Opportunistic Space-Division Multiple Access With Beam Selection

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***Abstract*—In this paper, a novel transmission technique for the multiple-input multiple-output (MIMO) broadcast channel is proposed that allows simultaneous transmission to multiple users with limited feedback from each user. During a training phase, the base station modulates a training sequence on multiple sets of randomly chosen orthogonal beamforming vectors. Each user sends the index of the best beamforming vector and the corresponding signal-to-interference-plus-noise ratio for that set of orthogonal vectors back to the base station. The base station opportunistically determines the users and corresponding orthogonal vectors that maximize the sum capacity. Based on the capacity expressions, the optimal amount of training to maximize the sum capacity is derived as a function of the system parameters. The main advantage of the proposed system is that it provides throughput gains for the MIMO broadcast channel with a small feedback overhead, and provides these gains even with a small number of active users. Numerical simulations show that a 20% gain in sum capacity is achieved (for a small number of users) over conventional opportunistic space division multiple access, and a 100% gain (for a large number of users) over conventional opportunistic beamforming when the number of transmit antennas is four.**

***Index Terms*—Beamforming, multiple-input multiple-output (MIMO), space-division multiple access (SDMA).**

I. Introduction

MULTIPLE-INPUT MULTIPLE-OUTPUT (MIMO) wireless communication can increase throughput in multiuser cellular systems by using multiple antennas to support simultaneous transmission to multiple users [1]–[7]. Recent theoretical results on the MIMO broadcast channel (MIMO-BC) have found that the sum capacity achieving strategy is dirty paper coding [1]–[4], [8]. Unfortunately, dirty paper coding is difficult to implement in practice, since it requires complete channel state information and high computational complexity [9], [10]. Several alternatives have been proposed that use beamforming [5], [6], [11]–[13] or block diagonalization [14]–[18], but not precancellation, to transmit parallel data streams to different users via space-division multiple access (SDMA), which still requires complete channel state information for each user at the transmitter.

There are several approaches for informing the base station about the transmit channels for each user. One approach is to use time-division duplexing and also reciprocity to allow the base station to estimate the downlink channel from uplink channel measurements [19]. Unfortunately, the time-division duplexing requires either special hardware [20], [21] or a special protocol [22] including guard times to solve the calibration problem. More generally a feedback channel can be used to inform the base station about the transmit channels using limited feedback for beamforming [23], [24] or SDMA systems [25]–[27]. Although limited feedback methods are effective in reducing feedback overhead, they require high-resolution codebooks since they are much more sensitive to quantization error than in the single user case. An effective approach for substantially reducing the feedback is to compute the beamforming (or precoding) weights based on mean or covariance channel information [28]–[31], which varies slowly and can easily be fed back. Mean- and covariance-based beamforming techniques do not perform well in channels with non-line-of-sight and low spatial correlation.

One approach to reduce feedback requirements is to employ the opportunism inherent in multiuser communication systems [32], [33]. Perhaps the best known approach is opportunistic beamforming (OBF) [32]–[34]. With OBF, the base station randomly selects a beam for transmission and uses it to send a training sequence. The users send back their SNR corresponding to this beam and the base station schedules the user with the highest SNR (or uses another scheduling rule) for transmission. The OBF approaches the performance of the optimal beamforming strategy for a large number of users [32]. When there are fewer users, a modification to OBF where minislots are used to send multiple beams and the optimal beam

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is selected for data transmission has been shown to improve the throughput [35]. The main difference in OBF with selection (OBF-S) is that the users respond with the best beam and corresponding SNR for that beam; thus, OBF-S converges faster to the optimal beamforming strategy. Both OBF and OBF-S send only one data stream, consequently, they do not take full advantage of the MIMO-BC capacity gains. A solution is the opportunistic SDMA (OSDMA), where the base station sends orthogonal beams [7]. In this case each user reports the best beam and their signal-to-interference-plus-noise ratio (SINR) to the base station. The base station then schedules transmissions to multiple users based on the received SINR. As with OBF, this approach requires a large number of users to approach full-CSI capacity gains.

In this paper, we present a novel transmission technique for the MIMO-BC based on the concept of OSDMA. The key idea of our approach is to randomly generate multiple sets of orthonormal weight vectors during the training period. Each user responds with their best beamforming weight and SINR for that beamforming vector in the corresponding orthogonal set. Then, the base station selects the set of users and beamforming weights, i.e., *beam selection*, that maximizes the sum capacity. We call this scheme OSDMA with beam selection (OSDMA-S). Our technique generalizes OBF-S [35] by enabling parallel data transmissions to multiple users, and improves on [7] by using beam selection to reap capacity benefits for a low number of users in the system. Compared with other MIMO-BC strategies [5], [6], [11]–[16], our approach requires very little channel state information (a beam index and quantized SINR value).

Throughout the paper, we consider the special case of a single receive antenna per user; the extension to multiple receive antennas is left to future work. Our main analytical contribution is a theoretical sum capacity expression for OSDMA-S accounting for the penalty due to training. From these expressions, we compute the number of training symbols needed for the beam selection at the transmitter by maximizing a bound on the sum capacity with training. We show that the number of training symbols derived from this capacity bound coincides with the optimal number of training symbols obtained numerically. By using Monte Carlo simulations, we show that about 100% gain in sum capacity is achieved over OBF and OBF-S [32], [35], when the number of transmit antennas is four and there are 50 users, thanks to our ability to spatially multiplex information to multiple users. We also show our scheme outperforms OSDMA without training in [7] (due to beam selection) for relatively low numbers of users and with minimal increased feedback overhead. For example, we show that OSDMA-S yields sum capacity gains higher than 20% over OSDM without training when there are less than five active users.

