allocation algorithms for precoded multi-cell based systems have been designed to maximize the sum rate, e.g., (Jing et al., 2008; Bjornson et al., 2010). In this paper, the criteria used to design power allocation are minimization of the average BER and sum of inverse of SNRs, which essentially lead to a redistribution of powers among users and therefore provide users fairness (which in practical cellular systems may be for the operators a goal as important as throughput maximization). The aim of these power allocation schemes is to improve the user's fairness, namely inside each super-cell.

A. Optimal minimum BER power allocation

We minimize the instantaneous average probability under the per-BS power constraint P_{tb} ,

i.e., $\sum_{k=1}^K \sum_{i=1}^{N_r} \sum_{l=1}^{N_c} p_{k,i,l} \left[\mathbf{W}_{b,k,l}^H \mathbf{W}_{b,k,l} \right]_{i,i} \leq P_{tb}$, $b = 1, \dots, B$. Without loss of generality, we assume a

4-QAM constellation, and thus the optimal power allocation problem with per-BS power constraint can be formulated as,

$$\min_{\{p_{k,i,l}\}} \left(\frac{1}{KN_r N_c} \sum_{k=1}^K \sum_{i=1}^{N_r} \sum_{l=1}^{N_c} Q \left(\sqrt{\frac{p_{k,i,l} \lambda_{k,i,l}}{\sigma^2}} \right) \right) \text{ s.t. } \begin{cases} \sum_{k=1}^K \sum_{i=1}^{N_r} \sum_{l=1}^{N_c} p_{k,i,l} \left[\mathbf{W}_{b,k,l}^H \mathbf{W}_{b,k,l} \right]_{i,i} \leq P_{tb}, b = 1, \dots, B \\ p_{k,i,l} \geq 0, k = 1, \dots, K, i = 1, \dots, N_r, l = 1, \dots, N_c \end{cases} \quad (12)$$

Since the objective function is convex in $p_{k,i,l}$, and the constraint functions are linear, this is a convex optimization problem. Therefore, it may be solved numerically by using for

example the interior-point method (Boyd & Vandenberghe, 2004). This scheme is referred as centralized per-BS optimal power allocation (Cent. per-BS OPA).

B. Suboptimal power allocation approaches

Since the complexity of the above scheme is too high, and thus it could not be of interest for real wireless systems, we also resort to less complex suboptimal solutions. The proposed strategy has two phases: first the power allocation is computed by assuming that all BSs of each super-cell can jointly pool their power, i.e., a TPC P_t is imposed instead and the above optimization problem reduces to,

$$\min_{\{p_{k,i,l}\}} \left(\frac{1}{KN_{r_k}N_c} \sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} Q \left(\sqrt{\frac{p_{k,i,l} \lambda_{k,i,l}}{\sigma^2}} \right) \right) \text{ s.t. } \begin{cases} \sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} p_{k,i,l} [\mathbf{W}_{k,l}^H \mathbf{W}_{k,l}]_{i,i} \leq P_t \\ p_{k,i,l} \geq 0, k=1, \dots, K, i=1, \dots, N_{r_k}, l=1, \dots, N_c \end{cases} \quad (13)$$

with $\sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} p_{k,i,l} [\mathbf{W}_{k,l}^H \mathbf{W}_{k,l}]_{i,i} = \sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} p_{k,i,l}$, note that the N_{r_k} columns of $\mathbf{W}_{k,l}$ have unit norm. Using the Lagrange multipliers method (Haykin, 1996), the following cost function with μ Lagrange multiplier is minimized,

$$J_{c,1} = \frac{1}{KN_{r_k}N_c} \sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} Q \left(\sqrt{\frac{p_{k,i,l} \lambda_{k,i,l}}{\sigma^2}} \right) + \mu \left(\sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} p_{k,i,l} - P_t \right) \quad (14)$$

The powers $p_{k,i,l}$ can be determined by setting the partial derivatives of $J_{c,1}$ to zero and as shown in (Holakouei et al., 2011), the solution is

$$p_{k,i,l} = \frac{\sigma^2}{\lambda_{k,i,l}} W_0 \left(\frac{\lambda_{k,i,l}^2}{8\pi\mu^2 (KN_{r_k}N_c)^2 \sigma^4} \right) \quad (15)$$

where W_0 stands for Lambert's W function of index 0 (Corless et al., 1996). This function $W_0(x)$ is an increasing function. It is positive for $x > 0$, and $W_0(0) = 0$. Therefore, μ^2 can be determined iteratively to satisfy $\sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} p_{k,i,l} = P_t$. The optimization problem of (13) is

similar to the single cell power allocation optimization problem, where the users are allocated the same total multi-cell power, which may serve as a lower bound of the average BER for the multi-cell with per-BS power constraint. One solution based on Lambert W function that minimizes the instantaneous BER was also derived in the context of single user single cell MIMO systems (Rostaing et al., 2002).

The second phase consists in scaling the power allocation matrix \mathbf{P}_t by a factor of β in order to satisfy the individual per-BS power constraints as discussed in (Zhang et al., 2009) which can be given by

$$\beta = \frac{P_{th}}{\max_{b=1, \dots, B} \left(\sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} p_{k,i,l} [\mathbf{W}_{b,k,l}^H \mathbf{W}_{b,k,l}]_{i,i} \right)} \quad (16)$$

This scaled power factor assures that the transmit power per-BS is less or equal to P_{th} . Note that this factor is less than one and thus the SNR given by (10) has a penalty of $10\log(\beta)$ dB. This scheme is referred as centralized per-BS suboptimal iterative power allocation (Cent. per-BS SOIPA).

