ENHANCED BROADCAST OPPORTUNISTIC SCHEME BASED ON SPATIAL COVARIANCE FEEDBACK

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ABSTRACT

Combination of multiuser diversity and spatial diversity is a promising strategy to support high-rate services over wireless broadcast channels. In multiple antenna systems optimization of linear spatial precoding (beamforming) is severly hampered by the amount of feedback. An efficient solution is provided by the opportunistic schemes, which generate a random beamforming and schedule the user (or the set of users) with the best channel conditions. In this paper we investigate the benefits that can be provided to random beamforming technique by the knowledge of the users spatial covariance. We propose to classify and cluster the users according to the channel correlation properties. A beamforming configuration is designed for each cluster of users and clusters are sequentially served by different time-blocks. Different optimization strategies are devised in order to achieve multiuser diversity gain or spatial multiplexing gain. Simulation results show that clustering provides a definite advantage in exploiting the knowledge of the users spatial covariance. The result is achieved at moderate complexity, thus making the strategy feasible to practical systems.

1. INTRODUCTION

Opportunistic beamforming (OB) was recently proposed to exploit the multiuser diversity in broadcast wireless communication systems when an antenna array is employed at the base station (BS). The main idea is to generate random precoding vectors and schedule each user according to the signal-to-noise ratio (SNR) and the proportional fair weighting rule [1]. Random precoding assumes no-knowledge of the instantaneous channel coefficients at the BS and each user is required to send back via feedback channel only the instantaneous SNR relative to the selected beamforming (partial channel state information (CSI)). This makes the OB scheme particularly suited to practical systems where assumption of perfect CSI is not reasonable especially if the number of users (or the number of transmit antennas) is large and/or the users are moving rapidly. The amount of feedback can be further restricted by employing the selective multi user diversity (MUD) approach proposed in [2]. The OB strategy has been enhanced to spatial multiplexing in [3] and [4], where multiple random and orthogonal beams are generated and assigned to the users with the best signal-to-interference-and-noise ratio (SINR).

Benefits of partial CSI in user scheduling has been recently investigated in literature for uncorrelated fading environment. Performance is very effective for systems with a large number (n) of users. In [1] Viswanath et al. show that for $n \to \infty$, the OB schedules at each time instant the user in beamforming configuration (i.e., maximum SNR). In [4] it has been demonstrated that the sum capacity for partial CSI-based scheme has the same asymptotic grow-rate $(\log(\log(n))$ as for the case of perfect CSI and optimum dirty paper coding at the transmitter.

In this paper we investigate the employment of OB in correlated fading environments. Under assumption of wide sense stationary (WSS) channel, the channel fading correlation is described by the second order statistic of the channel, also known as long term CSI (LT-CSI) or spatial covariance. Since LT-CSI can be assumed constant over a large time-scale [5], we assume that the transmitter is provided with perfect LT-CSI at the cost of negligible feedback rate. We enhance the conventional OB scheduling by capitalizing on the LT-CSI. The main idea here is to design the beamforming according to the fading correlation, while the user scheduling relies on the instantaneous SNRs (or SINRs), that reflect the instantaneous fading conditions.

We propose to arrange the users into groups based on their spatial covariance and to assign a beamforming configuration to each group. Since the aim is to devise strategies suited to be implemented in practical systems, complexity is a crucial issue. In Sect. 3 we present low-complexity clustering techniques to match different transmission strategies.

Users i and j are said spatially compatible when they have spatial covariance matrices $\mathbf{R}_i$ and $\mathbf{R}_j$ so that $range(\mathbf{R}_i) = range(\mathbf{R}_j)$. Clustering of spatially compatible users permits to tailor the beamforming according to the spatial covariance of each cluster. Then, the scheduler opportunistically selects the user within the cluster that has largest SNR. The technique is detailed in Sect. 4 and enhances the system throughput with respect to existing schemes as the knowledge of the common spatial subspaces improves the average users SNR while clustering provides multiuser diversity gain. Furthermore it permits to reduce the amount of feedback as only the users belonging to the same cluster are required to feed back the instantaneous SNR.

Clustering algorithm can be also devised to organize the users into long-term orthogonal (or quasi-orthogonal) sets, so that users i and j belong to the same cluster when $range(\mathbf{R}_i) = null(\mathbf{R}_j)$. LT-CSI is effective here in the selection of the users compatible to simultaneous transmission by spatial multiplex. Each cluster is assigned a set of beamforming vectors matched to the spatial subspaces of the grouped users, as shown in Sect. 5. This scheme reduces the average interference between spatially multiplexed sub-streams, thus enhancing the system throughput.

The strategies are here alternatively employed and investigated. A comparison under different users covariance matrices configurations is object of ongoing research.