The rest of this paper is organized as follows. In Section II, the system model of the proposed OSDMA-S is presented. Information theoretic capacity analysis is given in Section III. Section IV presents the performance results of the proposed OSDMA-S, and conclusions are drawn in Section V.

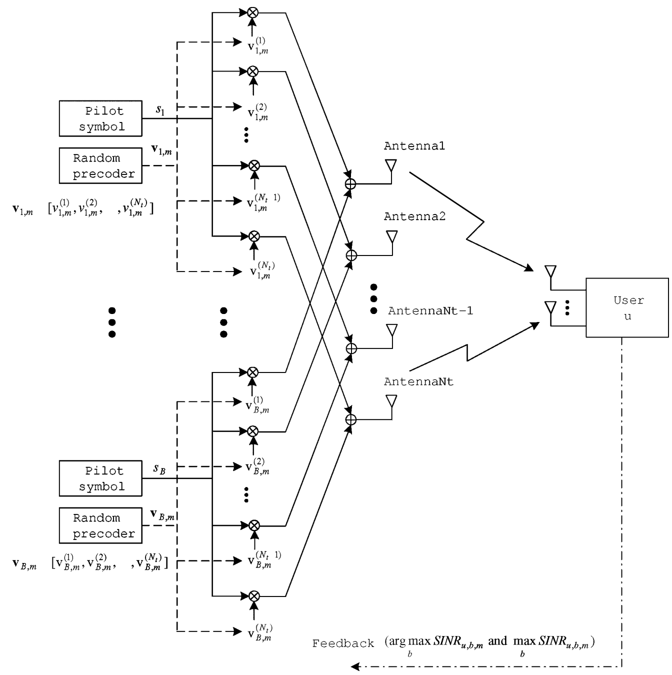

Fig. 1. Block diagram of the proposed system. In every minislot, B random beams are generated and transmitted.

II. Description of the Proposed OSDMA With Beam Selection

In this section, we present the system model and framing structure of OSDMA-S. Then, we describe the algorithm and performance metric used by our proposed method.

A. System Model and Framing Structure

We consider the MIMO broadcast channel with N_t transmit antennas and U users, each with a single receive antenna. Different transmission techniques can be used for the MIMO broadcast channel, but this paper mainly focuses on OSDMA schemes due to the dramatic reduction of feedback information required at the base station. The block diagram of a typical OSDMA system is given in Fig. 1, in which the centralized transmitter constructs $B(\leq N_t)$ random orthonormal beams and sends B pilot symbols to different users through these beams. Each user feeds back the best pilot symbol index and corresponding SINR level among B pilot symbols to the transmitter. Then, a subset of users is selected for data transmission, according to certain scheduling criterion, based on the SINR feedback information. OSDMA is known to effectively exploit multiuser diversity via user selection, and provide multiplexing gain by transmitting parallel data streams over orthonormal beams [7]. The performance of the OSDMA is limited if there are not a sufficient number of users or there are not large and fast channel fluctuations.

To effectively amplify the gain due to multiuser diversity (especially when the number of users in the system is low), we propose a new OSDMA scheme employing beam selection (OSDMA-S). In our proposed scheme, the base station constructs multiple sets of B orthonormal beamforming vectors during a training period. A method to construct random sets of orthonormal beams is given in [36]. Alternatively, random sets of orthonormal beams can be generated via singular value decomposition of randomly generated matrices of independent identically distributed (i.i.d.) complex Gaussian coefficients. Then, the set of beams that maximizes the sum capacity is selected, and parallel data streams are transmitted over the B orthogonal beams to different users. More details on the criterion used to select the optimal set of beams and users are provided in the next subsection. In practice, we assume that every time slot of length L has a training period consisting of M *minislots* of length τ each. The maximum value of M is $\lfloor \frac{L}{\tau} \rfloor$, where $\lfloor \cdot \rfloor$ is the floor function. That is, τM duration is used for training and $L - \tau M$ duration is used for data transmission in every time slot. The case of $M = 1$ corresponds to the OSDMA without training or OBF without training. In every minislot, B random orthonormal vectors $\{\mathbf{v}_{b,m} \in \mathbb{C}^{N_t \times 1}, m = 1, \ldots, M\}$ are generated, where the subscripts b and m denote the beam index and the minislot index, respectively. Then, B pilot symbols $\{s_b\}$ are multiplied by the respective beamforming vectors $\mathbf{v}_{b,m}$ and are transmitted over the wireless link at every minislot ($m = 1, \ldots, M$). The symbols $\{s_b\}$ are selected from a Gaussian codebook.

