Multiuser CoMP transmit processing with statistical channel state information at the transmitter

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***Abstract*—Coordinated Multi-Point (CoMP) transmission/reception is a candidate technique for increasing cell-average and cell-edge throughputs in next-generation wireless systems. Joint Processing (JP) can enhance CoMP systems' performance, mainly employing precoding algorithms based on channel state information at the transmitter (CSIT). Currently, many research efforts focus on reducing feedback and optimizing precoding with partial CSIT. This paper proposes a model to approximate the downlink multiuser CoMP channel based on the channel statistics and taking into account the channel temporal variation. The proposed model is relatively simple, highly reduces feedback overheads, and might be employed to perform precoding. Compared to using linear precoding with instantaneous CSIT, results show that throughput losses are negligible for low SNR values and moderate for high SNR values when using the proposed model. Analyses considering users all over the cell and in the cell-edge are also presented.**

I. Introduction

Coordinated Multi-Point (CoMP) transmission/reception has been considered as a promising approach to improve coverage with high data rates and cell-edge throughput [1]. CoMP transmission can be categorized into two classes: Joint Processing (JP), where data are simultaneously transmitted from multiple transmission points to a single user as to improve its received signal quality and/or actively cancel interference from other users; and Coordinated Scheduling/Beamforming (CS/CB), in which data is only available at the serving cell (data transmission from that point) but user scheduling/beamforming decisions are made with coordination among cells belonging to the CoMP cooperating set [1].

The benefits of Multiple-Input-Multiple-Output (MIMO) systems are enhanced when the transmitter exploits channel state information (CSI) to process, in an intelligent way, the signal before transmission. This can be accomplished by precoding techniques, which often rely on the assumption that the transmitter knows perfectly the MIMO channel matrix [2], [3]. However, this may not be realistic in many practical scenarios and considering partial availability of CSIT in MIMO systems becomes an important issue. This assumption might have a significant impact on the throughput that can be reliably obtained by the system.

Partial CSIT was firstly introduced in [4], where Lloyd's algorithm is used to quantize CSI. Indeed, some limited feedback multiuser MIMO schemes let each user quantize some function of the channel coefficients and feed this information back to the transmitter [5], [6]. Problems occur, e.g., when user signals can not be perfectly orthogonalized by precoding due to channel quantization errors. To avoid this, schemes have been proposed which select, at the receiver, a quantized precoder from a codebook. Then, only the precoder index is fed back to the transmitter [7], [8]. However, designing precoder codebooks is a quite difficult task, which must take into account the statistical characteristics of the channel. Other approaches focused on feeding back the mean [9] or the covariance matrix [10] of the channel, which convey important information about the slow fading and the mean spatial separability of the users. However, such techniques usually do not take into account the temporal variation of the channel, leading to accuracy degradation of CSIT.

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In this work, we propose a multicell multiuser dynamic channel model which assumes that the transmitter has only partial channel information, while the receiver has access to instantaneous CSI. This partial information consists of the channel statistics and the temporal correlation parameter. The simulation results show that the proposed channel model plays a significant role in low-SNR regimes in which the transmit power is only sufficient to excite a subset of the eigenmodes of the channel.

The remainder of this paper is organized as follows. In section II, the multicell multiuser MIMO system considering CoMP is presented. In section III we describe our proposal for modeling the CSIT. Simulation results are presented in section IV. Finally, conclusions are stated in section V.

II. System Model

We consider the downlink of a multicell multiuser MIMO communication system composed by N_b Base Stations (BSs) and K cochannel Mobile Stations (MS) arbitrarily distributed within the system coverage area. Each BS is equipped with N_t transmit antennas and each MS with N_r receive antennas. The BSs are connected to a central processing unit, thus characterizing a CoMP structure. Moreover, synchronization among the BSs is assumed. Hereafter (N_t, N_r, N_b, K) will be used to represent the overall structure of the system. Figure 1 shows this representation for a case with $N_b = K = 3$.