Although this suboptimal solution significantly reduces the complexity relative to the optimal one, it still needs an iterative search. To further simplify we propose an alternative power allocation method based on minimizing the sum of inverse of SNRs, and a closed-form expression can be obtained. Note that minimizing the sum of inverse of SNRs is similar to the maximization of the harmonic mean of the SINRs discussed in (Palomar, 2003). In this case, the optimization problem is written as,

$$\min_{\{p_{k,i,l}\}} \left(\sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} \frac{\sigma^2}{p_{k,i,l} \lambda_{k,i,l}} \right) \text{ s.t. } \begin{cases} \sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} p_{k,i,l} [\mathbf{W}_{k,l}^H \mathbf{W}_{k,l}]_{i,i} \leq P_t \\ p_{k,i,l} \geq 0, k = 1, \dots, K, i = 1, \dots, N_{r_k}, l = 1, \dots, N_c \end{cases} \quad (17)$$

Since the objective function is convex in $p_{k,i,l}$, and the constraint functions are linear, (17) is also a convex optimization problem. To solve it we follow the same suboptimal two phases approach as for the first problem. First, we impose a total power constraint and the following cost function, using again the Lagrangian multipliers method, is minimized,

$$J_{c,2} = \sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} \frac{\sigma^2}{p_{k,i,l} \lambda_{k,i,l}} + \mu \left(\sum_{k=1}^K \sum_{i=1}^{N_{r_k}} \sum_{l=1}^{N_c} p_{k,i,l} - P_t \right) \quad (18)$$

Now, setting the partial derivatives of $J_{c,2}$ to zero and after some mathematical manipulations, the powers $p_{k,i,l}$ are given by,

$$p_{k,i,l} = \frac{P_t}{\sqrt{\lambda_{k,i,l}} \sum_{j=1}^K \sum_{n=1}^{N_{r_k}} \sum_{p=1}^{N_c} \frac{1}{\sqrt{\lambda_{j,n,p}}}} \quad (19)$$

The second phase consists in scaling the power allocation matrix \mathbf{P}_l by a factor of β , using (19) instead of (15), in order to satisfy the individual per-BS power constraints. This scheme is referred as centralized per-BS suboptimal closed-form power allocation (Cent. per-BS SOCPA).

The above power allocation schemes can also be used, under minor modifications, for the case where the system is designed to achieve diversity gain instead of multiplexing gain. In diversity mode the same user data symbol is received on each receiver antenna, increasing the diversity order. Thus $x_{k,i,l} = x_{k,N_{r_k},l}$, $i = 1 \dots N_{r_k} - 1$ and then the SNR is given by

$$\text{SNR}_{k,l} = \frac{p_{k,l} \sum_{i=1}^{N_{r_k}} \lambda_{k,i,l}}{\sigma^2} = \frac{p_{k,l} \alpha_{k,l}}{\sigma^2} \quad (20)$$

and the power loading coefficient is computed only per user and subcarrier. In this case to compute the power allocation coefficients we should replace $\lambda_{k,i,l}$ by $\alpha_{k,l}$ and remove the script i in all equations.

4. Distributed multi-cell based system

As discussed in section 2 due to limitations in terms of delay and capacity on backhaul network, it is necessary to reduce signalling overhead. For this purpose, in this section the precoders are designed in a distributed fashion, i.e., based on local CSI at each BS but we still consider data sharing and centralized power allocation techniques.

4.1 System model

Assuming single antennas UTs and under the assumption of linear precoding, the signal transmitted by the BS b on sub-carrier l is given by,

$$\mathbf{x}_{b,l} = \sum_{k=1}^K \sqrt{p_{b,k,l}} \mathbf{w}_{b,k,l} s_{k,l}, \quad (21)$$

where $p_{b,k,l}$ represents the power allocated to UT k on sub-carrier l and BS b , $\mathbf{w}_{b,k,l} \in \mathbb{C}^{N_b \times 1}$ is the precoder of user k at BS b on sub-carrier l with unit norms, i.e., $\|\mathbf{w}_{b,k,l}\| = 1$, $b = 1, \dots, B$, $k = 1, \dots, K$, $l = 1, \dots, N_c$. The data symbol $s_{k,l}$, with $\mathbb{E}[|s_{k,l}|^2] = 1$, is intended for UT k and is assumed to be available at all BSs. The average power transmitted by the BS b is then given by,

$$\mathbb{E}[\|\mathbf{x}_b\|^2] = \sum_{l=1}^{N_c} \sum_{k=1}^K p_{b,k,l} \quad (22)$$

where \mathbf{x}_b is the signal transmitted over the N_c subcarriers. The received signal at the UT k on sub-carrier l , $y_{k,l} \in \mathbb{C}^{1 \times 1}$, can be expressed by,

$$y_{k,l} = \sum_{b=1}^B \mathbf{h}_{b,k,l}^H \mathbf{x}_{b,l} + n_{k,l} \quad (23)$$

where $\mathbf{h}_{b,k,l} \in \mathbb{C}^{N_b \times 1}$ represents the frequency flat fading channel between BS b and UT k on sub-carrier l and $n_{k,l} \sim \mathcal{CN}(0, \sigma^2)$ is the noise.