If we assume that the channels for all the users are static during a time slot, the signal received at user u in the mth minislot is given by

$$y_{u,m} = \sum_{b=1}^{B} \mathbf{h}_u^T \mathbf{v}_{b,m} s_b + n_u, \quad \text{for } u = 1, \ldots, U \tag{1}$$

where $\mathbf{h}_u \in \mathbb{C}^{N_t \times 1}$ is the channel vector for the uth user with i.i.d. complex Gaussian entries $\sim CN(0, 1)$, $\mathbf{v}_{b,m} \in \mathbb{C}^{N_t \times 1}$ is the bth random beamforming vector at the mth minislot, s_b is the bth transmit pilot symbol, and $n_u \in \mathbb{C}^1$ is the complex zero-mean additive Gaussian noise vector with variance N_o. The superscript T denotes the vector transpose. Moreover, we assume $\mathbb{E}[|s_m|^2] = P/B$, such that the total transmit power is P.

B. Algorithm Description

In every minislot, the uth user computes the following B values of SINR by assuming that s_b is the desired pilot signal (known both at the transmitter and receiver), while the other s_i's are treated as interference as

$$\mathrm{SINR}_{u,b,m} = \frac{|\mathbf{h}_u^T \mathbf{v}_{b,m}|^2}{1/\rho + \sum_{l \neq b} |\mathbf{h}_u^T \mathbf{v}_{l,m}|^2} \tag{2}$$

where $\rho = P/N_\mathrm{o}$ is the input SNR. Note that the random variables $\mathrm{SINR}_{u,b,m}$ are i.i.d. for $u = 1, \ldots, U$, whereas for $b = 1, \ldots, B$ and for $m = 1, \ldots, M$, are identically distributed but not independent. We assume, however, that $\mathrm{SINR}_{u,b,m}$ are i.i.d. in b and m as well for analytical tractability. The validity of this assumption is later justified by simulations, as in [35].

For every minislot, each user feeds back its maximum SINR (i.e., $\max_{1 \le b \le B} \mathrm{SINR}_{u,b,m}$ for a given minislot m) along with the index b in which the SINR is maximized. The transmitter computes the throughput R_m for all minislots as

$$R_m \triangleq \sum_{b=1}^{B} \log\left(1 + \max_{1 \le u \le U} \mathrm{SINR}_{u,b,m}\right), \quad \text{for } m = 1, \ldots, M. \tag{3}$$

Even though there is a small possibility that user u is the strongest for more than one signal s_b, we neglect this small probability because this is very unlikely as U increases. Therefore, we ignore the probability that user u has the maximum SINR for different b. If this is the case, the transmitter chooses another user with the second largest SINR user, so that B different users are assigned in every slot.

The base station determines a subset of B users (and corresponding beams allocated to those users) based on R_m in (3) for every minislot. After one training period (consisting of M minislots), the transmitter has M candidate sets of B users (and corresponding beams allocated to those users). Then, the transmitter selects the subset of users (and corresponding beams) with the largest R_m among the M candidates, according to maximum rate scheduling policy [37]–[39]. Let the required bits for quantizing R_m be Q, the total amount of required feedback per user becomes $M(\log_2 B + Q)$ bits (refer to Table I for other opportunistic MIMO techniques). Finally, parallel data streams are transmitted over the current time slot through the B selected beams, and the resulting throughput is given by

$$R \triangleq (L - \tau M) \max_{1 \le m \le M} R_m \tag{4}$$

where τM is the total overhead due to training. Note that, alternatively, different scheduling criteria can be applied for this user selection, and we will consider them in future work.

III. Information Theoretic Capacity of OSDMA With Beam Selection

Hereafter, we derive an analytical expression for the sum rate capacity in (4) that we use to determine the optimum number of minislots M, in the sense of maximum erogodic throughput, as a function of the SINR, number of users, number of transmit antennas, and training overhead. Although a long training period (i.e., large M) can increase the multiuser diversity gain, it reduces throughput due to a large training overhead. Therefore, the optimal value of M has to be computed to maximize ergodic throughput as

$$M^{\mathrm{opt}} = \arg \max_{m = 1, \ldots, \lfloor \frac{L}{\tau} \rfloor} \mathbb{E}[R] \tag{5}$$

with

$$\mathbb{E}[R] = (L - \tau M) \mathbb{E}\Big[\max_{1 \le m \le M} R_m\Big] \tag{6}$$

where R is defined as in (4). Because it is hard to obtain a closed-form expression of $\mathbb{E}[R]$, we consider an upper bound on $\mathbb{E}[R]$ expressed in terms of M to find the optimum value of M. By using order statistic theory on an upper bound on the maximum random variable [40, p. 62, eq. (4.2.6)], the following upper bound on $\mathbb{E}[\max_{1\le q\le Q} R_q]$ can be obtained by

$$\mathbb{E}\Big[\max_{1\le m\le M} R_m\Big] \le \mathbb{E}[R_m] + \frac{M-1}{\sqrt{2M-1}}\sqrt{\mathrm{Var}[R_m]} \qquad (7)$$

where R_m is defined in (3), and $\mathbb{E}[R_m]$ and $\mathrm{Var}[R_m]$ can be computed with the probability density function (pdf) of $\max_{1\le u\le U} \mathrm{SINR}_{u,b,m}$. Since $\mathbf{h}_u$ is an i.i.d. complex Gaussian channel vector, the pdf $f_s(x)$ of $\mathrm{SINR}_{u,b,m}$ is given by [7]

$$f_s(x) = \frac{e^{-x/\rho}}{(1+x)^B}\left(\frac{1}{\rho}(1+x)+B-1\right) \qquad (8)$$

and the cumulative density function (cdf) $F_s(x)$ is

$$F_s(x) = 1 - \frac{e^{-x/\rho}}{(1+x)^{B-1}}. \qquad (9)$$

Therefore, the pdf of $\max_{1\le u\le U} \mathrm{SINR}_{u,b,m}$ is $f_{\max}(x) = Uf_s(x)F_s^{U-1}(x)$, and $\mathbb{E}[R_m]$ and $\mathrm{Var}[R_m]$ are computed as [7]

$$\mathbb{E}[R_m] = B\int_0^\infty \log(1+x)Uf_s(x)F_s^{U-1}(x)dx \qquad (10)$$

$$\mathrm{Var}[R_m] = B\left[\int_0^\infty (\log(1+x))^2 Uf_s(x)F_s^{U-1}(x)dx - \left(\int_0^\infty \log(1+x)Uf_s(x)F_s^{U-1}(x)dx\right)^2\right]. \qquad (11)$$

