Efficient Selective Feedback Design for Multicell Cooperative Networks

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Abstract

Multicell Cooperative Processing (MCP) has been recognized as a promising technique for increasing spectral efficiency of future wireless systems. Unfortunately the provided benefits of downlink MCP come at the cost of increased radio feedback and backhaul overhead; in FDD systems users need to feed back their channel state information (CSI) to the network infrastructure, and user data needs to be exchanged between all cooperating Base Stations (BSs). For conventional non-cooperative networks it has been suggested that the radio feedback load can be reduced by preventing users with low quality channels from feeding back their CSI (concept of *selective feedback*), at the cost of a small fraction of the multiuser diversity gain. In this paper we investigate the translation of this selective feedback concept to MCP systems. According to this, users with weak interference links are prevented from feeding back their full CSI to the MCP scheduler. Although efficient, this technique alone cannot mitigate the backhaul overhead related to routing user data possibly to several BSs. In order to overcome this we propose two schemes, one based on PHY layer precoding and the other one based on MAC layer scheduling. These schemes combined with feedback load reduction allow for a substantial mitigation of the MCP

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overheads. We analyze the improvements in terms of both user-to-BS feedback reduction and backhaul load reduction, and we show that this framework leads to a good tradeoff between performance and overhead for MCP enabled networks.

I. INTRODUCTION

Fourth generation cellular systems (4G) and beyond are required to be spectrally efficient, to provide improved system fairness and to have the ability of being easily deployed [2]. In order to achieve high spectral efficiencies, it is necessary that aggressive frequency reuse (probably full frequency reuse) be employed, which not only leads to substantial gains in spectrum usage but also eases cell planning and Base Station (BS) deployment. The downside is that these systems suffer from Inter-Cell Interference (ICI) which limits user throughput, especially affecting users at the cell edge; this leads to a significant degradation of system fairness [3], [4].

Consequently 4G systems need to employ efficient *non-bandwidth expanding*[*] interference mitigation techniques, in both uplink and downlink. ICI mitigation can be achieved by two main signal processing based techniques, namely Advanced Receiver Processing, i.e. interference rejection in the spatial and other domains [5], [6], and *Multicell Cooperative Processing* (MCP), also known as Network Multiple-Input Multiple-Output (Network MIMO) or Coordinated Multi-Point (CoMP) transmission in the wireless standards community [7]–[9]. In MCP enabled networks, groups of BS exchange information and form virtual antenna arrays distributed across multiple cells. Therefore they are able to jointly process signals in order to minimize ICI by applying multiuser MIMO techniques in the downlink and/or the uplink. This allows cellular systems to operate at higher effective Signal to Interference plus Noise Ratios (SINRs) which is essential for improving system's spectral efficiency.

[*]These techniques mitigate interference without consuming any extra bandwidth.

A. Feedback and backhaul overheads of MCP

In the downlink, MCP comes with the important challenges of feedback and backhaul overhead which currently threaten its acceptance into commercial networks, such as the forthcoming 3GPP LTE-Advanced. The throughput of a downlink multiuser MIMO channel heavily relies on the quality of the Channel State Information (CSI) available at the transmitter [10]–[12]. Therefore in Frequency Division Duplexing (FDD) systems employing multiuser MIMO techniques (single-cell processing), Mobile Stations (MSs) need to estimate the downlink CSI and feed it back to the network infrastructure in order for MS scheduling and precoding design to take place (see Fig. 1). We refer to this as *feedback overhead*. Furthermore, in MCP enabled networks each BS potentially transmits to an increased number of users at a time using Space Division Multiple Access (SDMA), and thus needs to buffer an increased number of data streams (see Fig. 1). This places additional burden on the limited backhaul links. We will hereby refer to this as *backhaul overhead*. Consequently MCP enabled systems require backhaul links of higher capacity with tight synchronization and delay constraints, which implies an elevated deployment cost. Therefore it is desirable to reduce backhaul load by routing packets only to BSs that really need it as it can lead to substantial cost reductions. In addition it can make the use of MCP possible in scenarios where it was not initially considered feasible, due to imperfections in backhaul networks.

Techniques for reducing CSI feedback load in multiuser MIMO systems, where MCP is not enabled, have been researched extensively [13]–[17]. In the MCP case, the feedback load is even greater as MSs need to estimate the CSI related to all BSs that cooperate and feed it back to the system infrastructure. Note that techniques for reducing feedback overhead for MCP [1], [18], [19] and backhaul overhead [20], [21] have been already investigated but without attempting to jointly mitigate both of them at the same time.

B. Contributions

In this paper, we propose a framework that can jointly mitigate the feedback and backhaul overheads of MCP, based on the use of an MCP-specific selective feedback. *Selective feedback* has been previously introduced in the context of single-cell processing networks (networks where each user receives useful data only from one BS) and targeted at systems which exploit multiuser diversity [13], [14]. Selective feedback, as proposed in [13], [14], prevents users whose experienced channel quality does not exceed a threshold to charge the feedback channel by feeding back their CSI to their serving BS. This selective feedback scheme cannot be directly applied to MCP systems where users receive data not only from one but from several BSs. It should also be noted that contrary to MCP systems, conventional single-cell processing networks do not suffer from high backhaul overhead, as on that case a single-antenna BS can transmit only to one user on the same time/frequency resources. Therefore, as the framework of [13], [14] is not suitable, we propose an adaption of the selective feedback concept of in order to fit the purpose of MCP systems.

In the MCP context, our concept of selective feedback relies on users estimating their downlink channel seen from surrounding BSs and deciding, on the basis of the comparison with a predetermined threshold, whether they should engage in MCP or not [1] and if yes from which BSs they choose to receive useful data. Engaging in MCP implies that users feed back their CSI to the system infrastructure and that the BSs from which they will receive useful data obtain this data through the backhaul network before transmission. As MCP incurs the feedback and backhaul overheads mentioned before, the intuition is that only users that can really benefit from it should burden the system with this mode of transmission. The performance analysis of the proposed feedback load reduction scheme under MCP differs from [13], [14] in that the fed back channel coefficients are associated with more than one BSs and therefore have different power profiles. More crucially, the use of an MCP-specific selective feedback may strongly impact on the backhaul overhead. However, as it is pointed out in this paper, MCP-specific selective feedback does not generally lead to a reduction of backhaul overhead unless proper adjustments are done at the stage of precoding or scheduling.

More specifically, we propose an algorithm according to which each MS feeds back to the system infrastructure the channel coefficients whose average SNR is above an absolute threshold, in order to keep feedback load at prescribed target levels. The multicell setting impacts the channel statistics as channels to different BSs undergo different pathloss and shadowing. The feedback load as a function of a chosen SNR threshold is studied analytically. The other main point made in this paper is the combination of feedback load reduction with reduction of the inter-BS backhaul overhead. In that respect our contribution is two-fold; we exploit selective feedback for limiting data exchange through the backhaul either at the MAC layer, by employing a particular scheduling technique, or at the PHY layer by adjusting our precoding design.