The channel $\mathbf{h}_{b,k,l}$, as for the centralized approach, can be decomposed as the product of the fast fading $\mathbf{h}_{b,k,l}^c$ and slow fading $\sqrt{\rho_{b,k}}$ components, i.e., $\mathbf{h}_{b,k,l} = \mathbf{h}_{b,k,l}^c \sqrt{\rho_{b,k}}$, where $\rho_{b,k}$ represents the long-term power gain between BS b and user k and $\mathbf{h}_{b,k,l}^c$ contains the fast fading coefficients with $\mathcal{CN}(0, 1)$ entries. The antenna channels from BS b to user k , i.e. the components of $\mathbf{h}_{b,k,l}^c$, may be correlated but the links seen from different BSs to a given UT are assumed to be uncorrelated as the BSs of one super-cell are geographically separated.

4.2 Distributed precoder vectors

As discussed above, to design the distributed precoder vector we assume that the BSs have only knowledge of local CSI, i.e., BS b knows the instantaneous channel vectors $\mathbf{h}_{b,k,l}, \forall k, l$, reducing the feedback load over the backhaul network as compared with the full centralized precoding approach. We consider a zero forcing transmission scheme with the phase of the received signal at each UT aligned. From (21) and (23) the received signal at UT k on sub-carrier l can be decomposed in,

$$y_{k,l} = \underbrace{\sum_{b=1}^B \sqrt{p_{b,k,l}} \mathbf{h}_{b,k,l}^H \mathbf{w}_{b,k,l}}_{\text{Desired Signal}} s_{k,l} + \underbrace{\sum_{b=1}^B \mathbf{h}_{b,k,l}^H \sum_{j=1, j \neq k}^K \sqrt{p_{b,j,l}} \mathbf{w}_{b,j,l}}_{\text{Multiuser Multicell Interference}} s_{j,l} + \underbrace{n_{k,l}}_{\text{Noise}} \quad (24)$$

where $\mathbf{w}_{b,k,l}$ is a unit-norm zero forcing vector orthogonal to $K-1$ channel vectors, $\{\mathbf{h}_{b,j,l}^H\}_{j \neq k}$. Such precoding vectors always exist because we assume that the number of antennas at each BS is higher or equal to the number of single antenna UTs, i.e. $N_{t_b} \geq K$. Note that here K is the number of users that share the same set of resources. Considering an OFDMA based system, the total number of users can be significantly larger than K , since different set of resources can be shared by different set of users. By using such precoding vectors, the multi-cell interference is cancelled and each data symbol on each subcarrier is only transmitted to its intended UT. Also, for any precoding vector $\bar{\mathbf{w}}_{b,k,l}$ in the null space of $\{\mathbf{h}_{b,j,l}^H\}_{j \neq k}$, $\mathbf{w}_{b,k,l} = \bar{\mathbf{w}}_{b,k,l} e^{j\varphi}$ is also in the null space of $\{\mathbf{h}_{b,j,l}^H\}_{j \neq k}$. Thus, we can choose the precoding vectors such that the terms $\mathbf{h}_{b,k,l}^H \mathbf{w}_{b,k,l}$ all have zeros phases, i.e., $\angle(\mathbf{h}_{b,k,l}^H \mathbf{w}_{b,k,l}) = 0, \forall (b,k,l)$. These precoding vectors can be easily computed, so if $\bar{\mathbf{W}}_{b,k,l}$ is found to lie in the null space of $\{\mathbf{h}_{b,j,l}^H\}_{j \neq k}$, the final precoding vector $\mathbf{w}_{b,k,l}$, $b=1, \dots, B$, $k=1, \dots, K$, $l=1, \dots, N_c$, with the phase of the received signal at each UT aligned, is given by,

$$\mathbf{w}_{b,k,l} = \bar{\mathbf{W}}_{b,k,l} \frac{(\mathbf{h}_{b,k,l}^H \bar{\mathbf{W}}_{b,k,l})^H}{\|\mathbf{h}_{b,k,l}^H \bar{\mathbf{W}}_{b,k,l}\|} \quad (25)$$

where $\bar{\mathbf{W}}_{b,k,l} \in \mathbb{C}^{N_{t_b} \times (N_{t_b} - K + 1)}$ holds the $(N_{t_b} - K + 1)$ singular vectors in the null space of $\{\mathbf{h}_{b,j,l}^H\}_{j \neq k}$. For the case where $N_{t_b} = K$, only one vector lies in the null space of $\{\mathbf{h}_{b,j,l}^H\}_{j \neq k}$, but for $N_{t_b} > K$ more than one vector lie in the null space of $\{\mathbf{h}_{b,j,l}^H\}_{j \neq k}$. In this latter case, the final $\mathbf{w}_{b,k,l}$ vector is a linear combination of the $(N_{t_b} - K + 1)$ possible solutions. The equivalent channel between BS b and UT k , on sub-carrier l can be expressed as,

$$\mathbf{h}_{b,k,l}^H \mathbf{w}_{b,k,l} = \mathbf{h}_{b,k,l}^H \bar{\mathbf{W}}_{b,k,l} \frac{(\mathbf{h}_{b,k,l}^H \bar{\mathbf{W}}_{b,k,l})^H}{\|\mathbf{h}_{b,k,l}^H \bar{\mathbf{W}}_{b,k,l}\|} = \|\mathbf{h}_{b,k,l}^H \bar{\mathbf{W}}_{b,k,l}\| = h_{b,k,l}^{eq} \quad (26)$$

From (26) we can observe that the equivalent channel, $h_{b,k,l}^{eq}$, is a positive real number. By using the precoding vectors defined in (25) and considering (26), the received signal in (24) reduces to,

$$y_{k,l} = \sum_{b=1}^B \sqrt{p_{b,k,l}} h_{b,k,l}^{eq} s_{k,l} + n_{k,l} \quad (27)$$

It should be mentioned that at the UT, to allow high order modulations, only the $\sqrt{p_{b,k,l}}h_{b,k,l}^{eq}$ coefficients are needed to be estimated instead of all the complex coefficients of the channel, leading to a low complexity UT design.