The channel is considered frequency-flat, stationary and takes into account only the small-scale fading. Herein,

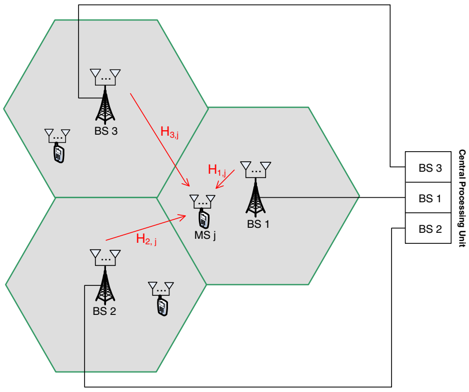


Figure 1. Multicell multiuser MIMO system model with $N_b = K = 3$.

Rayleigh-distributed small-scale fading is considered, which is modeled using Jake's model [11]. The spatial channel characteristics assume Kronecker-structured covariances with a transmit covariance matrix $\mathbf{R}_{\mathbf{t}j}$ and a receive covariance matrix $\mathbf{R}_{\mathbf{r}j}$ for each MS j. Considering this, the channel matrix from all BSs to MS j at time n can be modeled as

$$\mathbf{H}_{\Sigma j}[n] = \mathbf{R}_{\mathbf{r}j}^{1/2} \mathbf{H}_{\text{Jakes}}[n] \mathbf{R}_{\mathbf{t}j}^{1/2}, \tag{1}$$

where $\mathbf{H}_{\Sigma j} = \begin{bmatrix} \mathbf{H}_{1,j} & \mathbf{H}_{2,j} & \dots & \mathbf{H}_{N_b,j} \end{bmatrix}_{N_r \times N_b N_t}$ is the joint channel matrix from all BS to MS j with $\mathbf{H}_{b,j}$ being the channel matrix from base b to user j and $\mathbf{H}_{\text{Jakes}}[n]$ is a $N_r \times N_t N_b$ small-scale fading channel matrix. Here, $\mathbf{R}_{\mathbf{t}j}^{1/2}$ is the principal square-root of $\mathbf{R}_{\mathbf{t}j}$, such that, $\mathbf{R}_{\mathbf{t}j} = \mathbf{R}_{\mathbf{t}j}^{1/2} \mathbf{R}_{\mathbf{t}j}^{1/2}$. Analogously, $\mathbf{R}_{\mathbf{r}j} = \mathbf{R}_{\mathbf{r}j}^{1/2} \mathbf{R}_{\mathbf{r}j}^{1/2}$.

As already mentioned, in a CoMP-JP system, the transmit signal intended for each user j is spread over all N_b BSs. It can be expressed as $\mathbf{x}_j = \begin{bmatrix} \mathbf{x}_j^{[1]T} & \mathbf{x}_j^{[2]T} & \dots & \mathbf{x}_j^{[N_b]T} \end{bmatrix}^T$, where $\mathbf{x}_j^{[b]}$ is the signal transmitted from BS b for user j. The signal $\mathbf{y}_j$ received at MS j is

$$\mathbf{y}_j = \mathbf{H}_{\Sigma j} \mathbf{x}_j + \sum_{k \neq j} \mathbf{H}_{\Sigma j} \mathbf{x}_k + \mathbf{n}_j, \tag{2}$$

where $\mathbf{n}_j$ is the background noise and time n is omitted for simplicity.

Let L_j denote the number of data streams intended for MS j, $j = 1, 2, \dots, K$. For each MS, an $N_t N_b \times L_j$ precoder matrix $\mathbf{T}_j$ is designed based on the characteristics of $\mathbf{H}_{\Sigma j}$. Using $\mathbf{T}_j$, Equation (2) can be rewritten as

$$\mathbf{y}_j = \mathbf{H}_{\Sigma j} \mathbf{T} \mathbf{s} + \mathbf{n}_j, \tag{3}$$

where $\mathbf{T} = \begin{bmatrix} \mathbf{T}_1 & \mathbf{T}_2 & \dots & \mathbf{T}_K \end{bmatrix}_{N_t N_b \times L_T}$ is the joint precoding matrix, $\mathbf{s} = \begin{bmatrix} \mathbf{s}_1^T & \mathbf{s}_2^T & \dots & \mathbf{s}_K^T \end{bmatrix}_{L_T \times 1}^T$ is the joint data stream vector with $\mathbf{s}_j$ being a data stream intended for MS j and $L_T = \sum_{j=1}^{K} L_j$. For simplicity, streams are assumed to have i.i.d. zero-mean unit-variance complex Gaussian entries, i.e., Gaussian signaling is assumed.