C. Paper structure

The paper is structured in the following way: in Section II the system model is presented and in Section III the considered linear precoding framework is discussed. In Section IV the algorithm for feedback overhead reduction is described and its performance is studied analytically. In Section V the proposed schemes that exploit the reduced feedback load for limiting backhaul load are presented. In Section VI numerical results are presented and discussed and in Section VII the paper is concluded.

Notation: Lower and upper case boldface symbols denote vectors and matrices respectively, $(.)^T$ and $(.)^H$ denote the transpose and the transpose conjugate respectively. $|\mathcal{A}|$ represents the cardinality of the set $\mathcal{A}$ and $\mathbb{C}^k$ the complex space with k dimensions. $\mathbb{E}\left[.\right]$ and $\mathrm{var}\left[.\right]$ denote the expectation and the variance operators respectively. $\odot$ and $\oplus$ the element-wise multiplication and element-wise XOR operation respectively. $\mathbf{1}_{[m\times n]}$ and $\mathbf{0}_{[m\times n]}$ denote matrices with m rows and n columns filled with ones and zeros respectively. $[\mathbf{A}]_{ij}$ represents the ij-th element of the matrix $\mathbf{A}$. $\mathrm{diag}\left(\mathbf{A}_{11}, \ldots, \mathbf{A}_{nn}\right)$ denotes a block-diagonal matrix where $\mathbf{A}_{ii}$ are square submatrices and $\mathrm{vec}\left(.\right)$ denotes the column-wise vectorization operator. The identity matrix of dimension M is denoted by $\mathbf{I}_M$.

II. System Model

A network consisting of B single antenna BSs and K single antenna active MSs overall is considered. The assumption of single antenna BSs is mostly for expository reasons and does not preclude applying the same concepts to multiple antenna BSs. In the present paper we focus on downlink but similar ideas could be applied in the uplink. Furthermore, flat fading and spatio-temporally uncorrelated channels are assumed. The k-th user of the system receives

$$y_k = \mathbf{h}_k^T \mathbf{x} + n_k \tag{1}$$

where $\mathbf{h}_k = \left[h_{k1}, h_{k2}, \ldots, h_{kB}\right]^T$ is the channel vector corresponding to the k-th user, $\mathbf{x} \in \mathbb{C}^{B \times 1}$ is the vector containing the transmit signals sent by all the network antennas and $n_i \sim \mathcal{NC}\left(0, \sigma^2\right)$ represents the independent complex circularly symmetric additive Gaussian noise. The complete channel matrix of the system is

$$\mathbf{H} = \left[\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_K\right]^T. \tag{2}$$

It is assumed that the system operates in FDD mode and that each MS k obtains a perfect estimate of its CSI consisting of the vector of channel coefficients $\mathbf{h}_k$. In order for the feedback load to be reduced, not all the coefficients of the vector $\mathbf{h}_k$ are fed back to the network infrastructure. The coefficients whose channel gain is below a specified threshold are replaced with zeros, as detailed in Section IV, and this new vector $\hat{\mathbf{h}}_k$ is fed back to the network infrastructure through feedback links that do not introduce errors or delays.

Let $\mathbf{v}_k \in \{0,1\}^{[B\times 1]}$ be the vector indicating which coefficients are fed back and which are not by the k-th user (positions of 1s and 0s respectively), e.g. $\mathbf{v}_k = [1,0,\ldots,1,0,1]^T$ †. It is assumed that each MS k always feeds back the strongest coefficient of the vector $\mathbf{h}_k$, thus the vector $\mathbf{v}_k$ contains at least one 1. In the other limiting case, MS k feeds back its entire CSI vector $\mathbf{v}_k = \mathbf{1}_{[B\times 1]}$. Let the *feedback index matrix* $\mathbf{V}$ be the concatenation of all feedback index information across all users

$$\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_K]^T, \quad \text{e.g.} \quad \mathbf{V} = \begin{bmatrix} 1 & 1 & \ldots & 1 & 0 \\ 0 & 1 & \ldots & 0 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 1 & \ldots & 1 & 1 \end{bmatrix}. \tag{3}$$

Hence the acquired imperfect CSI matrix by the network infrastructure is of the form

$$\hat{\mathbf{H}} = \mathbf{H} \odot \mathbf{V} \tag{4}$$

where $\hat{\mathbf{H}} = \left[\hat{\mathbf{h}}_1, \hat{\mathbf{h}}_2, \ldots, \hat{\mathbf{h}}_K\right]^T$ and $\hat{\mathbf{h}}_k = \mathbf{h}_k \odot \mathbf{v}_k$. If a group of users $\mathcal{S}$ is scheduled for transmission in a specific time slot, their limited CSI matrix is $\hat{\mathbf{H}}(\mathcal{S}) = \mathbf{H}(\mathcal{S}) \odot \mathbf{V}(\mathcal{S})$.

III. Multicell Cooperation with Linear Precoding

Linear precoding is considered for MCP as it provides a good tradeoff between performance and complexity [22]. When B single antenna BSs cooperate under the linear precoding framework, at most B MSs can be spatially served by this BS cluster at the same time in an interference free manner. Let $\mathcal{S}$ be the set of scheduled MSs in a specific time slot. In this paper we assume that the number of scheduled users is always equal to the number of transmit antennas, $|\mathcal{S}| = B$, in order to fully exploit the available spatial degrees of freedom. Let $\mathbf{H}(\mathcal{S})$ be the channel submatrix of $\mathbf{H}$ related to the group of scheduled MSs. The vector containing the transmit

†A zero at the j-th position of the vector means that the channel coefficient to BS j is not fed back to the system infrastructure.

symbols $\mathbf{s} = \left[s_1, \ldots, s_{|\mathcal{S}|}\right]^T$ with power $\mathbf{p} = \left[p_1, \ldots, p_{|\mathcal{S}|}\right]^T$, where $p_i = \mathbb{E}\left[|s_i|^2\right]$ is the power allocated to user i, is mapped to the transmit antennas so that $x_i = \sum_{k=1}^{|\mathcal{S}|} w_{ik} s_k$ for $i = 1, \ldots, B$. $w_{ik} \in \mathbb{C}$ is the beamforming weight applied by the i-th BS to the symbol intended for MS k and $\mathbf{W} = \left[\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_{|\mathcal{S}|}\right]$ is the precoding matrix, where $\mathbf{w}_k \in \mathbb{C}^{B\times 1}$ is the beamforming vector of user k. The signal received by MS k, where $k \in \mathcal{S}$, is

$$y_k = \mathbf{h}_k^T \mathbf{w}_k s_k + \sum_{n\in\mathcal{S}, n\neq k} \mathbf{h}_k^T \mathbf{w}_n s_n + n_k. \tag{5}$$