Since the $(N_{t_b} - K + 1)$ components of $\mathbf{h}_{b,k,l}^H \bar{\mathbf{w}}_{b,k,l}$ are i.i.d. Gaussian variables, $(h_{b,k,l}^{eq})^2$ is a chi-square random variable with $2(N_{t_b} - K + 1)$ degrees of freedom. Once the $h_{b,k,l}^{eq}$ variables are independent, each user is expected to achieve a diversity order of $B(N_{t_b} - K + 1)$ (assuming that all channels have the same average power, i.e., $\rho_{b,k} = \rho$, $\forall(b,k)$ and $p_{b,k,l} = 1$, $\forall(b,k,l)$). Also, because the received signals from different BSs have the same phase, they are added coherently at the UTs, and thus an additional antenna gain is achieved.

4.3 Power allocation strategies

In this section the same three criteria considered for the centralized approach are used to design the power allocation. However, it should be emphasised that for this scenario only the equivalent channels, i.e., $h_{b,k,l}^{eq}$, are needed to be known at the JPU.

A. Optimal minimum BER power allocation

From (27) the instantaneous SNR of user k on sub-carrier l can be written as,

$$\text{SNR}_{k,l} = \frac{\left(\sum_{b=1}^B \sqrt{p_{b,k,l}} h_{b,k,l}^{eq} \right)^2}{\sigma^2} \quad (28)$$

The instantaneous probability of error for user k is obtained in similar way in section 3. We minimize the instantaneous average probability under the per-BS power constraint P_{t_b} , i.e., $\sum_{l=1}^{N_c} \sum_{k=1}^K p_{b,k,l} \leq P_{t_b}$, $b = 1, \dots, B$. By assuming a 4-QAM constellation, the optimal power allocation problem with per-BS power constraint can be formulated as,

$$\min_{\{p_{b,k,l}\}} \left(\frac{1}{KN_c} \sum_{l=1}^{N_c} \sum_{k=1}^K Q \left(\frac{\sum_{b=1}^B \sqrt{p_{b,k,l}} h_{b,k,l}^{eq}}{\sigma} \right) \right) \quad \text{s.t.} \quad \begin{cases} \sum_{l=1}^{N_c} \sum_{k=1}^K p_{b,k,l} \leq P_{t_b}, b = 1, \dots, B \\ p_{b,k,l} \geq 0, b = 1, \dots, B, k = 1, \dots, K, l = 1, \dots, N_c \end{cases} \quad (29)$$

In this distributed approach, the objective function is convex in $p_{b,k,l}$ and the constraint functions are linear this is also a convex optimization problem. Therefore, it may be also solved numerically by using for example the interior-point method. This scheme is referred as distributed per-BS optimal power allocation (Dist. per-BS DOPA). In this section, the distributed term is referred to the precoder vectors since the power allocation is also computed in a centralized manner.

B. Suboptimal power allocation approaches

As for the centralized approach, the complexity of the above scheme is too high, and thus it is not of interest for real wireless systems, we also resort to less complex suboptimal solutions. The proposed strategy has two phases: first the power allocation is computed by assuming that all BSs of each super-cell can jointly pool their power, i.e., a TPC P_t is imposed instead and the above optimization problem reduces to,

$$\min_{\{p_{b,k,l}\}} \left(\frac{1}{KN_c} \sum_{l=1}^{N_c} \sum_{k=1}^K Q \left(\frac{\sum_{b=1}^B \sqrt{p_{b,k,l}} h_{b,k,l}^{eq}}{\sigma} \right) \right) \text{ s.t. } \begin{cases} \sum_{b=1}^B \sum_{l=1}^{N_c} \sum_{k=1}^K p_{b,k,l} \leq P_t \\ p_{b,k,l} \geq 0, b=1, \dots, B, k=1, \dots, K, l=1, \dots, N_c \end{cases} \quad (30)$$

with $P_t = \sum_{b=1}^B P_{t_b}$ and using the Lagrange multipliers method, the following cost function with μ Lagrange multiplier is minimized,

$$J_{d,1} = \frac{1}{KN_c} \sum_{l=1}^{N_c} \sum_{k=1}^K Q \left(\frac{\sum_{b=1}^B \sqrt{p_{b,k,l}} h_{b,k,l}^{eq}}{\sigma} \right) + \mu \left(\sum_{b=1}^B \sum_{l=1}^{N_c} \sum_{k=1}^K p_{b,k,l} - P_t \right) \quad (31)$$

The powers $p_{b,k,l}, \forall (b,k,l)$ can be determined by setting the partial derivatives of $J_{d,1}$ to zero and as shown in (Silva et al., 2011) the solution is,

$$p_{b,k,l} = \frac{\sigma^2 (h_{b,k,l}^{eq})^2}{\left(\sum_{i=1}^B (h_{i,k,l}^{eq})^2 \right)^2} W_0 \left(\frac{\left(\sum_{i=1}^B (h_{i,k,l}^{eq})^2 \right)^2}{8\pi\mu^2 N_c^2 K^2 \sigma^4} \right) \quad (32)$$

Therefore, μ^2 can be determined iteratively, using constraint $\sum_{b=1}^B \sum_{l=1}^{N_c} \sum_{k=1}^K p_{b,k,l} = P_t$. The second phase consists of replacing μ^2 by $\mu_b^2, b=1, \dots, B$ in (32), and then computing iteratively different μ_b^2 to satisfy the individual per-BS power constraints instead, i.e., μ_b^2 are computed to satisfy,

$$\begin{cases} \sum_{l=1}^{N_c} \sum_{k=1}^K p_{b,k,l} \leq P_{t_b}, b=1, \dots, B \\ p_{b,k,l} \geq 0, b=1, \dots, B, k=1, \dots, K, l=1, \dots, N_c \end{cases} \quad (33)$$

This suboptimal scheme is referred as distributed per-BS sub-optimal iterative power allocation (Dist. per-BS SOIPA). Although this suboptimal solution significantly reduces the complexity relative to the optimal one, it still needs an iterative search. To further simplify we also propose for the distributed scenario, an alternative power allocation method based on minimizing the sum of inverse of SNRs.