Unfortunately, it is not possible to derive closed-form expressions of (10) and (11), and we rely on numerical integrations to compute $\mathbb{E}[R_m]$ and $\mathrm{Var}[R_m]$.

Substituting (7) into (6), we derive the following upper bound on the ergodic sum capacity

$$\mathbb{E}[R] \le (L-\tau M)\left[\mathbb{E}[R_m] + \frac{M-1}{\sqrt{2M-1}}\sqrt{\mathrm{Var}[R_m]}\right] \qquad (12)$$

and substituting (12) into (5), we derive the optimal value of M as

$$M^{\mathrm{opt}} = \underset{M=1,\ldots,\lfloor \frac{L}{\tau}\rfloor}{\arg\max}\left[\mathbb{E}[R_m] + \frac{M-1}{\sqrt{2M-1}}\sqrt{\mathrm{Var}[R_m]}\right] \qquad (13)$$

where we note that $\mathbb{E}[R_m]$ and $\mathrm{Var}[R_m]$ are not dependent on M. Hereafter, we show numerically that the value of M corresponding to the maximum of $\mathbb{E}[R]$ is the same as for the maximum of the upper bound in (12). Hence, (13) is in fact the optimal value of M.

Fig. 2 shows the normalized ergodic sum capacity versus the number of mini-slots M used for training, for different numbers of users (U). The ergodic sum capacity is obtained from (6) through Monte Carlo simulations, and from the upper bound in (12) computed through numerical integrations in Mathematica. These results assume SNR $= 10$ dB, $\tau/L = 5\%$, and $B = N_t = 4$. Note that the upper bound closely follows the empirical curves, especially for large number of users and low values of M. Moreover, for a given U, the capacity increases up to certain value of M due to the benefit of beam selection, and decreases afterwards due to the increasing training overhead. We observe that the optimal number of mini-slots (M^{opt}), corresponding to the maximum value of capacity, is

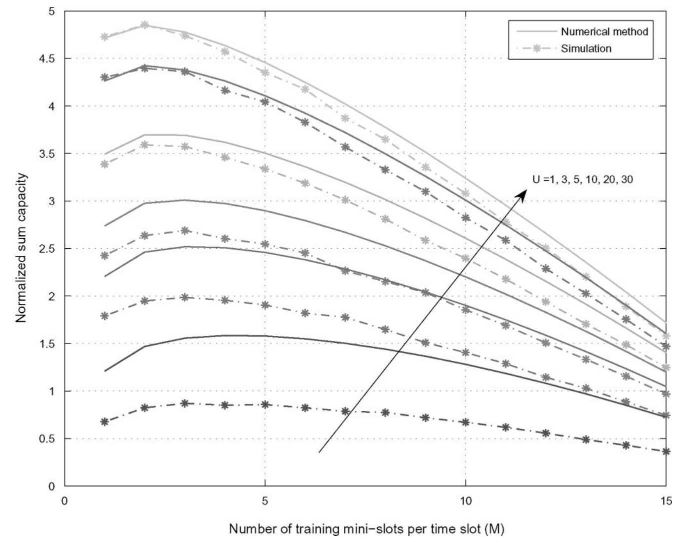

Fig. 2. Normalized throughput obtained through simulations and numerical method, assuming SNR $= 10$ dB, $\tau/L = 5\%$, and $B = N_t = 4$.

the same for both the empirical and numerical curves, for any number of users. Therefore, it is possible to use (13) to compute M^{opt}, reducing the computational complexity of the performance evaluation of our proposed OSDMA scheme. In Fig. 2, we observe that the value of M^{opt} decreases as the number of users increases due to the larger gain offered by the multiuser diversity against beam selection. Moreover, $M^{\mathrm{opt}} \le 5$ for any number of user reveals that the capacity gains of OSDMA with beam selection are available for a small number of training mini-slots (i.e., a small amount of feedback for the SINR information).