The term $\sum_{n\in\mathcal{S}, n\neq k} \mathbf{h}_k^T \mathbf{w}_n s_n$ corresponds to the detrimental ICI. In matrix notation the scheduled users receive

$$\mathbf{y} = \mathbf{H}(\mathcal{S})\,\mathbf{W}\mathbf{s} + \mathbf{n} \tag{6}$$

where $\mathbf{y} = \left[y_1, \ldots, y_{|\mathcal{S}|}\right]$ is the received signal vector and $\mathbf{n}$ is a vector of independent complex circularly symmetric additive Gaussian noise components. The SINR of the k-th MS is

$$\gamma_k = \frac{\left|\mathbf{h}_k^T \mathbf{w}_k\right|^2 p_k}{\sum\limits_{n\in\mathcal{S}, n\neq k} \left|\mathbf{h}_k^T \mathbf{w}_n\right|^2 p_n + \sigma^2}. \tag{7}$$

Per-base power constraints (PBPCs) are considered as the cooperating antennas are distributed and they cannot share their power. Thus $\mathbb{E}\left[|x_i|^2\right] \leq P_i$ for $i = 1, \ldots, B$. The optimal power allocation vector with respect to sum-rate maximization can be obtained by the use of an interior point method [23]. Here we consider a simpler and suboptimal equal power allocation policy. In this case $\mathbf{p} = p\mathbf{1}_{[B\times 1]}$ and the set of constraints reduces to $\left[\mathbf{W}\mathbf{W}^H\right]_{ii} p \leq P_i$ for all $i = 1, \ldots, B$ [8]. The power allocation vector that meets these constraints is [9]

$$\mathbf{p} = \min_{i=1,\ldots,B} \left\{ \frac{P_i}{\left[\mathbf{W}\mathbf{W}^H\right]_{ii}} \right\} \mathbf{1}_{[B\times 1]}. \tag{8}$$

The SINR of the k-th MS is

$$\gamma_k = \frac{\left|\mathbf{h}_k^T \mathbf{w}_k\right|^2}{\sum_{n\in\mathcal{S}, n\neq k} \left|\mathbf{h}_k^T \mathbf{w}_n\right|^2 + \sigma^2 / \min_{i=1,\ldots,|\mathcal{S}|} \left\{ \frac{P_i}{\left[\mathbf{W}\mathbf{W}^H\right]_{ii}} \right\}}. \tag{9}$$

With equal power allocation and equal PBPCs, $P_i = P$ for $i = 1, \ldots, B$, the expression for the power allocation vector (8) reduces to $\mathbf{p} = \frac{P}{\max_{i=1,\ldots,|\mathcal{S}|}\left\{\left[\mathbf{W}\mathbf{W}^H\right]_{ii}\right\}} \mathbf{1}_{[B\times 1]}$. The average sum-rate per cell is given by

$$\bar{C} = \frac{1}{B}\mathbb{E}_H \left[\sum_{k\in\mathcal{S}} \log_2\left(1+\gamma_k\right) \right]. \tag{10}$$

where the expectation is taken over all channel realizations and MS locations.

A. Feedback Overhead

Let $N(t)$ be the total number of channel coefficients fed back by the users in time t. Since each MS feeds back at least the strongest coefficient describing its channel state (feedback index matrix $\mathbf{V}$ contains at least K ones) $N(t) \in [K, BK]$. The feedback load reduction may be expressed by the average number of channel coefficients fed back per MS

$$\bar{L} = \frac{1}{K}\mathbb{E}_t\left[N(t)\right] \tag{11}$$

where $\bar{L} \in [1, B]$ as each user feeds back at least one channel coefficient and up to B.

B. Backhaul Overhead

Under a linear precoding framework and with single antenna BSs and MSs, the m-th row vector of the precoding matrix $\mathbf{W}$ corresponds to the weights applied to transmit symbols by the m-th BS, where $m = 1, \ldots, B$. The i-th weight of this vector (w_{mi}), where $i = 1, \ldots, B$ (when $|\mathcal{S}| = B$), is applied to the symbol intended for MS i. If this element is 0, BS m allocates zero power to MS i, hence it does not need to buffer the symbol s_i intended for MS i for the duration of the scheduling time window. Hence the number of zero elements of the precoding matrix **W** is directly related to the backhaul overhead.

Let $Z(t)$ be the number of streams transmitted per BS in time slot t, $Z(t) \in [1, B]$. This corresponds to the number of non-zero elements per line vector of the precoding matrix **W**. Backhaul overhead can be measured by the average number of data streams that each BS transmits per time slot per resource block

$$\bar{S} = \mathbb{E}_t \left[Z(t) \right]. \tag{12}$$

IV. Feedback Overhead Reduction

In this section the performance of the feedback overhead reduction scheme is estimated analytically. In each time slot each MS k is assumed to obtain a perfect estimate of the vector of channel coefficients to all BSs $\mathbf{h}_k$. The average SNR of a channel coefficient h_{kn} is defined as

$$\bar{\gamma}_{kn} = \mathbb{E}\left[\frac{|h_{kn}|^2 p_k}{\sigma^2} \right] \tag{13}$$

where expectation is taken over the statistics of fast fading only and p_k is the transmit power allocated to user k. Algorithm 1 is formulated where each MS k feeds back to the system infrastructure the vector $\hat{\mathbf{h}}_k = \mathbf{h}_k \odot \mathbf{v}_k$ comprised only by the channel coefficients whose corresponding average SNR exceeds a threshold γ_t. Note that each MS feeds back at least its strongest channel coefficient upon which no threshold is applied. This permits the scheduler to make decisions on the data streams to be transmitted by each BS, hence it also permits data routing to take place on a realistic time scale, longer than that of fast fading.

A. Feedback overhead reduction analysis

Let the channel coefficient between the k-th MS and the j-th BS be modeled as

$$h_{kj} = \Gamma_{kj} \sqrt{G\left(\phi\right) \beta d_{kj}^{-\alpha} \gamma_{kj}} \tag{14}$$

where d_{kj} is the distance between the k-th MS and the j-th BS. α is the pathloss exponent and β the pathloss constant, γ_{kj} is the corresponding log-normal random variable which models shadowing and Γ is the complex Gaussian fading coefficient modeling fast fading, $\Gamma \sim \mathcal{NC}\left(0,1\right)$. $G\left(\phi\right)$ is the BS antenna power gain as a function of the horizontal angle. The transmission power is determined by the System SNR which is defined as the average SNR received at the edge of the cell without taking into account the ICI.