2. OPPORTUNISTIC SYSTEM MODEL

Consider a Gaussian broadcast channel with n users equipped with a single antenna and a BS with M antennas. Let $\mathbf{x}(t)$ the $M \times 1$ symbols vector transmitted during time-block t by the BS and let

$y_i(t)$ the signal at the receiver i related as

$$y_i(t) = \mathbf{h}_i^T(t)\mathbf{x}(t) + n_i(t), \quad (1)$$

where $\mathbf{h}_i(t) = [h_i^{(1)}(t) \cdots h_i^{(M)}(t)]^T$ is the complex valued channel vector (assumed known at the receiver) and $n_i(t)$ is the AWGN at the receiver i with $n_i(t) \sim CN(0, \sigma_i^2)$. Channel vector $\mathbf{h}_i(t)$ is assumed Gaussian distributed (Rayleigh fading) according to the model

$$\mathbf{h}_i(t) = \mathbf{R}_i^{1/2}\mathbf{w}(t), \quad (2)$$

where $\mathbf{w}(t) \sim CN(0, \mathbf{I}_M)$ and $\mathbf{R}_i = E[\mathbf{h}_i(t)\mathbf{h}_i^H(t)]$ is the $M \times M$ covariance matrix for user i. According to block-fading assumption, the fading coefficients vector $\mathbf{w}(t)$ is assumed constant within each time-block and varies independently across the time-blocks and among users. Covariance matrix $\mathbf{R}_i$ is constant over a large time-scale and it is drawn according to the propagation model in [6], which assumes that the mobile terminal is surrounded by a ring of scatterers. These scatterers cause an angular spread $\gamma_{\max}$ defined as the ratio of the radius of the ring and the distance between the terminal and the BS. Correlation of each pair (p, q) of antenna elements of user i can be expressed as

$$[\mathbf{R}_i]_{p,q} = E[h_i^{(p)}(t)h_i^{(q)}(t)^H] = J_0(2\pi(p-q)\Delta \cdot \gamma_{\max}\cos(\phi_i))e^{-j2\pi(p-q)\Delta\sin(\phi_i)}. \quad (3)$$

where J_o is the Bessel function of the first kind of order zero, Δ is the antenna spacing in wavelength and ϕ_i is the angle between the user i and the broadside direction. We normalize the channel as $trace(\mathbf{R}_i) = M$ and we define the average system SNR as $\mu = \frac{1}{n}\sum_{i=1}^{n}\sigma_i^{-2}$.

At the beginning of each time slot the BS constructs a set of K beamforming vectors $\mathbf{u}_m(t)$ so that the transmitted signal $\mathbf{x}(t)$ is the superposition of K beams

$$\mathbf{x}(t) = \sum_{m=1}^{K}\mathbf{u}_m(t)s_m(t), \quad (4)$$

where $s_m(t)$ stands for the unitary power information symbols stream. Power is uniform distributed to the beams ($||\mathbf{u}_m(t)||^2 = \frac{1}{K}$) as we do not account for adaptive power allocation. The receiver i is assumed to perfectly know the value $\mathbf{h}_i^T(t)\mathbf{u}_m(t)$ (this can be readily arranged during training) and it computes the SINRs by assuming that $s_m(t)$ is the desired signal and $s_z(t)$ is interference (for $z \neq m$)

$$\gamma_{i,m}(t) = \frac{|\mathbf{h}_i^T(t)\mathbf{u}_m(t)|^2}{\sigma_i^2 + \sum_{z=1,z\neq m}^{K}|\mathbf{h}_i^T(t)\mathbf{u}_z(t)|^2}, m = 1\ldots K. \quad (5)$$

Each users feeds back to the BS the maximum SINR and the corresponding beamforming index. We assume that the feedback channel is error-free and instantaneous. An analysis of the effect of imperfect and outdated feedback is proposed in [7]. At the BS, optimal strategy with the aim of maximizing the sum-rate capacity is to assign each stream to the user with the instantaneous highest SINR. Nevertheless real systems are also concerned to guarantee fairness and latency requirements, thus a proportional fairness (PF) algorithm is considered. This keeps track of the average scheduled SINR of each user in a past window t_c and selects within each time slot the user i that maximizes the ratio between the actual SINR $\gamma_{i,m}(t)$ and the average scheduled SINR. Specifically the PF scheduler maximizes

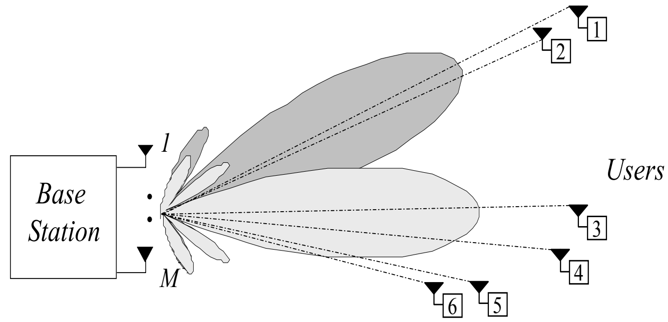

Fig. 1. Broadcast system with $M = 6$ antennas at the BS and $n = 6$ users. Users position determines the correlation metric (directional model).

(for each m) the metric

$$D_m(t) = \max_i \frac{\gamma_{i.m}(t)}{S_i(t)}, \quad (6)$$

where $S_i(t)$ is updated at each time slot as

$$S_i(t+1) = \begin{cases} (1 - \frac{1}{t_c})S_i(t) + \sum_{m=1}^{K}\frac{\gamma_{i,m}(t)}{t_c} & \text{user } i \text{ scheduled} \\ (1 - \frac{1}{t_c})S_i(t) & \text{otherwise.} \end{cases} \quad (7)$$

As shown in [8], the PF algorithm for large t_c converges in probability at steady state to a unique long-term resource allocation in which every user is scheduled for equal fraction of time. This result holds independently to the single user noise power σ_i^2. Accordingly, in the following we assume that PF guarantees a fair long-term resource allocation and we gear our analysis toward the maximization of the system sum-rate.