Next, we compute upper bounds on $\mathbb{E}[R_m]$ and $\mathrm{Var}[R_m]$ to avoid the numerical integrations in (10) and (11). By using Jensen's inequality and order statistic theory on an upper bound on the maximum random variable [40, p. 62, eq. (4.2.6)], an upper bound on $\mathbb{E}[R_m]$ is obtained as

$$\mathbb{E}[R_m] = B\mathbb{E}\left[\log(1+\max_{1\le u\le U}\mathrm{SINR}_{u,b,m})\right] \qquad (14)$$

$$\le B\log\left(1+\mathbb{E}\left[\max_{1\le u\le U}\mathrm{SINR}_{u,b,m}\right]\right) \qquad (15)$$

$$\le B\log\left(1+\mu+\frac{U-1}{\sqrt{2U-1}}\sigma\right) \qquad (16)$$

where μ and σ are the mean and standard deviation of $\mathrm{SINR}_{u,b,m}$, given by

$$\mu = \int_0^\infty \frac{xe^{-x/\rho}}{\rho(1+x)^{B-1}} - \frac{(B-1)xe^{-x/\rho}}{(1+x)^B}dx \qquad (17)$$

$$\sigma^2 = \int_0^\infty \frac{x^2e^{-x/\rho}}{\rho(1+x)^{B-1}} - \frac{(B-1)x^2e^{-x/\rho}}{(1+x)^B}dx - \mu^2. \qquad (18)$$

The closed-form expressions of μ and σ can be obtained by the following integral formula [41]:

$$\int_0^\infty \frac{e^{-x/\rho}}{(1+x)^n}dx = \begin{cases} -e^{1/\rho}\mathrm{Ei}\left(-\frac{1}{\rho}\right), & n=1 \\ \rho e^{1/\rho}\mathrm{Ei}\left(-\frac{1}{\rho}\right)+1, & n=2 \\ \frac{1}{(n-1)!}\sum_{k=1}^{n-1}(k-1)!\left(-\frac{1}{\rho}\right)^{n-k-1} \\ \quad -\frac{(-1/\rho)^{n-1}}{(n-1)!}e^{1/\rho}\mathrm{Ei}\left(-\frac{1}{\rho}\right), & n>2 \end{cases}$$

where $\mathrm{Ei}(x)$ is the exponential integral function defined by $\mathrm{Ei}(x) = -\int_{-x}^{\infty} e^{-t}/t\,dt$. For example, μ and σ when $B=4$ are given by

$$\mu = \frac{1}{\rho^2}\left(\frac{5}{2}+\frac{1}{\rho}\right)e^{1/\rho}\mathrm{Ei}\left(-\frac{1}{\rho}\right)+\frac{1}{\rho^2}+\frac{3}{2\rho}-\frac{1}{2} \quad (19)$$

$$\sigma^2 = -\frac{1}{\rho}\left(4+\frac{5}{\rho}+\frac{1}{\rho^2}\right)e^{1/\rho}\mathrm{Ei}\left(-\frac{1}{\rho}\right) - \frac{1}{\rho^2}-\frac{7}{2\rho}+2-\mu^2. \quad (20)$$

An upper bound on $\mathrm{Var}[R_m]$ can be obtained by using Jensen's inequality and order statistic theory on an upper bound on the maximum random variable [40, p. 62, eq. (4.2.6)]

$$\begin{aligned}\mathrm{Var}[R_m] &= \mathrm{Var}\left[\sum_{b=1}^{B}\log\left(1+\max_{1\le u\le U}\mathrm{SINR}_{u,b,m}\right)\right] \\ &= B\mathrm{Var}\left[\log\left(1+\max_{1\le u\le U}\mathrm{SINR}_{u,b,m}\right)\right] \\ &= B\mathbb{E}\left[\left(\log\left(1+\max_{1\le u\le U}\mathrm{SINR}_{u,b,m}\right)\right)^2\right] \\ &\quad - B\left(\mathbb{E}\left[\log(1+\max_{1\le u\le U}\mathrm{SINR}_{u,b,m})\right]\right)^2 \\ &\le B\left(\log\left(1+\mathbb{E}\left[\max_{1\le u\le U}\mathrm{SINR}_{u,b,m}\right]\right)\right)^2 \\ &\quad - B\left(\mathbb{E}\left[\log(1+\max_{1\le u\le U}\mathrm{SINR}_{u,b,m})\right]\right)^2 \quad (21) \\ &\le B\left(\log\left(1+\mu+\frac{U-1}{\sqrt{2U-1}}\sigma\right)\right)^2 \\ &\quad - B\left(\mathbb{E}\left[\log(1+\max_{1\le u\le U}\mathrm{SINR}_{u,b,m})\right]\right)^2 \quad (22)\end{aligned}$$

where the inequality (21) comes from Jensen's inequality based on the fact that $(\log(\cdot))^2$ is a concave function. The inequality holds from the result of order statistic theory used in (7). Unfortunately, it is difficult to obtain a closed expression for the second term in (22). A closed-form tight lower bound on the second term in (22) is also difficult to derive. Therefore, a closed-form upper bound on $\mathrm{Var}[R_m]$ with reasonable accuracy is unavailable.

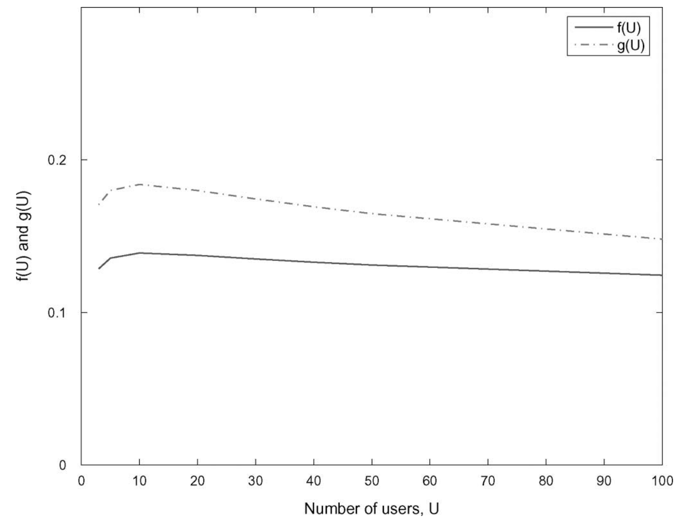

Fig. 3. Tight upper bound on $f(U) \triangleq \mathrm{Var}[\log(1+\max_{1\le u\le U}\mathrm{SINR}_{u,b,m})]$ when $\alpha = 0.75$.