In this case, the optimization problem is written as,

$$\min_{\{p_{b,k,l}\}} \left(\sum_{l=1}^{N_c} \sum_{k=1}^K \frac{\sigma^2}{\left(\sum_{b=1}^B \sqrt{p_{b,k,l}} h_{b,k,l}^{eq} \right)^2} \right) \text{ s.t. } \begin{cases} \sum_{l=1}^{N_c} \sum_{k=1}^K p_{b,k,l} \leq P_{t_b}, b=1, \dots, B \\ p_{b,k,l} \geq 0, b=1, \dots, B, k=1, \dots, K, l=1, \dots, N_c \end{cases} \quad (34)$$

The objective function is convex in $p_{b,k,l}$, and the constraint functions are linear, (34) is also a convex optimization problem. To solve it we follow the same suboptimal two phases approach as for the first problem.

First, we impose a total power constraint and the following cost function, using again the Lagrangian multipliers method, is minimized,

$$J_{d,2} = \sum_{l=1}^{N_c} \sum_{k=1}^K \frac{\sigma^2}{\left(\sum_{b=1}^B \sqrt{p_{b,k,l}} h_{b,k,l}^{eq} \right)^2} + \mu \left(\sum_{b=1}^B \sum_{l=1}^{N_c} \sum_{k=1}^K p_{b,k,l} - P_t \right) \quad (35)$$

Now, setting the partial derivatives of $J_{d,2}$ to zero and after some mathematical manipulations, the powers $p_{b,k,l}$ can be shown to be given by,

$$p_{b,k,l} = \frac{\left(h_{b,k,l}^{eq} \right)^2}{\beta \sqrt{\left(\sum_{i=1}^B \left(h_{i,k,l}^{eq} \right)^2 \right)^3}} \quad (36)$$

where $\beta = \sqrt{\mu / \sigma^2}$. As for the first approach, (36) can be re-written by replacing β by β_b , $b = 1, \dots, B$, which are computed to satisfy the individual per-BS power constraints and the closed-form solution achieved is then given by,

$$p_{b,k,l} = \frac{P_{t_b} \left(h_{b,k,l}^{eq} \right)^2}{\sqrt{\left(\sum_{i=1}^B \left(h_{i,k,l}^{eq} \right)^2 \right)^3} \sum_{p=1}^{N_c} \sum_{j=1}^K \frac{\left(h_{b,j,p}^{eq} \right)^2}{\sqrt{\left(\sum_{i=1}^B \left(h_{i,j,p}^{eq} \right)^2 \right)^3}}} \quad (37)$$

This second suboptimal scheme is referred as distributed per-BS closed-form power allocation (Dist. per-BS SOCPA).

The precoder vectors are designed by assuming that BSs have only knowledge of local CSI. However, since we consider a centralized power allocation, to compute all powers the $h_{b,k,l}^{eq}$, $\forall b,k,l$ coefficients should be available at the joint processing unit (JPU). In the distributed multi-cell system each BS should send a real vector of size KN_c to the JPU. Note that in the centralized approach discussed in section 3, each BS should send to the JPU a complex vector of size $N_{t_b} KN_c$, i.e. $2N_{t_b}$ more information.

Although, in this section single antenna UTs were assumed, the formulation can be straightforwardly extended for multiple antenna UTs just by considering each antenna as a single antenna UT. The main difference is that the long term channel power will be the same for all antennas belonging to the same UT.

5. Results and discussions

5.1 Simulation parameters

In order to evaluate the proposed centralized and distributed multi-cell cooperation schemes, we assume ITU pedestrian channel model B (Guidelines IMT2000, 1997), with the

modified taps' delays, used according to the sampling frequency defined on LTE standard (3GPP LTE, 2007). This time channel model was extended to space-time by assuming that the distance between antenna elements of each BS is far apart to assume uncorrelated channels. To evaluate centralized and distributed schemes, the following scenarios are considered:

- Scenario 1, we assume that each supercell has 2 BSs, $B = 2$ which are equipped with 2 antennas, $N_{t_b} = 2$ and 2 UTs, $K = 2$, equipped with 2 antennas, $N_{r_k} = 2$.
- Scenario 2, we assume that each supercell has 2 BSs, $B = 2$ which are equipped with 2 antennas, $N_{t_b} = 2$ and 2 single antenna UTs, $K = 2$.
- Scenario 3, we assume that each supercell has 2 BSs, $B = 2$ which are equipped with 4 antennas, $N_{t_b} = 4$ and 2 single antenna UTs, $K = 2$.