3. CLUSTERING ALGORITHM

Clustering algorithm allocates the users set $\mathcal{C}$ into G clusters $\mathcal{C}_k$ for $k = 1\ldots G$, each one containing $|\mathcal{C}_k|$ users, such that where $\mathcal{C}_k \cap \mathcal{C}_h = 0$ for $k \neq h$, $\bigcup_{k=1}^{G}\mathcal{C}_k = \mathcal{C}$ and $\sum_{k=i}^{G}|\mathcal{C}_k| = n$. The partitioning policy can be tailored according to two different transmission strategies. If users belonging to the same cluster $\mathcal{C}_k$ have covariance matrices that span the common subspace, opportunistic scheduler can achieve multiuser diversity gain by using one beamforming design per transmission ($K = 1$) matched to the spatial subspace of $\mathcal{C}_k$. Alternatively, grouping users having mutually orthogonal covariance matrices permits to achieve spatially multiplexing gain by simultaneously beamforming ($K > 1$) the users in the same cluster. An intuitive insight on the two schemes is provided by Fig. 1 under assumption that $\gamma_{\max} = 0$ in (3) (i.e., the covariance matrix depends only on the direction of arrival). Users located along similar directions (1 and 2) have covariance matrices so that $range(\mathbf{R}_1) = range(\mathbf{R}_2)$. The scheduler can achieve multiuser diversity gain by grouping the users and by using the same spatial filtering (in figure the beamforming is focused on the middle so as it serves both users). Differently, user 3 is along an orthogonal direction ($range(\mathbf{R}_3) = null(\mathbf{R}_2) = null(\mathbf{R}_1)$) and it can be served by spatial multiplexing jointly with user 1 or 2.

For both transmission strategies, optimum grouping would be based on the range-spaces of each covariance matrix, thus requiring the modal decomposition $\mathbf{R}_i = \mathbf{U}_i\mathbf{\Lambda}_i\mathbf{U}_i^H$, where matrices $\mathbf{U}_i = [\mathbf{u}_i^{(1)}, \ldots, \mathbf{u}_i^{(M)}]$ and $\mathbf{\Lambda}_i = diag(\lambda_i^{(1)}, \ldots, \lambda_i^{(M)})$ contain respectively the eigenvectors and the eigenvalues of $\mathbf{R}_i$. However, the corresponding computational complexity is unfeasible during scheduling process. To overcome this problem, we pursue here a low complexity clustering framework based on a scalar metric $\eta_{i,j}$ that provides a measure of the spatial subspace correlation for each pair of users (i, j). Specifically, we propose to adopt the following metric

$$\eta_{i,j} = \frac{tr[\mathbf{R}_i\mathbf{R}_j^H]}{\sqrt{tr[\mathbf{R}_i\mathbf{R}_i^H]tr[\mathbf{R}_j\mathbf{R}_j^H]}}, \quad (8)$$

that can be rearranged as

$$\eta_{i,j} = \frac{\sum_{p,q}\lambda_i^{(p)}\lambda_j^{(q)}|\mathbf{u}_i^{(p)H}\mathbf{u}_j^{(q)}|^2}{\sqrt{\sum_p(\lambda_i^{(p)})^2\sum_q(\lambda_j^{(q)})^2}}. \quad (9)$$

It can be noticed from (9) that metric is an average of the (square) correlation between each pair of spatial modes $(\mathbf{u}_i^{(p)}, \mathbf{u}_j^{(q)})$ weighted by the corresponding modal components $(\lambda_i^{(p)}, \lambda_j^{(q)})$. Normalization guarantees that the metric lies in the range $\eta_{i,j} \in [0, 1]$. The maximum $\eta_{i,j} = 1$ is achieved when $\mathbf{R}_i$ is a scaled version of $\mathbf{R}_j$, while $\eta_{i,j} = 0$ is obtained when $range(\mathbf{R}_i) = null(\mathbf{R}_j)$.

We compute the metric $\eta_{i,j}$ for each couple of users (i, j) with $i, j \in \{1, \ldots, n\}$. This requires the evaluation of the product $\mathbf{R}_i\mathbf{R}_j^H$ for each pair of users, thus leading to an overall computation complexity of $n^2/2$ matrix products. Once metric values have been computed, we cluster the users in order to maximize (or minimize) the average metric of the users belonging to the same group, described by the object function

$$J\{\mathcal{C}\} = \frac{1}{n}\sum_{k=1}^{G}\left(\sum_{i,j\in\mathcal{C}_k}\eta_{i,j}\right). \quad (10)$$

By maximizing (10) we cluster spatially compatible users and we can achieve multiuser diversity gain as discussed in Sect. 4. Object function (10) is minimum when each group contains users spanning quasi-orthogonal subspaces and it is suited to spatial multiplexing as shown in Sect. 5. In the following we will refer to the procedures that search for partitioning $\mathcal{C}_k$ that maximizes (10) to cluster spatially compatible users, as minimization is equivalent.

3.1. Tree-Based clustering

Hierarchical clustering consists of building a tree approach like one depicted in Fig. 2. In the exemplary tree we have the 6 users of Fig. 1, that are sequentially grouped in $G = 2$ clusters. At the first step each users corresponds to a group. At each step we have one group less. This is achieved by merging two groups at the previous level in a single group. Between all the possible combinations, we select the pair (i, j) that maximizes the metric $\eta_{i,j}$. Users 1 and 2 are grouped at the first step according with Fig. 1. The metric between the group $\{i, j\}$ obtained by merging and any user z is approximated as $\eta_{(ij),z} = (\eta_{i,z} + \eta_{j,z})/2$. Algorithm requires $n - G$ iterations and it is well suited for a practical implementation.