In (2), the term $\sum_{k \neq j} \mathbf{H}_{\Sigma j} \mathbf{T}_k \mathbf{s}_k$ represents the asynchronous reception by MS j of the signal sent for the MS k, $k \neq j$. Since MS j is not interested in correctly detecting $\mathbf{s}_k$, the design of the joint transmit matrix $\mathbf{T}$ is not affected by asynchronous receptions of interfering signals and $\mathbf{s}_k$ can be simply viewed as the data of some virtual synchronous interfering MSs.

III. Multiuser Multicell Dynamic CSIT Model

A. Covariance and Auto-covariance of the Channel

The channel covariance $\mathbf{R}_j[0]$ of MS j captures the spatial correlation among all transmit and the receive antennas of MS j being a $N_r N_b N_t \times N_r N_b N_t$ positive semi-definite Hermitian matrix defined as

$$\mathbf{R}_j[0] = \mathbb{E}\left\{ \mathbf{h}_{\Sigma j} \mathbf{h}_{\Sigma j}^* \right\}, \tag{4}$$

where $\mathbf{h}_{\Sigma j} = \text{vec}\left(\mathbf{H}_{\Sigma j}\right)$, and $(.)^*$ denotes a conjugate transpose. Its diagonal elements represent the power gain of the $N_r N_b N_t \times N_r N_b N_t$ scalar channels from all BSs to MS j, and the off-diagonal elements are the cross-coupling between these scalar channels.

Assuming that $\mathbf{R}_j[0]$ has the simplified, separable Kronecker structure [12], it can be decomposed as

$$\mathbf{R}_j[0] = \mathbf{R}_{\mathbf{t}j}^T[0] \otimes \mathbf{R}_{\mathbf{r}j}[0], \tag{5}$$

where $\otimes$ denotes the Kronecker product. Moreover, assuming stationarity, the auto-covariance between two channel samples $\mathbf{H}_{\Sigma j}[m]$ and $\mathbf{H}_{\Sigma j}[m+n]$ depends on the time difference n but not on the absolute time and is given by

$$\mathbf{R}_j[n] = \mathbb{E}\left\{ \mathbf{h}_{\Sigma j}[m] \mathbf{h}_{\Sigma j}^*[m+n] \right\}, \tag{6}$$

which coincides with $\mathbf{R}_j[0]$ in (4) when $n = 0$ and eventually decays to zero when n becomes large.

The channel auto-covariance characterizes how fast the channel decorrelates with time. While the covariance $\mathbf{R}_j[0]$ captures the spatial correlation among all transmit and receive antennas of user j, the channel auto-covariance at a non-zero time difference $\mathbf{R}_j[n]$ captures both channel spatial and temporal correlations.

Based on the premise that the channel temporal statistics for all antenna pairs of the same MS j can be the same, the channel gains between all the $N_t N_b$ transmit antennas and N_r receive antennas of the BSs-MS link have the same temporal correlation function. Then, at each time n, it is possible to separate the temporal correlation $\rho_j[n]$ from the spatial correlation $\mathbf{R}_j[0]$ and the auto-covariance $\mathbf{R}_j[n]$ becomes their product as

$$\mathbf{R}_j[n] = \rho_j[n] \mathbf{R}_j[0], \text{with} \tag{7}$$

$$\rho_j[n] = J_0\left(2\pi n f_{d_j}\right), \tag{8}$$

where $J_0(.)$ is the zero-th order Bessel function of the first kind and f_{d_j} is the maximum Doppler spread of MS j at time n [11] [13].

B. Channel Estimation at the Transmitter

Firstly, we assume that the transmitter has an initial channel measurement at time $n = 0$ and relevant channel statistics for each MS j, namely $\mathbf{H}_{\Sigma j}[0]$ and $\mathbf{R}_j[0]$.

The channel information at the transmitter, at the time n, is composed by a channel estimate and the estimation error covariance. Since the initial channel measurement is considered error-free, the main source of irreducible error in channel estimation will be the channels' random variation in time. Thus, the error in the channel estimate depends only on the time difference n between this initial measurement and its use by the transmitter.