Here we study analytically the average feedback load defined in (11). Let $P_{\bar{\gamma}}\left(\gamma\right)$ denote the cumulative distribution function (CDF) of the average SNR $\bar{\gamma}$ of each channel coefficient. If $N\left(t\right) = n$, it is implied that the average SNR of n out of BK channel coefficients is above the defined SNR threshold γ_t, and that the average SNR of the rest $BK-n$ coefficients is below this threshold. In a multicell scenario each channel coefficient experiences a different average SNR due to the difference in pathloss and shadowing related to different BSs; therefore the global distribution followed by the channel coefficients is hard to derive in an exact form. Instead we suggest the following approach; the average SNR distribution of $\bar{\gamma}_{kn}$ can be empirically well approximated by a log-normal distribution [24]. The CDF of the log-normal distribution is

$$P_{\bar{\gamma}}\left(x\right) = \frac{1}{2}\left[1 + \operatorname{erf}\left(\frac{\ln\left(x\right) - \mu_{\bar{\gamma}}}{\sqrt{2}\sigma_{\bar{\gamma}}}\right)\right] \tag{15}$$

where $\mu_{\bar{\gamma}}$ and $\sigma_{\bar{\gamma}}$ are the logarithmic mean and standard deviation respectively that can be obtained by using standard fitting techniques [24]. $\operatorname{erf}\left(x\right)$ is the error function defined as $\operatorname{erf}\left(x\right) = \frac{2}{\sqrt{\pi}} \int_0^x \exp\left(-t^2\right) dt$, where $\exp\left(x\right)$ denotes the exponential function. $N\left(t\right)$ follows a binomial distribution and its probability mass function, i.e. the probability that n out of the BK channel coefficients are fed back, is

$$\Pr\left\{N\left(t\right)=n\right\}=\binom{BK}{n}\left(1-P_{\bar{\gamma}}\left(\gamma_t\right)\right)^n\left(P_{\bar{\gamma}}\left(\gamma_t\right)\right)^{BK-n}. \tag{16}$$

Therefore the expected number of $N\left(t\right)$ is

$$\begin{aligned}\mu_N &= \mathbb{E}\left\{N\left(t\right)\right\}=\sum_{n=0}^{BK} n\Pr\left\{N\left(t\right)=n\right\}\\ &= BK\left[1-P_{\bar{\gamma}}\left(\gamma_t\right)\right].\end{aligned} \tag{17}$$

Hence, the average number of fed back coefficients per user is

$$\bar{L}=\frac{1}{K}\mu_N=B\left[1-P_{\bar{\gamma}}\left(\gamma_t\right)\right]. \tag{18}$$

By plugging (15) to (18) we obtain the following expression for the average number of fed back channel coefficients per MS as a function of the SNR threshold γ_t

$$\bar{L}=B\left[\frac{1}{2}-\frac{1}{2}\text{erf}\left(\frac{\ln\left(\gamma_t\right)-\mu_{\bar{\gamma}}}{\sqrt{2}\sigma_{\bar{\gamma}}}\right)\right]. \tag{19}$$

Since the average number of fed back coefficients per MS is expressed as a function of the SNR threshold γ_t, we can design the power threshold in order to achieve specific average feedback load targets

$$\gamma_t=\exp\left(\mu_{\bar{\gamma}}+\sqrt{2}\sigma_{\bar{\gamma}}\text{erf}^{-1}\left(1-\frac{2\bar{L}}{B}\right)\right). \tag{20}$$

As an indicative example, the followed global PDF of the channel coefficients' average SNR, for the practical case of 3 mutually interfering sectors as shown in Fig. 2, is well approximated by the log-normal distribution. This approximation can be seen in Fig. 3 (the evaluation parameters of Section VI are used). In Fig. 4 the average feedback load $\bar{L}$ is plotted against the threshold γ_t for different values of system SNR. It can be seen that the greater the system SNR is, and thus the transmit power, the higher the feedback load becomes for a specific threshold value.

Theoretical results are shown by the dashed lines while numerical results are shown by the solid ones. It can be seen that numerical results can be very well approximated by the model presented above.

B. Feedback variation prediction

Another important quantity is the variation of the total number of fed back channel coefficients as it permits the feedback channel to be provisioned for appropriately. The variation of $N(t)$ can be defined as

$$V_N = \frac{\mathrm{var}\left[N(t)\right]}{\mathbb{E}\left[N(t)\right]^2} = \frac{\mathbb{E}\left[\left(N(t)-\mu_N\right)^2\right]}{\mathbb{E}\left[N(t)\right]^2} \tag{21}$$

where

$$\begin{aligned} \mathrm{var}\left[N(t)\right] &= BK\left(1-P_{\bar{\gamma}}(\gamma_t)\right)P_{\bar{\gamma}}(\gamma_t), \\ \mathbb{E}\left[N(t)\right]^2 &= \left[BK\left(1-P_{\bar{\gamma}}(\gamma_t)\right)\right]^2. \end{aligned} \tag{22}$$

This results to the following expression for the variation of radio feedback

$$V_N = \frac{P_{\bar{\gamma}}(\gamma_t)}{KB\left(1-P_{\bar{\gamma}}(\gamma_t)\right)} = \frac{1+\mathrm{erf}\left(\frac{\ln(\gamma_t)-\mu_{\bar{\gamma}}}{\sqrt{2}\sigma_{\bar{\gamma}}}\right)}{KB\left(1-\mathrm{erf}\left(\frac{\ln(\gamma_t)-\mu_{\bar{\gamma}}}{\sqrt{2}\sigma_{\bar{\gamma}}}\right)\right)}. \tag{23}$$

V. Backhaul Overhead Reduction

According to the proposed feedback load reduction framework, MSs estimate and feed back to the system infrastructure a limited number of channel coefficients in each time slot depending on a SNR threshold. CSI feedback may be targeted only to one BS [3], requiring CSI exchange between BSs and centralized scheduling or to several BSs, in which case scheduling can be performed in a distributed fashion without requiring exchange of CSI and scheduling decisions [25]. However this consideration is beyond the scope of this paper and it is only assumed that CSI is fed back to the system infrastructure and then made available to the MS scheduler. Which channel coefficients are fed back by each MS depends on their associated average SNR that is a function of the MS location due to pathloss and shadowing. In general, selective feedback introduces zeros in matrix $\hat{\mathbf{H}}$ but not necessarily in the precoding matrix $\mathbf{W}$ [26]. Hence further adjustments in either the PHY or the MAC layer design should be carried out to ensure an actual mitigation of the backhaul overhead.