The main parameters used in the simulations are, FFT size of 1024; number of resources, i.e., available subcarriers (N_c) shared by the K users set to 16; sampling frequency set to 15.36 MHz; useful symbol duration is $66.6 \mu\text{s}$; cyclic prefix duration is $5.21 \mu\text{s}$; overall OFDM symbol duration is $71.86 \mu\text{s}$; subcarrier separation is 15 kHz and modulation is 4-QAM. We assume that each UT is placed on each cell. The long-term channel powers are assumed to be $\rho_{b,k} = 1$, $b = k$ for the intracell links, and $\rho_{b,k}$, $b \neq k$ are uniformly distributed on the interval $[0.2, 0.6]$ for the intercell links. All the results are presented in terms of the average BER as a function of per-BS SNR defined as $SNR = P_{t_b} / \sigma^2$.

5.2 Performance evaluation

5.2.1 Centralized scenario

This section presents the performance results of centralized proposed precoding approaches for scenario 1. We compare the performance results of four centralized precoding schemes: one with non power allocation, which is obtained for the single cell systems by setting $\mathbf{P}_l = \mathbf{I}_{N_r}$, i.e., the power per data symbol is constrained to one. For multi-cell systems the power matrix $\mathbf{P}_l = \mathbf{I}_{N_r}$ should be scaled by β as defined in (16) (setting $p_{k,i,l} = 1, \forall k, i, l$), i.e., $\mathbf{P}_l = \beta \mathbf{I}_{N_r}$ ensuring a per-BS power constraint instead. This scheme is referred as centralized per-BS non-power allocation (Cent. per-BS NPA). The two suboptimal approaches are Cent. per-BS SOCPA and Cent. per-BS SOIPA; and the optimal one is Cent. per-BS OPA. Also, we present results for optimal approach considering total power allocation (Cent. TPC OPA), as formulated in (13), which may serve as a lower bound of the average BER for the centralized multi-cell system with per-BS power constraint.

Fig. 3 shows the performance results of all considered precoding schemes for scenario 1, considering multiplexing mode. It can be observed that the Cent. per-BS SOCPA, Cent. per-BS SOIPA and Cent. per-BS OPA schemes have significant outperformance comparing to the Cent. per-BS NPA approach, because they redistribute the powers across the different subchannels more efficiently. Comparing the two suboptimal approaches we can see that the iterative one, Cent. per-BS SOIPA, outperforms the closed-form, Cent. per-BS SOCPA because the former is obtained by explicitly minimizing average probability of error. The performance of the proposed suboptimal Cent. per-BS SOIPA and Cent. per-BS SOCPA approaches is close, a penalty less than 0.7 dB for a BER= 10^{-2} can be observed. Also, the penalty of the Cent. per-BS SOIPA against the lower bound given by the Cent. TPC OPA is only about 0.5 dB considering also a target BER= 10^{-2} .

Fig. 4 shows the performance results of all considered precoding schemes for scenario 1, considering diversity mode. Comparing these results with the last ones, it can be easily seen that there is a large gain due to operating in diversity mode. Since now each data symbol is

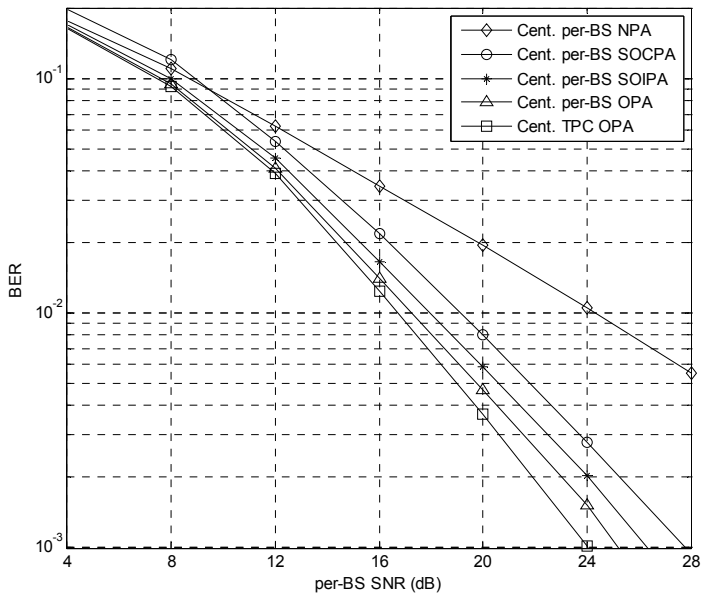


Fig. 3. Performance evaluation of the proposed centralized multi-cell schemes considering multiplexing mode, for scenario 1

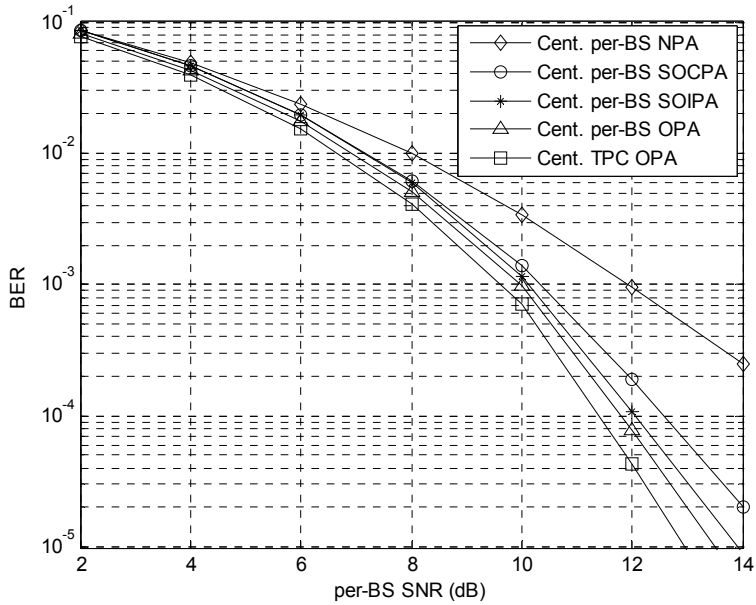


Fig. 4. Performance evaluation of the proposed centralized multi-cell schemes considering diversity mode, for scenario 1