Let $\hat{\mathbf{H}}_{\Sigma j}[n]$ be the channel estimate for MS j at time n and $\mathbf{E}_{\Sigma j}[n]$ the estimation error with correlation $\mathbf{R}_{\mathbf{e}j}[n]$. The CSIT model can be written as

$$\mathbf{H}_{\Sigma j}[n] = \hat{\mathbf{H}}_{\Sigma j}[n] + \mathbf{E}_{\Sigma j}[n], \quad (9)$$

$$\mathbf{R}_{\mathbf{e}j}[n] = \mathbb{E}\left\{\mathbf{e}_{\Sigma j}[n]\mathbf{e}_{\Sigma j}[n]^*\right\} \quad (10)$$

where $\mathbf{e}_{\Sigma j}[n] = \text{vec}\left(\mathbf{E}_{\Sigma j}[n]\right)$. In the following, we show how the CSIT of each user j, which consists of the estimate $\hat{\mathbf{H}}_{\Sigma j}[n]$ and its error covariance $\mathbf{R}_{\mathbf{e}j}[n]$, can be obtained using MMSE estimation theory.

C. Linear Estimation Theory for the CSIT Problem

Since the $\mathbf{h}_{\Sigma j}[n]$ and $\mathbf{h}_{\Sigma j}[0]$ vectors are dependent random variable vectors, the value assumed by $\mathbf{h}_{\Sigma j}[n]$ can be estimated when the value by $\mathbf{h}_{\Sigma j}[0]$ is known or measured. Indeed, the estimate $\hat{\mathbf{h}}_{\Sigma j}[n]$ can be described as a function of the value assumed by $\mathbf{h}_{\Sigma j}[0]$, i.e.,

$$\hat{\mathbf{h}}_{\Sigma j}[n] = f\left(\mathbf{h}_{\Sigma j}[0]\right). \quad (11)$$

The challenge is to suitably choose $f(\cdot)$ to yield a reasonable estimate $\hat{\mathbf{h}}_{\Sigma j}[n]$, which means to satisfy a desired optimality criterion. Considering the mean square error criterion, it can be shown that the optimum estimate is [14]

$$\hat{\mathbf{h}}_{\Sigma j}[n] = \mathbb{E}\left\{\mathbf{h}_{\Sigma j}[n] | \mathbf{h}_{\Sigma j}[0]\right\}. \quad (12)$$

Calculating this expectation requires full knowledge of the joint probability density function of $\mathbf{h}_{\Sigma j}[n]$ and $\mathbf{h}_{\Sigma j}[0]$, which is often hard to obtain. However, if we restrict the estimation function $f(\cdot)$ to be a linear function of the observations[1], then it turns out that all we shall need is knowledge of first- and second-order statistics $\mathbb{E}\left\{\mathbf{h}_{\Sigma j}[n]\right\}$, $\mathbb{E}\left\{\mathbf{h}_{\Sigma j}[0]\right\}$, $\mathbb{E}\left\{\mathbf{h}_{\Sigma j}[n]\mathbf{h}_{\Sigma j}[n]^*\right\}$, $\mathbb{E}\left\{\mathbf{h}_{\Sigma j}[0]\mathbf{h}_{\Sigma j}[0]^*\right\}$ and $\mathbb{E}\left\{\mathbf{h}_{\Sigma j}[n]\mathbf{h}_{\Sigma j}[0]^*\right\}$. Thus, the estimation function will be given by

$$\hat{\mathbf{h}}_{\Sigma j}[n] = \mathbf{K}_O \mathbf{h}_{\Sigma j}[0] \quad (13)$$

where $\mathbf{K}_O \in \mathbb{C}^{N_r N_b N_t \times N_r N_b N_t}$ is a coefficient matrix minimizing the resulting error covariance matrix and which we need to determine.