If the number of cluster is a statement of the problem, the clustering algorithm terminates when the pre-defined number of clusters is reached. Otherwise it can be selected by introducing an adaptive stopping criteria. Conventional algorithm terminate the merging procedure when the object function (10) goes below a prescribed threshold.

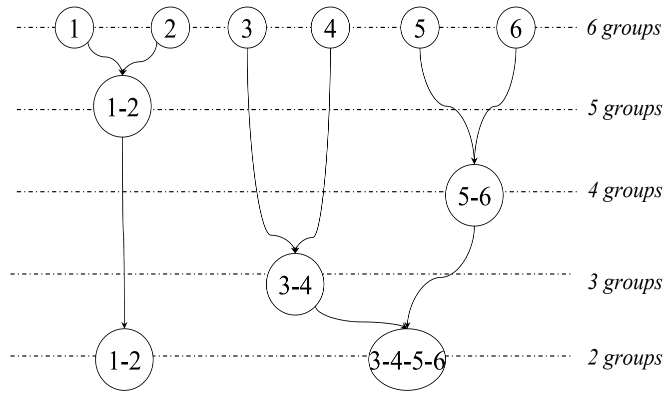

Fig. 2. Tree-based clustering for $n = 6$ users (see geometrical view in Fig. 1).

3.2. Equal-elements clustering

When the clusters are required to contain an equal number of elements, hierarchical clustering can not be employed. A solution at moderate complexity is provided by the compatibility optimization algorithm [9], where n users are allocated to G groups such as $\lfloor n/G \rfloor \leq |\mathcal{C}_k| \leq \lceil n/G \rceil$ for $1 < k < G$. We devise here a simplified version of the compatibility optimization algorithm [9], that is summarized in the following.

We design the $n \times n$ Hermitian matrix $\mathbf{N}$, whose elements are defined as $[\mathbf{N}]_{i,j} = \eta_{i,j}$ and $[\mathbf{N}]_{i,i} = 1$. Each column (or row) contains the metric relative to a single user. Let define the $n \times n$ block-diagonal matrix $\mathbf{F} = diag(\mathbf{F}_1, \ldots, \mathbf{F}_G)$, whose diagonal is composed by $|\mathcal{C}_k| \times |\mathcal{C}_k|$ square matrices $\mathbf{F}_k$ consisting of all ones. Each users ordering corresponds to a clustering solution, in which sequence of users are partitioned in sets of $|\mathcal{C}_k|$ elements. Maximizing (10) corresponds to find the optimum users ordering that maximize the function $\mathbf{1}^T(\mathbf{N} \odot \mathbf{F})\mathbf{1}$, where symbol $\odot$ stands the element-wise product and $\mathbf{1} = [1 \ldots 1]^T \in \mathbb{R}^{n\times 1}$.

Let $\mathbf{N}_o$ be the matrix $\mathbf{N}$ at the first step for users in arbitrarily order. Let generate a set of $n(n-1)/2$ pair of integers (i, j) taken from the set $\{1, \ldots, n\}$ and iterate the following procedure for each pair (i, j).

At the $t - th$ step

i) Compute the matrix $\mathbf{N}_t(i, j)$ by switching the columns $i - th$ and $j - th$ in $\mathbf{N}_t$.

ii) If $\mathbf{1}^T(\mathbf{N}_t(i, j) \odot \mathbf{F})\mathbf{1} > \mathbf{1}^T(\mathbf{N}_t \odot \mathbf{F})\mathbf{1}$, then $\mathbf{N}_{t+1} = \mathbf{N}_t(i, j)$, otherwise $\mathbf{N}_{t+1} = \mathbf{N}_t$.

This algorithm finds the global optimum of the object function (10) at the complexity of $n(n-1)/2$ iterations (steps i) and ii)).

4. MULTIUSER DIVERSITY STRATEGY (K=1)

In this Section we design a transmission strategy based on a clustering policy that groups users i and j so that $range(\mathbf{R}_i) = range(\mathbf{R}_j)$. The goal is to enhance the system throughput by capitalizing both on the LT-CSI and on multiuser diversity within each cluster.

A single beam $\mathbf{u}(t)$ is employed in each time block and scheduling is based on the instantaneous SNR

$$\gamma_i(t) = |\mathbf{h}_i^T(t)\mathbf{u}(t)|^2/\sigma_i^2 \tag{11}$$

of each user. This is the scenario of the conventional OB strategy [1], where the beam $\mathbf{u}(t)$ is randomly generated according to the channel distribution.

Several improvement to the OB have been proposed in literature. In [10] the performances of many algorithms are compared under correlated fading assumption. The best performance is achieved by eigenbeamforming (EB) strategy, that maximize the average SNR of each user

$$\overline{\gamma}_i = \frac{E[|\mathbf{u}^H(t)\mathbf{h}_i|^2]}{\sigma_i^2} = \frac{\mathbf{u}^H(t)\mathbf{R}_i\mathbf{u}(t)}{\sigma_i^2} \tag{12}$$

The solution consists in transmitting (in different time-blocks) the set of eigenvectors corresponding to the largest eigenvalues of the users covariance matrices.