Our chosen precoding scheme is Zero-Forcing (ZF), according to which the precoding matrix inverts the imperfect channel matrix of the scheduled MSs under some constraints. Let $\mathcal{S}$ be the set of scheduled users in a specific time slot. Generally there might be zero elements in random positions of $\hat{\mathbf{H}}(\mathcal{S})$ apart from its main diagonal; $\hat{\mathbf{H}}(\mathcal{S})$ in the low feedback load regime is in principle a sparse matrix. In the limiting case, where all MSs feed back just their strongest coefficients, $\hat{\mathbf{H}}(\mathcal{S})$ is a diagonal matrix and this corresponds to single-cell processing (absence of MCP). ZF precoding directly inverts the imperfect channel matrix $\hat{\mathbf{H}}(\mathcal{S})$. Hence the precoding matrix is

$$\begin{aligned}\mathbf{W} &= [\mathbf{H}(\mathcal{S}) \odot \mathbf{V}(\mathcal{S})]^{-1} \mathbf{D} \\ &= \hat{\mathbf{H}}(\mathcal{S})^{-1} \mathbf{D}\end{aligned}$$

where $\mathbf{D}$ is a diagonal matrix that normalizes the columns of $\mathbf{W}$ to unit norm. If the zero elements of $\hat{\mathbf{H}}(\mathcal{S})$ are in random positions there might be some zero elements in its inverse, $\mathbf{W}$, although their number will be smaller than the one of $\hat{\mathbf{H}}(\mathcal{S})$ and their position cannot be predicted in a straightforward manner [26]. Therefore the main disadvantage of this approach is that all the B collaborating BSs need to buffer as many data streams per slot as the maximum number of serving MSs $|\mathcal{S}|$ (which is assumed equal to B), regardless of how much reduction is achieved in feedback. Therefore in this case the average backhaul load per BS takes its maximum value ($\bar{S} = B$) and it is not related with the feedback load.

A. Scheduling for Backhaul Load Reduction

ZF transmission without any constraints on the scheduled users is unable to mitigate backhaul load. A scheduling algorithm that can translate feedback load reduction into backhaul overhead reduction is formed by selecting a suitable set of users $\mathcal{S}$. A suitable set $\mathcal{S}$ is obtained if the channel matrix $\hat{\mathbf{H}}(\mathcal{S})$ to be inverted is in a block-diagonal or equivalent to block-diagonal form. A matrix $\hat{\mathbf{H}}(\mathcal{S})$ is equivalent to block-diagonal if

$$\boldsymbol{\pi}^r \hat{\mathbf{H}}(\mathcal{S})\, \boldsymbol{\pi}^c = \operatorname{diag}\left(\mathbf{H}_{11}, \mathbf{H}_{22}, \ldots, \mathbf{H}_{NN}\right) \tag{24}$$

where $\mathbf{H}_{nn}$ are submatrices of $\hat{\mathbf{H}}(\mathcal{S})$ and N is the number of blocks of possibly different sizes. $\boldsymbol{\pi}^r = \pi_1^r \pi_2^r \ldots \pi_N^r$ and $\boldsymbol{\pi}^c = \pi_1^c \pi_2^c \ldots \pi_M^c$ represent row and column permutations. An important property of block-diagonal matrices is that their inverse is also block-diagonal and thus retains the same number of zeros. This can be exploited for limiting the backhaul load of a system employing selective feedback.

The block-diagonal structure of $\mathbf{H}(\mathcal{S})$ can be achieved in a simple manner by introducing the concept of BS subgroups. Let $\mathcal{D} = \left\{\mathbf{d}_1, \ldots, \mathbf{d}_{|\mathcal{D}|}\right\}$ be the set of all potential BS subgroups, each one intended to serve users which have fed back the coefficients corresponding to the same BSs, where $|\mathcal{D}| = \sum_{k=1}^{B} \binom{B}{k}$. Let $\mathbf{d}_i \in \{0,1\}^{[B\times 1]}$ be a vector in which the position of ones indicate which BSs participate in subgroup i[‡]. Thus each subgroup described by $\mathbf{d}_i$ consists of a set of BSs which jointly transmit to a set of users aiming at receiving useful signals from these BSs. Let $z_i \in [1, B]$ contain the number of ones in each vector $\mathbf{d}_i$, $i = 1, \ldots, |\mathcal{D}|$ which represents the number of BSs of subgroup i. We assume that the BS subgroups transmitting in each time slot are disjoint; each transmitting BS belongs only to one subgroup.

As we are interested in guaranteeing fairness, scheduling does not aim to provide multiuser diversity gains. As detailed in Algorithm 2, in each time slot a MS set related to each BS subgroup is selected in a round-robin manner. Then a group of disjoint BS subgroups is formed, also in round-robin fashion, and its associated users are served in this time slot. In this way the channel matrix $\hat{\mathbf{H}}(\mathcal{S})$ either is or it can be converted to a block diagonal matrix with appropriate

[‡]E.g. if $d_{ij} = 1$, BS j participates in subgroup i.

row and/or column permutations. Therefore the inverse of $\hat{\mathbf{H}}(\mathcal{S})$ is also a block-diagonal matrix and in this way every BS needs to transmit a limited number of data streams in each time slot. The average number of transmitted data streams per time slot is then directly related to $\bar{L}$

$$\bar{S} = \bar{L} \quad \text{where} \quad \bar{S} \in [1, B]\,. \tag{25}$$

B. Zero-Forcing with Backhaul Load Reduction

We presented above a scheduling rule that can achieve backhaul load reduction by selecting users who have specific CSI feedback patterns. Here we provide an alternative PHY layer approach that translates reduced feedback load to gains on the backhaul without any specific constraints on the scheduler. This alternative approach is particularly useful when the scheduler needs to provide multiuser diversity gains, i.e. capacity performance should be optimized through scheduling. In order to achieve multiuser diversity gains the scheduler should have the maximum available degrees of freedom in selecting users; it should be able to select amongst all the available active users. This is not possible under the scheduling framework presented above as in that case the scheduler is designed to select users that minimize the backhaul overhead and not the users that maximize capacity performance.

As it has been outlined before, the zero elements of the precoding matrix $\mathbf{W}$ determine the backhaul load of the system. Consequently it is highly desirable that the zero elements of $\hat{\mathbf{H}}(\mathcal{S})$ result in the same number of zero elements in $\mathbf{W}$. Let $\mathcal{S}$ be the set of users selected for transmission in a specific time slot under any scheduling rule. The following optimization problem can be formulated

$$\begin{aligned} \mathbf{W} \quad &= \quad \arg\min \left| \hat{\mathbf{H}}(\mathcal{S})\,\mathbf{W} - \mathbf{I}_B \right|^2 \\ \text{subject to} \quad & \mathbf{W} \odot \mathbf{G}^T = \mathbf{0}_{[B\times B]} \end{aligned} \tag{26}$$

where $\mathbf{G} = \mathbf{V}(\mathcal{S}) \oplus \mathbf{1}_{[B \times B]}$[§] is the "bit inverted" version of the feedback index matrix $\mathbf{V}(\mathcal{S})$ for the selected users $\mathcal{S}$ (3). The matrix $\mathbf{G}^T$ determines which elements of $\mathbf{W}$ are forced to be zero. Problem (26) offers in fact a classical solution. Firstly we vectorize the problem