Since $P(\mathbf{K})$ is the mean square error matrix given by

$$P(\mathbf{K}) = \mathbb{E}\left\{(\mathbf{h}_{\Sigma j}[n] - \mathbf{K}\mathbf{h}_{\Sigma j}[0])(\mathbf{h}_{\Sigma j}[n] - \mathbf{K}\mathbf{h}_{\Sigma j}[0])^*\right\}, \quad (14)$$

our optimization problem will be

$$\mathbf{K}_O = \arg\min_{\mathbf{K}} P(\mathbf{K}), \quad (15)$$

which is equivalent to require

$$\mathbf{a}P(\mathbf{K})\mathbf{a}^* \geq \mathbf{a}P\left(\mathbf{K}_O\right)\mathbf{a}^* \quad (16)$$

for every $\mathbf{K}$ and for every row vector $\mathbf{a}$ [14]. This change simplifies the optimization problem, since $\mathbf{a}P(\mathbf{K})\mathbf{a}^*$ is a scalar function of a complex-valued (row) quantity $\mathbf{aK}$, which is more tractable. Thus, $\mathbf{K}_O$ solves (13) if, and only if, for all vectors $\mathbf{a}$, $\mathbf{a}\mathbf{K}_O$ is a minimum of $\mathbf{a}P(\mathbf{K})\mathbf{a}^*$.

Differentiating $\mathbf{a}P(\mathbf{K})\mathbf{a}^*$ with respect to $\mathbf{aK}$ and setting the derivative equal to zero at $\mathbf{K} = \mathbf{K}_O$, i.e.,

$$\left.\frac{\partial\left(\mathbf{a}\left(\mathbf{R}_j[0] - \mathbf{R}_j[n]^*\mathbf{K}^* - \mathbf{K}\mathbf{R}_j[n] + \mathbf{K}\mathbf{R}_j[0]\mathbf{K}^*\right)\mathbf{a}^*\right)}{\partial \mathbf{aK}}\right|_{\mathbf{K}=\mathbf{K}_O} = 0$$

yields

$$\mathbf{K}_O = \mathbf{R}_j[n]^*\mathbf{R}_j^{-1}[0]. \quad (17)$$

After some mathematical manipulations on (17), the minimum mean square error matrix $P(\mathbf{K}_O)$ is obtained as

$$\begin{aligned} P(\mathbf{K}_O) &= \mathbb{E}\left\{(\mathbf{h}_{\Sigma j}[n] - \mathbf{K}_O\mathbf{h}_{\Sigma j}[0])(\mathbf{h}_{\Sigma j}[n] - \mathbf{K}_O\mathbf{h}_{\Sigma j}[0])^*\right\} \\ &= \mathbf{R}_j[0] - \mathbf{R}_j[n]^*\mathbf{R}_j^{-1}[0]\mathbf{R}_j[n]. \end{aligned} \quad (18)$$

Thus, the CSIT at time n for MS j given by the estimate $\hat{\mathbf{H}}_{\Sigma j}[n]$ and its error covariance $\mathbf{R}_{\mathbf{e}j}[n]$ become

$$\hat{\mathbf{H}}_{\Sigma j}[n] = \mathbf{K}_O\mathbf{H}_{\Sigma j}[0] = \mathbf{R}_j[n]^*\mathbf{R}_j^{-1}[0]\mathbf{H}_{\Sigma j}[0], \text{ and} \quad (19)$$

$$\mathbf{R}_{\mathbf{e}j}[n] = P(\mathbf{K}_O) = \mathbf{R}_j[0] - \mathbf{R}_j[n]^*\mathbf{R}_j^{-1}[0]\mathbf{R}_j[n] \quad (20)$$

The two quantities $\hat{\mathbf{H}}_{\Sigma j}[n]$ and $\mathbf{R}_{\mathbf{e}j}[n]$ constitute the CSIT. They effectively function as channel mean and channel covariance at time n for MS j.

Using the homogeneous channel temporal correlation assumption given in (7), the channel estimate and its error covariance become

$$\hat{\mathbf{H}}_{\Sigma j}[n] = \rho_j[n]\mathbf{H}_{\Sigma j}[0], \text{ and} \quad (21)$$

$$\mathbf{R}_{\mathbf{e}j}[n] = \left(1 - \rho_j[n]^2\right)\mathbf{R}_j[0]. \quad (22)$$

Thus, the CSIT for each user j is simply characterized as a function of $\rho_j[n]$, $\mathbf{H}_j[0]$ and $\mathbf{R}_j[0]$.