We show that users clustering based on covariance matrices permits to simultaneously enhance the throughput and reduce the feedback rate. Specifically, we group the users with high-correlated spatial subspaces by using the tree-based algorithm depicted in Sect. 3 and we associate a single beam $\mathbf{u}_k$ to each cluster $\mathcal{C}_k$. The strong channel correlation of the users sharing the same cluster guarantees high $\overline{\gamma}_i$ (comparable to that of EB) for each user $i \in \mathcal{C}_k$. Beamforming to a cluster of users permits to enhance the diversity gain with respect to EB where each beam is matched to the spatial subspace of a single user. Furthermore, if the beam $\mathbf{u}_k$ is properly selected to be matched to the clustered users, only the users belonging to the correspondent cluster $\mathcal{C}_k$ compete for the highest scheduling metric (6). As a consequence, the proposed scheme permits to reduce the feedback rate as only the users belonging to the selected cluster are required to send back the instantaneous SNR.

If further restrictions on the feedback channel are required, the selective MUD approach [2] can be employed jointly with the clustering technique. In this case, only terminals belonging to the selected cluster and experiencing SNR above a pre-defined threshold are allowed to report their channel state information to the BS. This alternative (selective MUD) will be not further pursued in the sequel.

The algorithm performance and the optimal design are investigated in terms of the average steady-state scheduled SNR $S_i = lim_{t\to\infty}S_i(t)$, where $S_i(t)$ is defined in Eq. (7). Since clusters are served in different time-blocks, we can investigate the performance of each cluster separately. Without loss of generality we assume that users $\{1,\ldots,|\mathcal{C}_k|\}$ belong to cluster $\mathcal{C}_k$ and we analyze the performance of cluster k. When PF scheduler is employed at the BS and the scheduler temporal window t_c is large enough (i.e., $t_c \to \infty$), the average steady-state scheduled SNR S_i for user $i \in \mathcal{C}_k$ is described by the following equation (see [8])

$$S_i = \pi_k \cdot E[\gamma_i(t)|\frac{\gamma_i(t)}{S_i} = \max(\frac{\gamma_1(t)}{S_1},\cdots,\frac{\gamma_{|\mathcal{C}_k|}(t)}{S_{|\mathcal{C}_k|}})] \cdot \Pr\text{ob}(\frac{\gamma_i(t)}{S_i} = \max(\frac{\gamma_1(t)}{S_1},\cdots,\frac{\gamma_{|\mathcal{C}_k|}(t)}{S_{|\mathcal{C}_k|}})), \tag{13}$$

where π_k is the fraction of time allocated to the cluster k and the average is over the SNR statistic. In the sequel, the subscript t will be dropped for easy of notation. It follows from (13) that at steady-state each user is selected for equal fraction of time [8], thus

$$\Pr\text{ob}(\frac{\gamma_i}{S_i} = \max(\frac{\gamma_1}{S_1},\cdots,\frac{\gamma_{|\mathcal{C}_k|}}{S_{|\mathcal{C}_k|}})) = \frac{1}{|\mathcal{C}_k|}. \tag{14}$$

Analytic derivation of S_i needs the knowledge of the probability density function of the instantaneous SNR γ_i. Since the the users belonging to cluster $\mathcal{C}_k$ are always served by beam $\mathbf{u}_k$, the SNR γ_i of each users is distributed as χ_2^2 RVs (under Rayleigh fading assumption). Furthermore, the normalization over S_i in Eq. (13) makes the statistic of the maximum equivalent to the statistic of the maximum of $|\mathcal{C}_k|$ i.i.d. χ_2^2 RVs. Thus it holds

$$S_i = \frac{\pi_k}{|\mathcal{C}_k|}\cdot\Gamma(|\mathcal{C}_k|)\cdot\frac{\mathbf{u}_k^H\mathbf{R}_i\mathbf{u}_k}{\sigma_i^2} = \frac{\pi_k}{|\mathcal{C}_k|}\cdot\Gamma(|\mathcal{C}_k|)\cdot\overline{\gamma}_i, \tag{15}$$

where $\overline{\gamma}_i = \mathbf{u}_k^H\mathbf{R}_i\mathbf{u}_k/\sigma_i^2$ is the average user SNR, $\mathbf{u}_k$ is the beam associated to cluster k and $\Gamma(|\mathcal{C}_k|) = \sum_{k=1}^{|\mathcal{C}_k|} 1/k$ is the multiuser diversity gain for $|\mathcal{C}_k|$ i.i.d. χ_2^2 RVs (see [8]). To provide a fair resource allocation, time-blocks are allocated proportionally to the number of elements of each cluster, thus it is $\pi_k = \frac{|\mathcal{C}_k|}{n}$. Consequently the scheduled SNR for cluster k is

$$\sum_{i\in\mathcal{C}_k} S_i = \frac{\Gamma(|\mathcal{C}_k|)}{n}\sum_{i\in\mathcal{C}_k}\frac{\mathbf{u}_k^H\mathbf{R}_i\mathbf{u}_k}{\sigma_i^2}. \tag{16}$$

According to (16), steady-state scheduling SNR is maximized when the beam $\mathbf{u}_k$ corresponds to the eigenvectors relative to the largest eigenvalue of the matrix $\mathbf{R}_{\mathcal{C}_k}$, which contains the users spatial subspaces scaled by the noise power

$$\mathbf{R}_{\mathcal{C}_k} = [\frac{\mathbf{R}_1}{\sigma_1^2},\cdots,\frac{\mathbf{R}_{|\mathcal{C}_k|}}{\sigma_{|\mathcal{C}_k|}^2}], \tag{17}$$

where we recall that users $\{1,\ldots,|\mathcal{C}_k|\}$ belong to cluster $\mathcal{C}_k$. Thus, the proposed strategy reduces to a cluster eigenbeamforming (Cluster-EB). Finally, the steady-state system scheduled SNR reads

$$S = \sum_{i=1}^{G} S_i = \frac{1}{n}\sum_{k=1}^{G}\Gamma(|\mathcal{C}_k|)\sum_{i\epsilon\mathcal{C}_k}\overline{\gamma}_i. \tag{18}$$