$$\begin{aligned} \mathbf{W} \quad = \quad & \arg\min \left| \tilde{\mathbf{H}} \operatorname{vec}(\mathbf{W}) - \operatorname{vec}(\mathbf{I}_B) \right|^2 \\ \text{subject to} \quad & \mathbf{W} \odot \mathbf{G}^T = \mathbf{0}_{[B \times B]} \end{aligned} \tag{27}$$

where $\tilde{\mathbf{H}} = \operatorname{diag}\left(\hat{\mathbf{H}}^1(\mathcal{S}), \hat{\mathbf{H}}^2(\mathcal{S}), \ldots, \hat{\mathbf{H}}^B(\mathcal{S})\right)$ is a block-diagonal matrix of dimension $B^2 \times B^2$ whose blocks on the main diagonal are copies of $\hat{\mathbf{H}}(\mathcal{S})$. Following this, we rewrite the same problem having eliminated the zero elements of $\operatorname{vec}(\mathbf{W})$ together with the columns of $\tilde{\mathbf{H}}$ corresponding to these zero elements. This results in the following linear equation

$$\tilde{\mathbf{H}}_{el}\, \mathbf{w}_{el} = \operatorname{vec}(\mathbf{I}_B) \tag{28}$$

where $\mathbf{w}_{el}$ results from $\operatorname{vec}(\mathbf{W})$ after the elimination of its zero elements and $\tilde{\mathbf{H}}_{el}$ results from $\tilde{\mathbf{H}}$ after the elimination of the corresponding columns. Therefore the column vector $\mathbf{w}_{el}$ containing the non-zero elements of $\mathbf{W}$ can be obtained in closed form

$$\mathbf{w}_{el} = \tilde{\mathbf{H}}_{el}^H \left(\tilde{\mathbf{H}}_{el} \tilde{\mathbf{H}}_{el}^H\right)^{-1} \operatorname{vec}(\mathbf{I}_B)\,. \tag{29}$$

Thus the non-zero elements of $\mathbf{W}$ are the ones contained in $\mathbf{w}_{el}$. Once again the average backhaul load resulting from the use of this technique is directly related to $\bar{L}$ ($\bar{S} = \bar{L}$) as in (25).

VI. Numerical Results

A scenario of particular practical interest is mitigating interference of mutually interfering sectors as shown in Fig. 2. In this scenario the 3 mutually interfering sectors cooperate under the reduced feedback load regime and jointly serve MSs in their area of coverage (40 uniformly

[§] $G_{ij} = 1$ if user i does not feed back the coefficient to BS j.

distributed MSs are assumed). The channel coefficient between the k-th MS and the j-th sector is modeled as in (14) and the shadowing follows a log-normal distribution $\gamma_{dB} \sim \mathcal{N}(0\,dB, 8\,dB)$. The sector antenna power gain as a function of the horizontal angle ϕ in degrees is following the 3GPP LTE evaluation parameters [27]

$$G^{dB}(\phi) = 14 - \min\left\{12\left(\frac{\phi}{70}\right)^2, 20\right\}, -180 < \phi < 180. \tag{30}$$

The pathloss also follows the LTE evaluation model

$$PL_{kj}^{dB} = 148.1 + 37.6 \log_{10}\left(d_{kj}^{km}\right). \tag{31}$$

An important parameter which determines the transmission power is the *System SNR*. This is the average SNR received at the edge of the cell taking into account the transmit power, the average propagation characteristics and the thermal noise.

A. Feedback load performance

The distribution of the average SNR of the channel coefficients for the case of Fig. 2 has been approximated by a log-normal distribution. The average channel coefficient SNR distributions for System SNRs of 0 dB, 10 dB, 20 dB and 30 dB are approximated by log-normal distributions with means $\mu_{0dB} = -0.8$, $\mu_{10dB} = 1.4$, $\mu_{20dB} = 3.8$ and $\mu_{30dB} = 6.1$ respectively and standard deviation $\sigma = 2.1$ for all System SNRs (Fig. 3). In Fig. 4 the average number of fed back coefficients per MS $\bar{L}$ is plotted against the SNR threshold γ_t for various values of System SNR. It can be seen that the theoretical approximation matches well the numerical results.

B. Average sum-rate performance

Fig. 5 plots the average sum-rate per cell as a function of the radio feedback $\bar{L}$ (11) for the aforementioned approaches and for System SNR of 20 dB (interference limited regime). The solid curve represents the capacity of the pure ZF approach under round-robin scheduling which does not achieve backhaul load reduction (w/o BLR), the dotted curve represents the attained sum-rate of the proposed scheduling approach for BLR (the precoding matrix is block-diagonal) and the dashed curve corresponds to the case of ZF which achieves BLR through precoding (pure round-robin sceduling is assumed). It should be pointed out that the scheduling scheme that achieves BLR is also based on round-robin without being pure round-robin as the selected users have some constraints on their CSI feedback patterns (the coefficients that they feed back) so that the precoding matrix has a block-diagonal structure.

It can be seen that the ZF approach that does not achieve BLR outperforms the other approaches as this scheme perfectly inverts the $\hat{\mathbf{H}}(\mathcal{S})$ matrix; $\hat{\mathbf{H}}(\mathcal{S})$ can contain zero elements in any position (apart from its main diagonal) without any constraints. This transmission framework leads to superior capacity performance as the precoding matrix $\mathbf{W}$ is not constrained to have as many zero elements as $\hat{\mathbf{H}}(\mathcal{S})$. In principle the resulting $\mathbf{W}$ has less zero elements than $\hat{\mathbf{H}}(\mathcal{S})$. This implies that under ZF that does not achieve BLR each user receives useful data from more BSs than it has chosen to, and although this results to a capacity advantage it does not mitigate backhaul overhead. In the proposed backhaul load mitigation schemes, the feedback load savings of Algorithm 1 do translate into savings on the backhaul exchanges. As it can be seen in Fig. 5 the proposed scheduling framework for BLR achieves higher sum-rate than the BLR approach through precoding. This is due to the fact that the scheduling scheme although based on round-robin, it is not pure round-robin like the scheduling assumed for drawing the dashed curve; this leads to some capacity gains that result from scheduling.

C. Backhaul overhead

Fig. 6 plots the backhaul overhead, as measured by the average number of data streams transmitted per time slot and per BS, for all the considered approaches. It can be seen that the ZF without BLR scheme does not achieve any backhaul load mitigation, the three considered single-antenna BSs on average transmit to three users per time slot. This is because the precoding matrix $\mathbf{W}$ in this case does not have any zero elements in predictable positions. It can be seen that the reduction on the backhaul charge achieved by our two proposed scheme, the one based on scheduling and the other based on precoding, is directly proportional to the radio feedback load and this is the main advantage of these methods.