From (5), the error covariance $\mathbf{R}_{\mathbf{t}e,j}[n]$ can similarly be decomposed in effective antenna correlations as

$$\begin{aligned} \mathbf{R}_{\mathbf{t}e,j}[n] &= \sqrt{1 - \rho_j[n]^2}\mathbf{R}_{\mathbf{t}j}[0], \text{and} \\ \mathbf{R}_{\mathbf{r}e,j}[n] &= \sqrt{1 - \rho_j[n]^2}\mathbf{R}_{\mathbf{r}j}[0]. \end{aligned} \quad (23)$$

Thus, the channel matrix at time n for MS j is becomes

$$\mathbf{H}_{\Sigma j}[n] = \hat{\mathbf{H}}_{\Sigma j}[n] + \mathbf{R}_{\mathbf{r}e,j}[n]^{1/2}\mathbf{H}_w\mathbf{R}_{\mathbf{t}e,j}[n]^{1/2}, \quad (24)$$

where $\mathbf{H}_w$ is a $N_r \times N_b N_t$ channel matrix whose entries are zero-mean circular symmetric complex Gaussian variables.

In this CSIT model, $\rho_j[n]$ acts as a channel estimate quality dependent on the time n. For small n values, $\rho_j[n]$ is close to 1, the estimate depends heavily on the initial channel measurement and the error covariance is small. As n increases, $\rho_j[n]$ decreases, the impact of the initial channel measurement is reduced and the error covariance grows towards the channel covariance $\mathbf{R}_j[0]$.

IV. Simulation and Results

A. Scenario, Channel Model and Main Simulation Parameters

The CoMP cell scenario consists of 3 coordinated cells with BSs placed in the center of each cell. Initially, one user is placed randomly in each cell. These users are considered as the ones selected by a scheduling algorithm to transmit.

[1]This restriction is not so hard since when $\mathbf{h}_{\Sigma j}[n]$ and $\mathbf{h}_{\Sigma j}[0]$ are jointly Gaussian, an assumption that is often reasonable, the unconstrained least mean squares estimation function is linear [14].

For simulation of the multicell multiuser dynamic model, we have the following steps:

1) The covariance matrix $\mathbf{R}_j[0]$ is measured at the BS based on the pilot symbols sent in uplink by MS j. Due to channel stationarity, $\mathbf{R}_j[0]$ keeps valid all over the simulation.
2) Blocks of N_S symbols are considered and, at the beginning of each block, MSs send their initial channel measurement $\mathbf{H}_{\Sigma j}[0]$ to the BS.
3) For each symbol period T_S, users send their corresponding parameter $\rho_j[n]$ to BSs and the CSIT is estimated using (21), (23) and (24) at the central processing unit. We can note that if the transmitter knows the users' speed, the parameter ρ can be evaluated by BSs and it is not needed as feedback.

The most relevant parameters considered in the simulations are shown in table I.

Table I
PARAMETER OF THE SIMULATIONS.

Parameters	Value
Cell radius	1 km
Number of Tx antennas per BS N_t	2
Number of Rx antennas per MS N_r	2
Carrier Frequency	1.8 GHz
System Bandwidth	100 kHz
Users velocity	60 km/h
Doppler frequency f_D	100 Hz
Coherence Time	$\frac{1}{2f_D} = 5\text{ms}$
Noise power	-103 dBm

The initial antenna correlations are fixed for all MSs as

$$\mathbf{R}_{\mathbf{t}j}[0] = \left(\begin{bmatrix} 1 & 0.3 \\ 0.3 & 1 \end{bmatrix} \otimes \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \right)_{N_b N_t \times N_b N_t}$$

and $\mathbf{R}_{\mathbf{r}j}[0] = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}_{N_r \times N_r}$.