The performance metric S is affected by two main components. The user SNR $\overline{\gamma}_i$ depends on the cluster geometrical properties, while the multiuser diversity $\Gamma(|\mathcal{C}_k|)$ is related on the number of users for each cluster. When the clusters consist in a single element ($|\mathcal{C}_k| = 1$) the technique reduces to EB. On the other hand, large clusters enhance the MUD gain, but reduce the average users SNR. Thus, system throughput is maximized by selecting a proper number of clusters. Optimum strategy would be to compute the S at each step of the clustering tree and stop the procedure when maximum is reached. Nevertheless computation of S during the scheduling process would require additional complexity, thus we propose to terminate the clustering procedure whenever the object function J goes below the threshold value J_{th}. From our simulation experience we set $J_{th} = 0.75$.

4.1. Numerical results

The effectiveness of the proposed Cluster-EB is shown here by means of simulation results. Performance is shown as the aggregate sum-rate, defined as the sum of the single users average throughput. The channels correlation matrices $\mathbf{R}_i$ are drawn according to

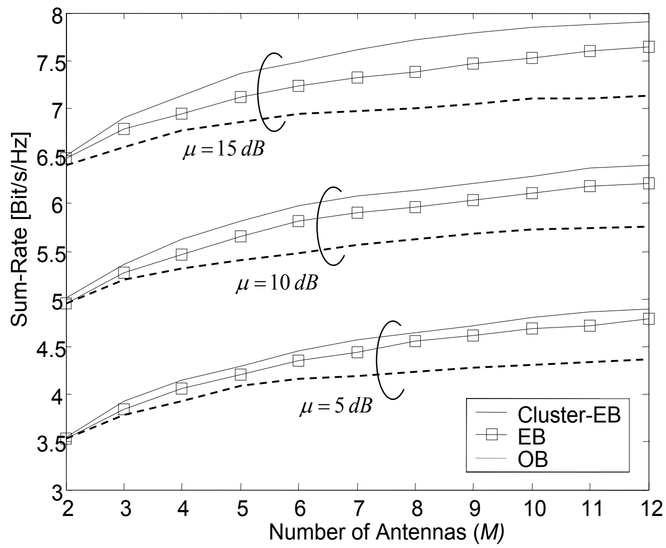

Fig. 3. Sum-rate vs. number of antennas M for opportunistic beamforming (OB) [1], Eigenbeamforming (EB) [10] and Cluster-Eigenbeamforming (Cluster-EB) strategy. The number of users is $n = 30$ and the average SNR is $\mu = 5, 10, 15dB$.

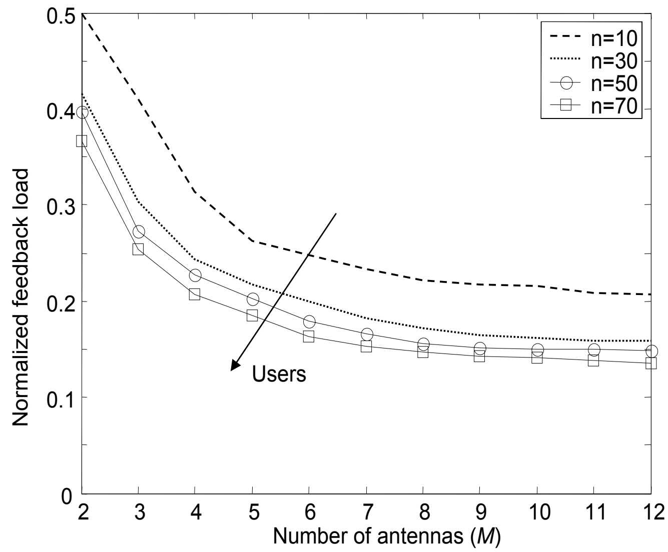

Fig. 4. Normalized feedback load $\overline{F}$ vs. number of antennas M for Eigenbeamforming (EB) strategy. The number of users is $n = 10, 30, 50, 70$.

the model described in Sect. 2. The maximum angular spread is set to $\gamma_{\max} = 0.1$ for all the users, while the angles of arrival ϕ_i are randomly selected from a uniform distribution within the range $-\frac{2}{3}\pi \leq \phi_i \leq \frac{2}{3}\pi$. All users are affected by the same noise power ($\sigma_1^2 = \cdots = \sigma_n^2$). In the following simulation results we set the temporal window of the proportional fairness scheduling to $t_c = n$ time-blocks.

We compare the Cluster-EB with the conventional EB and the OB strategies. Fig. 3 shows the sum-rate versus the number of antennas M at the BS for $n = 30$ users and average system SNR $\mu = 5, 10, 15\ dB$. We notice that the clustering-EB outperforms both OB and EB techniques and the sum-rate improvement increases with the average SNR μ and the number M of antennas at the BS. For large M the proposed strategy is very effective as the degrees of freedom in users spatial clustering increase.

We recall that Cluster-EB scheme simultaneously enhances the throughput and reduces the feedback rate. Fig. 4 shows the normalized feedback load $\overline{F}$ of Cluster-EB, defined as in [2] as the feedback channel usage ratio per time-block averaged over the total number of users. This measure can also be interpreted as the average (over the users) probability to effectively send the SNR report over the feedback channel. We recall that in OB and EB strategies all the user send back the instantaneous SNRs in every time-block, thus it is $\overline{F} = 1$. The feedback load of Cluster-EB is shown in figure for different antenna array configuration (M from 2 to 12) and different number of users in the cell ($n = 10, 30, 50, 70$). For large M the feedback load $\overline{F}$ is lower than 0.2.