collected by each receive antenna of each UT. From this figure we basically can point out the same conclusions as for the results obtained in the previous one. However, one important thing that can be found out by comparing multiplexing and diversity modes is that the difference between Cent. per-BS NPA curves and power allocation based curves (e.g. Cent. per-BS SOIPA) is bigger in multiplexing mode (approximately 4dB) than diversity mode (1.5dB) considering a BER=10⁻². This can be explained by the fact that in the diversity mode the equivalent channel gain of each data symbol is the addition of N_{r_k} individual channel gains and thus the dynamic range of the SNRs of the different data symbols is reduced, i.e., somewhat leads to an equalization of the SNRs.

5.2.2 Distributed scenario

This section presents the performance results of proposed distributed precoding approaches for scenario 2. We compare the results of four distributed precoding schemes with different per-BS power allocation approaches: distributed per-BS equal power allocation (Dist. per-BS EPA), in this case $p_{b,k,l} = P_{t_b} / KN_c, \forall (b,k,l)$; the two suboptimal approaches Dist. per-BS SOIPA and Dist. per-BS SOCPA and the optimal one Dist. per-BS OPA. Also, the results for optimal approach considering total power allocation (Dist. TPC OPA), as formulated in (30) are presented. This serves as lower bound for the distributed multi-cell scenario under per-BS power constraint.

Fig. 5 shows the performance results of all considered distributed precoding schemes for scenario 2. It can be observed that the Dist. per-BS SOCPA, Dist. per-BS SOIPA and Dist. per-BS OPA schemes outperform the Dist. per-BS EPA approach, because they redistribute the powers across the different subchannels more efficiently. For this case the performance

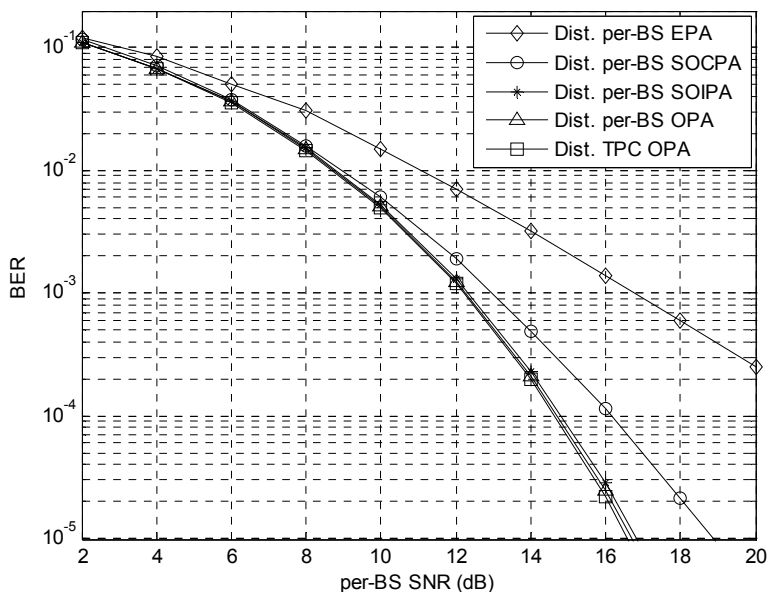


Fig. 5. Performance evaluation of the proposed distributed multi-cell schemes, for scenario 2

of the suboptimal Dist. per-BS SOIPA and optimal Dist. per-BS OPA is very close (penalty less than 0.1dB), but the gap between these two schemes and the suboptimal Dist. per-BS SOCPA is considerable. These results show that the Dist. per-BS SOIPA outperforms the Dist. per-BS SOCPA for large number of subchannels. We can observe a penalty of approximately 0.6 dB of the Dist. per-BS SOCPA scheme against the Dist. per-BS SOIPA for a BER=10⁻³. Also, a gain of approximately 4.2 dB of the suboptimal Dist. per-BS SOIPA scheme against the Dist. per-BS EPA is obtained, considering BER=10⁻³.

5.2.3 Performance comparison

This section presents the performance results of both distributed and centralized proposed precoding approaches for scenarios 2 and 3.

Fig. 6 shows the results for scenario 2, from this figure we can see that the performance of all power allocation schemes with centralized precoding outperforms the one with distributed scheme, because there are more degrees of freedom (DoF) to remove the interference and enhance the system performance. In the distributed case, the performance of the suboptimal Dist. per-BS SOIPA and optimal Dist. per-BS OPA is very close (penalty less than 0.1dB), but the gap between these two schemes and the suboptimal per-BS SOCPA is almost increased to 0.8dB (BER=10⁻³). In the case of centralized precoding the performances of Cent. per-BS SOIPA and Cent. per-BS OPA are still very close but both are degraded from Cent. TPC OPA (about 0.5dB at BER=10⁻³) and also there is 0.5dB gap among these curves and Cent. per-BS SOCPA at the same BER. Another important issue that should be emphasized is that the penalty of the per-BS OPA against the TPC OPA is approximately 0.1 dB (BER=10⁻³) for distributed scheme, against 0.5dB for centralized case.