B. Precoding Technique and Power Allocation

For the considered CoMP scenario, power constraints are per BS and for simplification the precoding matrix $\mathbf{T}$ is determined in a suboptimal way as follows. First, precoders are determined without considering the per BS power constraints (yielding unit-norm beamformers) according to existent precoding techniques, namely, Zero Forcing (ZF) and Minimum Mean Square Error (MMSE) [13]. Afterwards the per-BS power constraints are imposed using a power loading matrix, so that we have $\mathbf{T} = \mathbf{F}\boldsymbol{\Omega}$, where $\mathbf{F} = \begin{bmatrix} \mathbf{F}_1 & \mathbf{F}_2 & \ldots & \mathbf{F}_K \end{bmatrix}_{N_t N_b \times L_T}$ is the precoder matrix with $\mathbf{F}_j$ representing the precoding matrix for the MS j and $\boldsymbol{\Omega}$ the power loading matrix.

The matrix $\boldsymbol{\Omega} = \mu\mathbf{I}$ is an $L_T \times L_T$ diagonal matrix with μ being the power allocated equally for the original data streams. Then, $\boldsymbol{\Omega}$ can be calculated as

$$\boldsymbol{\Omega} = \mu\mathbf{I}, \quad \mu = \min_{b=1,2,\cdots,N_b} \sqrt{\left(\frac{P_{\text{BS\_}b}}{\left\| \mathbf{F}^{[b]} \right\|_{\mathcal{F}}^2} \right)}, \quad (25)$$

where $\mathbf{F}^{[b]}$ contains the rows of $\mathbf{F}$ corresponding to the transmit antennas at BS b [15], $\|.\|_{\mathcal{F}}$ is the Frobenius norm, and $P_{\text{BS\_}b}$ is the power constraint of BS b.

C. Performance Metrics

In order to evaluate the simulation results, the average throughput per user TR_{avg} is adopted as performance measure. It is given by

$$\text{TR}_{\text{avg}} = \frac{1}{K} \sum_{i=1}^{N_r K} \log_2 \left(1 + \frac{\|\mathbf{H}_{\text{eq}_{i,i}}\|^2}{\sum_{j \neq i} \|\mathbf{H}_{\text{eq}_{i,j}}\|^2 + \|\mathbf{n}\|^2} \right), \quad (26)$$

where $\mathbf{H}_{\text{eq}} = \mathbf{HT}$ is the product of the channel matrix by the precoding matrix and $\mathbf{H}$ is the channel matrix of all users given by $\mathbf{H} = [\mathbf{H}_{\Sigma 1}^T, \ldots, \mathbf{H}_{\Sigma K}^T]^T$ and $\mathbf{H}_{\text{eq}_{i,j}}$ is the element of the i-th row and j-th column of the matrix $\mathbf{H}_{\text{eq}}$.

D. Results

In figure 2, the average throughput using ZF and MMSE precoding considering perfect and dynamic CSIT are compared for the scenario $(2, 2, 3, 3)$ with $N_S = 5$ symbols per block. At low SNRs, the performance obtained with the dynamic CSIT model is quite similar to the perfect channel. Only from an SNR value of 15 dB, the performance gap between perfect and dynamic CSIT increases.

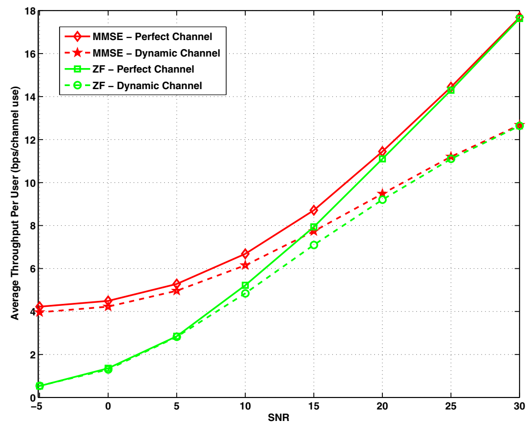


Figure 2. Throughput curves for ZF and MMSE precoding using perfect CSIT and the dynamic CSIT model ($N_S = 5$).

The proposed CSIT model has been simulated using precoding techniques originally designed for perfect CSIT. Thus, it is interesting to notice the good results obtained with the proposed model even in this non-ideal situation.

In order to evaluate how the performance of proposed schemes changes when the number N_S of symbols per block varies, the previous scenario has been simulated using MMSE precoding for increasing values of N_S. The obtained throughput results are shown in figure 3. Therein, we can note that the results are similar in the SNR range $[-5, 15]$ dB for N_S equal to 1, 3 and 5. For these values of N_S, the performance gap increases when the SNR value is higher than 15 dB.