Fig. 5 shows the sum-rate versus the number of users n for $\mu = 15\ dB$, $M = 8$ and $M = 4$ antennas. As expected the aggregate throughput grows up with the number of users. Cluster-EB provides a large performance gain with respect to EB and OB for realistic number of users, while the performance gap between the methods decreases for large n. Knowledge of the LT-CSI is much more effective for low number of users, while asymptotically ($n \to \infty$) EB and Cluster-EB provide performance similar to OB. This result corroborates the idea that random beam selection is asymptotically nearly optimum.

5. SPATIAL MULTIPLEXING(K>1)

In this Section we devise a transmission strategy that capitalizes on users clustering to achieve spatial multiplexing gain ($K > 1$). Let $K \leq M$ be the maximum number of sub-strems employed in each time-block. We allocate the users in $G = \lceil \frac{n}{K} \rceil$ sets, each one containing $|\mathcal{C}_k|$ elements with $K - 1 \leq |\mathcal{C}_k| \leq K$ by using the equal-elements clustering (see Sect. 3). The object function (10) is minimized here so that the users belonging to the same groups have low mutual covariance correlation (i.e., $\eta_{i,j} \simeq 0$). Thus, the users sharing the same cluster are compatible to be simultaneously served as the spatially multiplexed sub-streams are affected by low mutual interference.

The BS sequentially serves clusters $\mathcal{C}_1, \mathcal{C}_2, \ldots, \mathcal{C}_G$ by different time-blocks. It simultaneously transmits the $|\mathcal{C}_k|$ (for $1 \leq k \leq G$) eigenbeamforming vectors $\mathbf{u}_1^{(k)} \ldots \mathbf{u}_{|\mathcal{C}_k|}^{(k)}$ relative to the users belonging to cluster $\mathcal{C}_k$. Thus, the method can be seen as simultaneous EB to a set of users that are compatible to be spatial multiplexed. According to the opportunistic scheme depicted in Sect. 2, the scheduler assigns each stream to the user with the highest SINR (up to PF weighting rule). In the following we refer to the proposed technique as Mux-Cluster-EB.

Let us assume that users $\{1, \ldots, |\mathcal{C}_k|\}$ belong to cluster $\mathcal{C}_k$ and $\mathbf{u}_1^{(k)} \ldots \mathbf{u}_{|\mathcal{C}_k|}^{(k)}$ are the corresponding eigenbeamforming vectors. When precoding is matched to cluster $\mathcal{C}_k$, it holds (for $i \in \mathcal{C}_k$)

$$\gamma_{i,m}(t) = \frac{|\mathbf{h}_i^T(t)\mathbf{u}_m^{(k)}|^2}{\sigma_i^2 + \sum_{z=1, z\neq m}^{|\mathcal{C}_k|} |\mathbf{h}_i^T(t)\mathbf{u}_z^{(k)}|^2}, m = 1 \ldots |\mathcal{C}_k|. \quad (19)$$

We notice that users $i \in \mathcal{C}_k$ are affected by reduced mutual interference as precoding vectors $\mathbf{u}_z^{(k)}$ and the channel vectors $\mathbf{h}_i^T(t)$ are

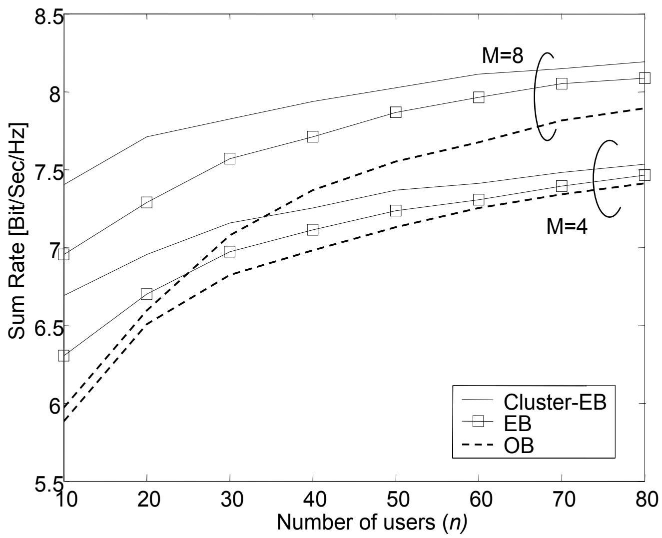

Fig. 5. Sum-rate vs. number of users $n = 30$ for opportunistic beamforming (OB) [1], Eigenbeamforming (EB) [10] and Cluster-Eigenbeamforming (Cluster-EB). The average system SNR is $\mu = 15dB$ and the number of antennas is $M = 4, 8$.