VII. Conclusion

Multicell cooperative processing although very promising for future cellular systems, comes at the cost of increased feedback and backhaul overhead. In the downlink of FDD systems, MSs need to estimate and feed back several channel coefficients and BSs need to exchange user data. This necessitates the mitigation of these overheads in order for MCP to be brought into practice. In this paper a feedback load reduction technique has been proposed based on SNR thresholds and its effects have been analytically approximated. Furthermore it has been shown that reduction on the over-the-air feedback load can be efficiently exploited for reducing backhaul load through scheduling or precoding design. The proposed techniques achieve a good tradeoff between performance and complexity that can facilitate the introduction of MCP to future systems.

VIII. Acknowledgement

The research leading to these results has been partially funded by the European Commission's seventh framework programme (FP7/2007-2013) under grant agreements n^o 247223 (ARTIST4G) and n^o 248267 (BuNGee).

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Algorithm 1 Feedback Load Reduction

Require: Define SNR threshold γ_t

for all MSs $k = 1, \ldots, K$ **do**

  Initialize $\mathbf{v}_k = \mathbf{0}_{[B\times 1]}$

  Find BS $n = \arg \max_{n=1,\ldots,B} |h_{kn}|^2$ (BS providing the strongest channel gain to MS k)

  Set $v_{kn} = 1$ (coefficient h_{kn} is fed back to the system infrastructure)

  for all BSs $j = 1, \ldots, B$, $j \neq n$ **do**

    if $\bar{\gamma_{kj}} = \mathbb{E}\left[\frac{|h_{kj}|^2 p_k}{\sigma^2}\right] \geq \gamma_t$ **then**

      Set $v_{kj} = 1$ (h_{kj} is fed back to the system infrastructure)

    else

      Set $v_{kj} = 0$ (h_{kj} is not fed back to the system infrastructure)

    end if

  end for

end for

The acquired CSI for user k by the system infrastructure is $\hat{\mathbf{h}}_k = \mathbf{h}_k \odot \mathbf{v}_k$

Algorithm 2 Scheduling for backhaul load reduction

Let $\mathcal{K}_i$ be the set of users of the i-th BS subgroup (users that have fed back the channel coefficients of the BSs of this subgroup), $i = 1, \ldots, |\mathcal{D}|$

for all MSs $k = 1, \ldots, K$ **do**

    for all BS subgroups $\mathbf{d}_i$, $i = 1, \ldots, |\mathcal{D}|$ **do**

        if $\mathbf{v}_k = \mathbf{d}_i$ **then**

            MS $k \in \mathcal{K}_i$ (MS k is grouped in subgroup i)

        end if

    end for

end for

for all BS subgroups $i = 1, \ldots, |\mathcal{D}|$ **do**

    Select a set of users $\mathbf{U}_i \in \mathcal{K}_i$, where $|\mathbf{U}_i| = z_i$ (the cardinality of the user set should equal the one of the BS subgroup), in a round-robin manner.

end for

Select a group of N disjoint BS subgroups also in a round-robin manner (the MSs $\mathcal{S}$ to be served are related to these subgroups).

The matrix to be inverted either is block-diagonal or it is converted to a block-diagonal matrix with the application of row and/or column permutations, $\boldsymbol{\pi}^r = \pi_1^r \pi_2^r \ldots \pi_N^r$ and/or $\boldsymbol{\pi}^c = \pi_1^c \pi_2^c \ldots \pi_M^c$ respectively, such that $\boldsymbol{\pi}^r \mathbf{H}(\mathcal{S}) \boldsymbol{\pi}^c = \operatorname{diag}(\mathbf{H}_{11}, \mathbf{H}_{22}, \ldots, \mathbf{H}_{NN})$. The number of blocks N is equal to the number of the selected disjoint BS subgroups.

The precoding matrix is: $\mathbf{W} = \left[\hat{\mathbf{H}}(\mathcal{S})\right]^{-1} \mathbf{D} = \operatorname{diag}\left(\mathbf{H}_{11}^{-1}, \mathbf{H}_{22}^{-1}, \ldots, \mathbf{H}_{NN}^{-1}\right) \mathbf{D}$.

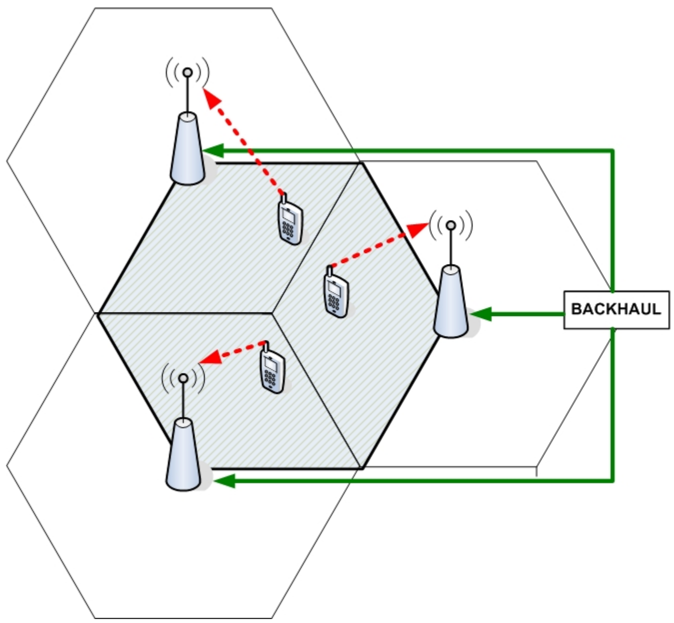

Fig. 1. Overheads of MCP enabled systems. Red arrows represent the overhead related to CSI feedback (*feedback overhead*) while the green arrows represent the overhead related with distributing the user symbols to all the cooperating BSs for transmission through the backhaul (*feeddback overhead*). Note that the MCP scenario shown entails a three-fold increase of both overheads compared to conventional cellular systems if these overheads are not addressed, as users feed back the CSI of 3 BSs and each BS receives the transmit symbols of 3 users through the backhaul.

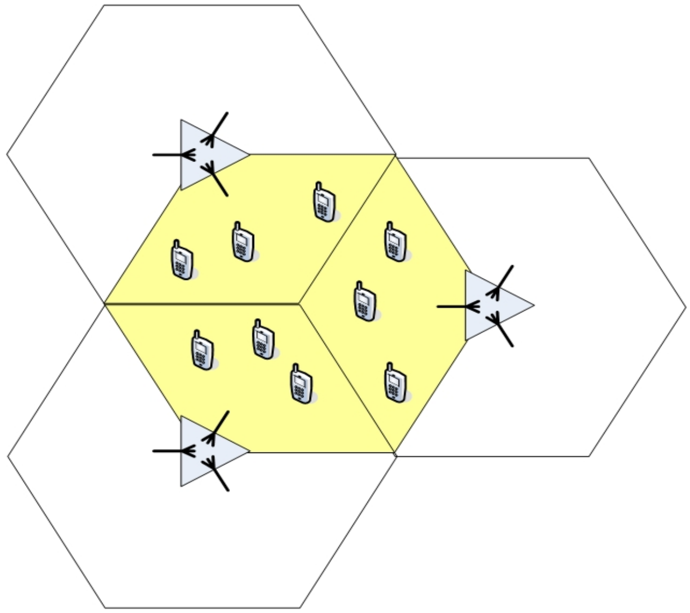

Fig. 2. A scenario of particular practical importance: 3 mutually interfering sectors.