In practical communication systems employing OSDMA-S, it may be desirable to adaptively compute M^{opt} as the number of users varies, to maximize the system performance in any scenario. Hence, we empirically derive a closed-form upper bound on (22) as an alternative to a mathematical closed-form upper bound, and analytically calculate M^{opt} as a function of U by substituting (16) and (22) into (12).

Let

$$f(U) \triangleq \mathrm{Var}\left[\log\left(1+\max_{1\le u\le U}\mathrm{SINR}_{u,b,m}\right)\right] \quad (23)$$

$$g(U) \triangleq \left(\log\left(1+\mu+\frac{U-1}{\sqrt{2U-1}}\sigma\right)\right)^2 - \left(\log\left(\alpha+\mu+\frac{U-1}{\sqrt{2U-1}}\sigma\right)\right)^2. \quad (24)$$

Then, we can guarantee $f(U) \le g(U)$ in the interested region of U by properly selecting the value of α. When $B = N_t = 4$ and SNR is 10 dB, we empirically found that $g(U)$ provides a tight upper bound on $f(U)$ if α is around 0.75 as in Fig. 3.

Using (23) and (24), the empirical upper bound on $\mathrm{Var}[R_m]$ can be obtained by

$$\mathrm{Var}[R_m] \le B\left(\log\left(1+\mu+\frac{U-1}{\sqrt{2U-1}}\sigma\right)\right)^2 - B\left(\log\left(0.75+\mu+\frac{U-1}{\sqrt{2U-1}}\sigma\right)\right)^2. \quad (25)$$

Fig. 4 compares the empirical ergodic sum capacity in (6) against the analytical upper bound obtained by substituting (16) and (25) into (12). We observe that this bound is looser than the one shown in Fig. 2, due to the bounds in (16) and (22). The value of M^{opt}, however, is still the same for both the empirical and analytical curves, for any number of users. Based on these results, the analytical expressions can be used to determine an

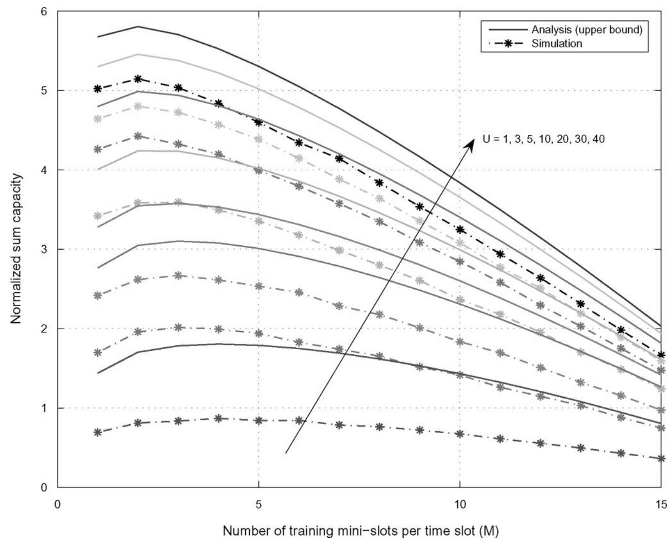

Fig. 4. Normalized through put obtained through simulations and analytical method, assuming SNR $= 10$ dB, $\tau/L = 5\%$, and $B = N_t = 4$.

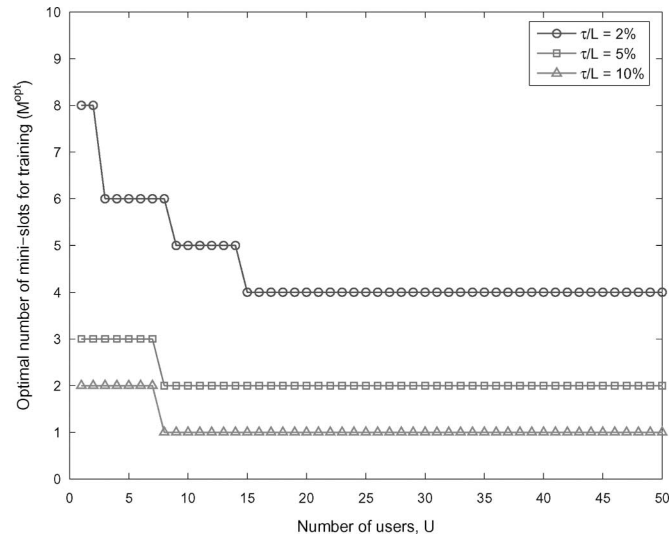

Fig. 5. Optimal number of minislots (M^{opt}) for OSDMA versus U, for different normalized lengths of minislot (τ/L), with $B = N_t = 4$.

appropriate M^{opt} with reduced computational complexity for Rayleigh fading channels.