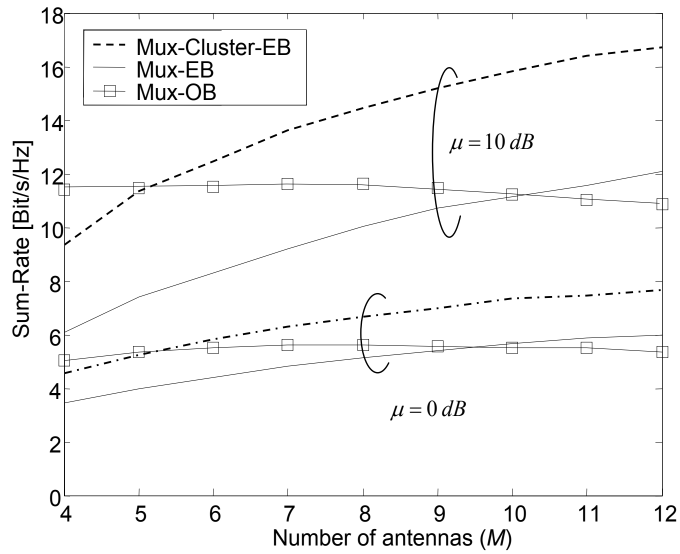

Fig. 6. Sum-rate vs. number of antennas M for Mux-OB [3], Mux-EB and MUX-Cluster-EB. The number of users is $n = 30$, tha average system SNR is $\mu = 0, 10dB$ and $K = 4$ beams are simultaneously transmitted.

(ideally) orthogonal (for $i \neq z$). At the same time each beam $\mathbf{u}_z^{(k)}$ is matched to the spatial subspace of the corresponding user ($i = z$) due to EB technique. Thus, users $i \in \mathcal{C}_k$ obtain maximum average SINRs and they are in favorable condition to be scheduled (up to fading deeps) and to provide high throughput (spatial multiplexing gain).

5.1. Numerical results

The Mux-Cluster-EB scheme is compared to the conventional opportunistic scheme (here referred to as Mux-OB) in [3][4], that generates a set K random orthogonal beams. To measure the benefits provided by clustering, we also show the performance of the technique (here referred to as Mux-EB) that at each time-block randomly selects K users and transmit the corresponding EB vectors. Fig. 6 shows the sum-rate versus the number of antennas at the BS when $K = 4$ beams are transmitted and $n = 30$ users are served. The propagation scenario is the same as in Sect 4 and the average SNR is set to $\mu = 0$ and $10\ dB$ ($\sigma_1^2 = \cdots = \sigma_n^2$). Mux-EB strategy is inefficient as it does not account for the spatial properties of the users selected for simultaneous transmission. Mux-Cluster-EB outperforms OB for $M > K$ and the gain increases with M. For large number of antennas (as compared with K) the clustering algorithm has enough degrees of freedom and the users grouped in each cluster can effectively achieve spatial multiplexing gain. On the contrary for $M = K$, the assumption of users orthogonality does not hold and interference among the substreams is not negligible (particularly for high μ). In this case the best performance is obtained by using random orthogonal beams (Mux-OB).

Fig. 7 shows the sum-rate versus the SNR μ for $M = 8, n = 30$ and $K = 2, 4, 6$. We still notice that Mux-Cluster-EB provides a large performance gain in SNR with respect to conventional OB, particularly for $K \ll M$ (as for $K = 2$ and $K = 4$). The gain reduces when the number of beams approaches number of the antennas M.

6. CONCLUSIONS

In this paper we have shown that clustering the users according to the spatial covariance is a powerful tool to enhance the performance of the opportunistic schemes in broadcast communication systems. We have proposed two algorithms for assigning users to groups according to different optimization criteria. Grouping users with spatially compatible channel is suited to a transmission strategy that enhances the multiuser diversity by transmitting a single beam matched to the spatial subspace of each cluster. Alternatively clustering can be devised to select the users compatible to be simultaneously served, so that spatial multiplexing gain can be achieved by transmitting a set of beamforming vectors matched to the users spatial subspaces. Simulation results show that both the schemes permit a considerable throughput gain, particularly when the BS is provided by a large number of antennas and it serves a reasonable number of users. Since clustering algorithms require moderate complexity, the proposed schemes, even if sub-optimum, are suited to practical implementation when a reduced feedback is mandatory compared to other optimal strategy, that requires that transmitter schedules users based on instantaneous CSI.

7. ACKNOWLEDGMENTS

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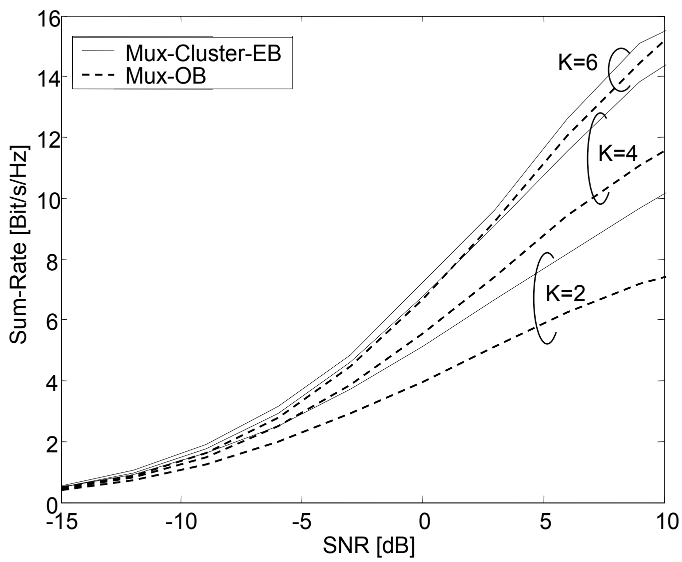

Fig. 7. Sum-rate vs. SNR μ for Mux-OB [3], Mux-EB and MUX-Cluster-EB. The number of users is $n = 30$, the number of antennas is $M = 8$ and $K = 2, 4, 6$ beams are simultaneously transmitted.

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