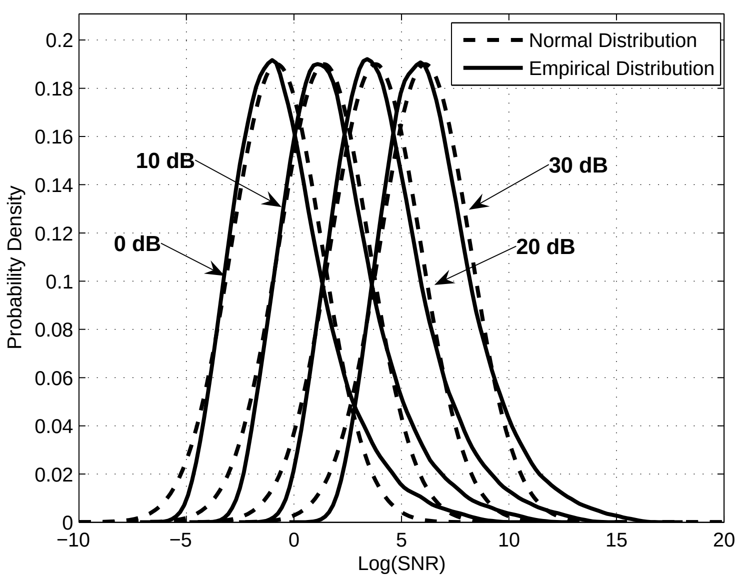

Fig. 3. A plot of the empirical PDF of the logarithmic average SNR associated with the channel coefficients for System SNR of 0 dB, 10 dB, 20 dB and 30 dB (solid lines). These empirical PDFs are well approximated by normal distributions (dashed lines) with mean values of $\mu_{0dB} = -0.8$, $\mu_{10dB} = 1.4$, $\mu_{20dB} = 3.8$ and $\mu_{30dB} = 6.1$ respectively. The approximate standard deviation for all the PDFs is $\sigma = 2.1$.

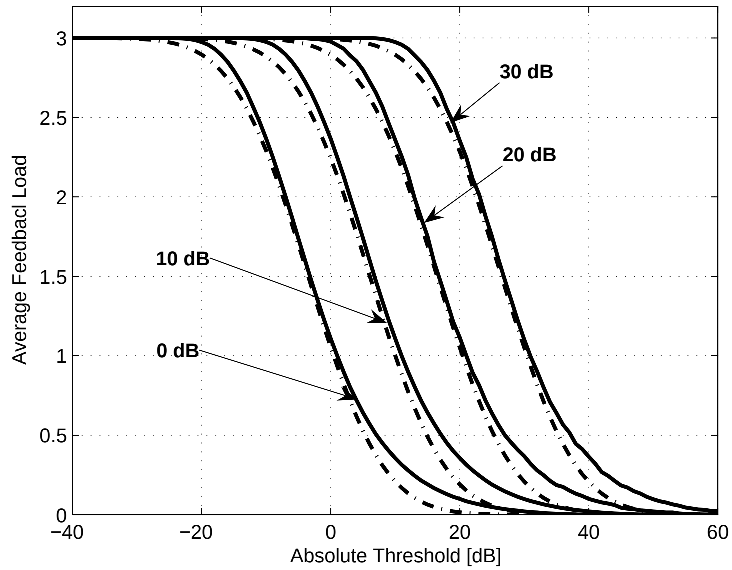

Fig. 4. A plot showing the relation between threshold and the resulting average feedback per MS for different values of System SNR (0 dB, 10 dB, 20 dB, 30 dB). Theoretical results are shown by the dashed lines and numerical ones by the solid ones.

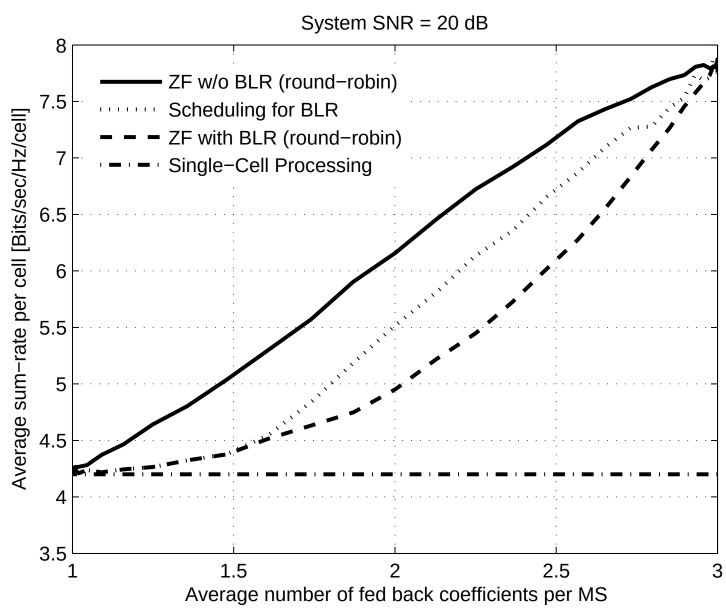

Fig. 5. Average sum-rate against feedback load of the proposed approaches for the simulated scenario.

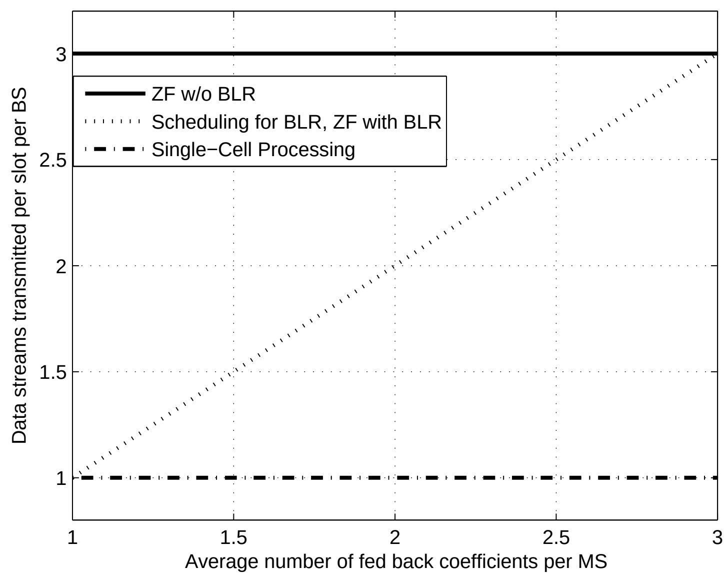

Fig. 6. Backhaul overhead of the proposed approaches for the simulated scenario.