In order to analyze the macrodiversity advantages of CoMP systems, two scenarios with the MSs located at fixed points are simulated, as illustrated in figure 4.

In scenario 1, the MSs' positions in each cell are fixed near the cell-edge so that MSs are close to each other. For single-cell processing, the expected interference in this scenario would be high since the distance from the serving

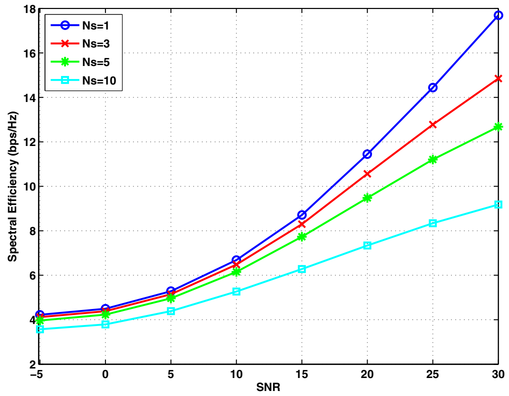
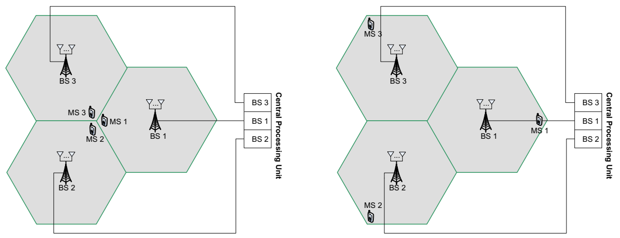


Figure 3. Throughput curves of MMSE precoding using the dynamic CSIT model and different block sizes N_S.



(a) Scenario 1 (b) Scenario 2

Figure 4. Multicell Multiuser System with fixed users' position.

and interfering BSs to the MS is almost the same. However, because CoMP joint processing is adopted, interference can be controlled and each MS receives higher SNRs compared to the single-cell processing case. In scenario 2, MSs are placed again near the cell-edge, but distant from each other. For CoMP joint processing, lower SNR values are now expected compared to scenario 1, since MSs are away from adjacent BSs, which are sources of useful signal.

Figure 5 shows the throughput curves with ZF precoding, $N_S = 5$, and using both perfect CSIT and the dynamic CSIT model in two referred scenarios. We can note that scenario 1 presents better performance results, as expected. This improvement comes from the better joint processing performed by the BSs in this scenario compared to scenario 2. Thus, the CoMP improves the system performance, exploiting macrodiversity with various BSs transmitting to the same MS.

V. Conclusions

In this work, the use of linear precoding with statistics-based CSIT obtained in a dynamic way has been studied. The scenario considers a multiuser CoMP system with joint processing, which is an architecture of great interest for future wireless systems due, e.g., to macrodiversity and good channel conditioning. The proposed CSIT model has been obtained from error estimation theory and compared to the case with perfect CSIT using the ZF and MMSE precoding. The results have shown that the performance gap between the proposed CSIT model and the cases with perfect CSIT is negligible for low SNR values and moderate for medium to high SNR values. Combined with reductions on the needed CSI feedback, we can concluded that the proposed CSIT model has an attractive signaling-performance trade-off compared to the case with perfect CSI.

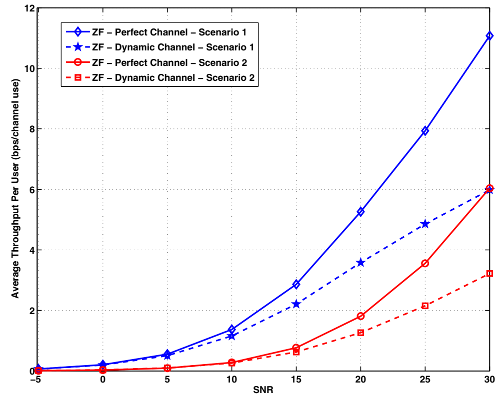


Figure 5. Throughput curves for ZF precoding using perfect CSIT and the dynamic CSIT model for fixed MSs' positions.

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