IV. Performance Results

In this section, we first compute, through simulations, the optimal number of minislots used for training in the proposed OSDMA-S scheme. Then, we compare the performance of the proposed OSDMA-S against conventional OBF, OBF-S, and OSDMA by using the theoretical capacity results derived in Section III.

A. Optimal Number of MiniSlots for Training (M^{opt}) in the Proposed OSDMA-S

We evaluate the optimal number of minislots used for training as a function of the number of users (U), SNR, the number of transmit antennas ($N_t = B$), and the length of the minislots (τ/L) through simulation. It should be noted, however, that the same value of M^{opt} can also be obtained through the analytical results in Section III, as shown through Fig. 2 and 4.

In Fig. 5, the values of M^{opt} are plotted as a function of U for different normalized mini-slot lengths (τ/L), with $B = N_t = 4$. The value of M^{opt} decreases for increasing the number of users (as for the previous results) and the length of the minislots. We observe that for a fixed number of users, different values of τ/L yield similar values of percentage overhead ($M\tau/L$) due to training. For example, when 10 users are in the system, all three values of minislot length in Fig. 5 produce the same training overhead $M^{\mathrm{opt}}\tau/L = 10\%$. Moreover, higher training overhead (i.e., $M^{\mathrm{opt}}\tau/L \sim 15\%$) is required for lower number of users (i.e., $U < 5$) to achieve the maximum sum capacity, due to lack of multiuser diversity gain.

B. Performance Comparison Against Conventional OBF

Hereafter, we compare the performance of the proposed OSDMA-S (with $B = N_t$) against conventional OBF and OBF-S schemes (with $B = 1$) presented in [32] for $M = 1$ and in [35], for $M = M^{\mathrm{opt}}$.

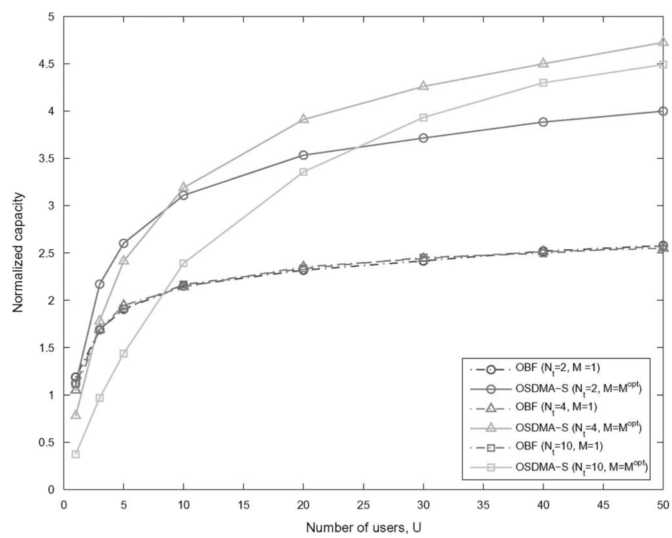

Fig. 6. Normalized sum capacity of OSDMA (with $M = M^{\mathrm{opt}}$ and $B = N_t$) and OBF (with $M = 1$ and $B = 1$) as a function of the number of users for different values of N_t, with SNR $= 5$ dB and $\tau/L = 5\%$.

Fig. 6 shows the normalized sum capacity of OSDMA-S and OBF in [32] as a function of the number of users, with different values of N_t, $\tau/L = 5\%$, and $\mathrm{SNR} = 5$ dB. We observe that for small number of users (i.e., < 10) and $N_t = 10$, OSDMA-S performs worse than the OBF due to the interference between different users. As the number of users served at the same time ($B = N_t$) via SDMA decreases, the interference is reduced, resulting in better performance of OSDMA-S. Moreover, for a large number of users, OSDMA-S always outperforms OBF due to the multiplexing gain of SDMA. Interestingly, the case of $B = N_t = 10$ never outperforms $B = N_t = 4$ due to the increased amount of spatial interference and the high dimensionality of the random beamforming—the probability that the

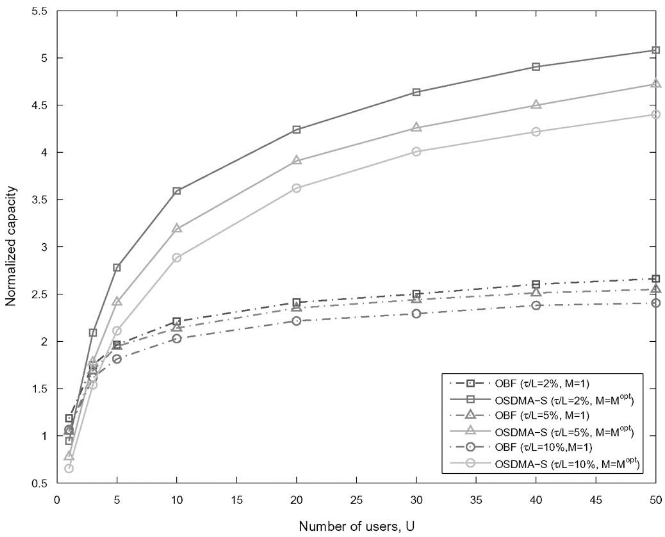

Fig. 7. Normalized sum capacity of OSDMA (with $M = M^{\mathrm{opt}}$ and $B = N_t$) and OBF (with $M = 1$ and $B = 1$) as a function of the number of users for different values of τ/L, with SNR $= 5$ dB and $N_t = 4$.