Figure 7 shows the performance results of both distributed and centralized schemes for scenario 3. By observing this figure almost the same conclusions can be drawn. An interesting result is that the performances of distributed and centralized schemes are much closer comparing with scenario 2. This can be explained by the fact that for the centralized approach the number of DoF, which is given by the number of total transmit antennas BN_{t_b} , increased from 4 (scenario 2) to 8 (scenario 3); while for the distributed approach, the number of DoF, which is given by $B(N_{t_b} - K + 1)$ as discussed before; is increased from 2 (scenario 2) to 6 (scenario 3), i.e., the number of DoF of both centralized and distributed approaches is closer than that in scenario 2. From the presented results two important facts should be also emphasized: first is that in case of distributed precoding, the performance improvement achieved with the three proposed power allocation techniques, is higher than the case of centralized scheme; the second is that in the case of distributed precoding, the suboptimal techniques are more successful in achieving the lower bound of average BER.

6. Conclusion

In this chapter we proposed and evaluated centralized and distributed multi-cell multiuser precoding schemes for MIMO OFDM based systems. The proposed precoder vectors were computed either jointly and centrally at JPU benefiting from high DoF or on each BS in a distributed manner allowing a low feedback load over the backhaul network, while the power allocation was computed in a centralized fashion at the JPU.

The criteria considered was the minimization of the BER and two centralized power allocation algorithms with per-BS power constraint: one optimal that can be achieved at the expense of some complexity and one suboptimal with lower complexity aiming at practical

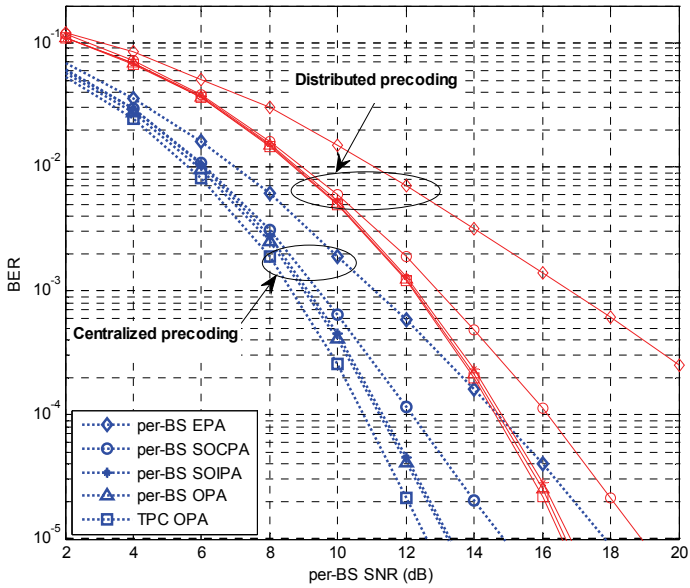


Fig. 6. Performance evaluation of the proposed distributed and centralized multi-cell schemes for scenario 2

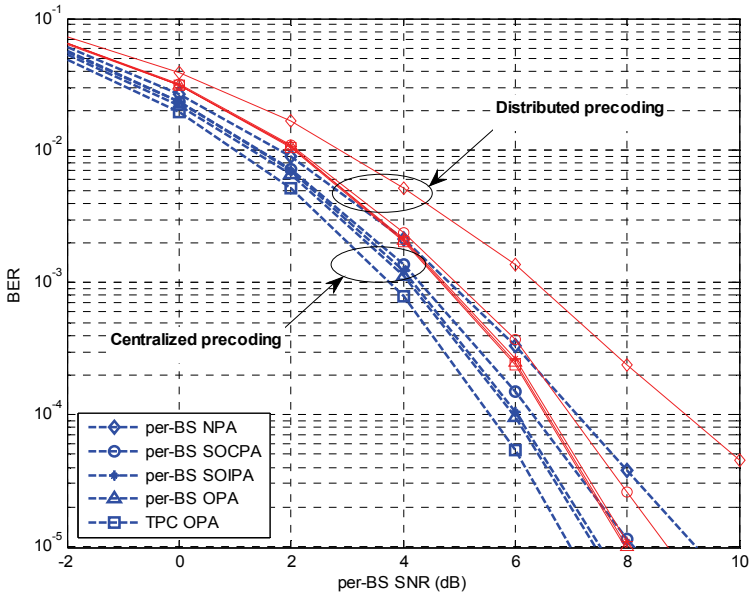


Fig. 7. Performance evaluation of the proposed distributed and centralized multi-cell schemes for scenario 3

implementations. In both the optimal (per-BS OPA) and the suboptimal (per-BS SOIPA), the computation of the transmitted powers required an iterative approach. To circumvent the need for iterations further proposed another suboptimal scheme (per-BS SOCPA), where the power allocation was computed in order to minimize the sum of inverse of SNRs of each UT allowing us to achieve a closed-form solution.

The results have shown that the proposed multi-user multi-cell schemes cause significant improvement in system performance, in comparison with the case where no power allocation is used. Also for both approaches, the performance of the proposed suboptimal algorithms, namely the per-BS SOIPA approach, is very close to the optimal with the advantage of lower complexity. Also, the performance of the distributed approach tends to the one achieved by the centralized, when the number of DoF available tends to the number of DoF available in the centralized system. Therefore, distributed schemes can be interesting in practice when the backhaul capacity is limited.

It is clear from the presented results the suboptimal proposed either distributed or centralized precoding schemes allow a significant performance improvement with very low UT complexity and moderate complexity at both BS and JPU, and therefore present significant interest for application in next generation wireless networks for which cooperation between BSs is anticipated.

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