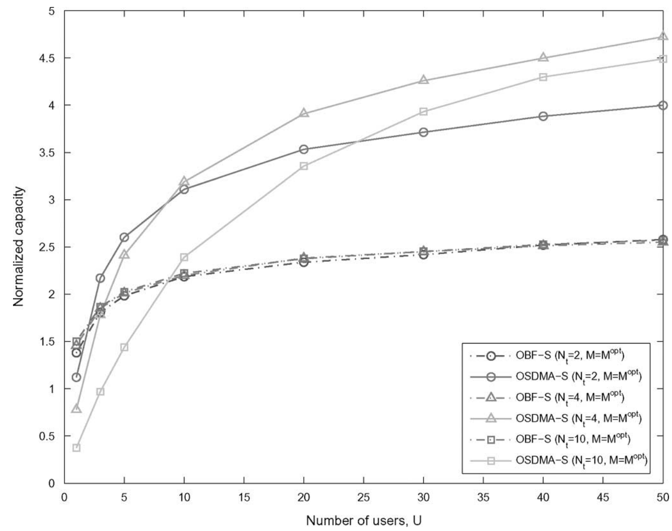

Fig. 8. Normalized sum capacity of OSDMA (with $M = M^{\mathrm{opt}}$ and $B = N_t$) and OBF (with $M = M^{\mathrm{opt}}$ and $M = 1$) as a function of the number of users for different values of N_t, with SNR $= 5$ dB and $\tau/L = 5\%$.

random beamforming configuration becomes the optimal beamforming configuration decreases with the number of antennas. OSDMA-S with $N_t = 4$ outperforms other antenna configurations if $U > 10$, while $N_t = 2$ achieves the highest capacity for a low number of users.

Similar results are shown in Fig. 7 where the sum capacity versus U is plotted for different values of minislot length (τ/L), with $N_t = 4$ and SNR $= 5$ dB. The performance of OBF decreases for increasing values of τ/L due to the larger overhead for training. On the other hand, the training overhead ($M^{\mathrm{opt}}\tau/L$) of OSDMA-S is almost constant for the various values of τ/L, as observed in Fig. 5. Then, the increased capacity for smaller minislot lengths is due to the larger number of minislots (M^{opt}), which yields more degrees of freedom for beam selection. This capacity gain is obtained, however, at the cost of higher feedback overhead over the uplink channel to transmit the users' SINR information corresponding to each of the training mini-slots.

In Fig. 8, we compare OSDMA-S versus OBF-S with $M = M^{\mathrm{opt}}$ as in [35], for different values of N_t, $\tau/L = 5\%$, and SNR $= 5$ dB. Once more, OSDMA-S outperforms OBF-S, especially for large number of users, due to the multiplexing gain of SDMA. By comparing Fig. 8 against Fig. 7, we observe that OBF-S with $M = M^{\mathrm{opt}}$ yields higher sum capacity than does OBF with $M = 1$ because of the higher degrees of freedom in the selection of the optimal beamforming weights. This gain, however, is not enough to reach the multiplexing gain of OSDMA-S.

C. Performance Comparison Against OSDMA Without Training

Finally, we compare the performance of OSDMA with and without beam selection. For the case of no beam selection, we assume $M = 1$ and $B = N_t$, as in [7].

Fig. 9 depicts the capacity of different OBF and OSDMA schemes as a function of the number of users. We assume that $N_t = 4$, $\tau/L = 2\%$, and SNR $= 5$ dB. We observe that

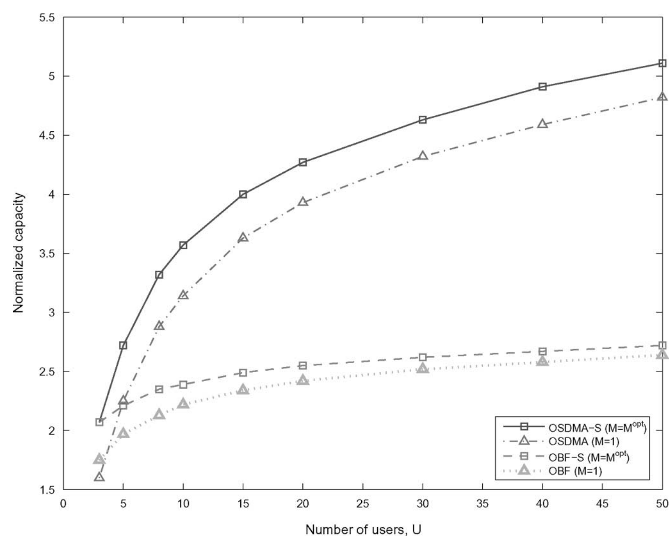

Fig. 9. Performance comparison of OBF and OSDMA schemes with and without beam selection as a function of the number of users U, with SNR $=$ 5 dB, $\tau/L = 2\%$, and $B = N_t = 4$.

OSDMA-S always outperforms OSDMA, without training for any value of U. Although the gain of OSDMA-S over OSDMA without training is almost constant, the gain of our method corresponds to 20% gain in sum capacity over OSDMA without training for $U = 5$, while this gain is reduced to 5% for $U = 50$. For increasing number of users, the relative performance of our proposed scheme converges to OSDMA without training, since the gain due to multiuser diversity becomes dominant compared to the gain of beam selection. Note that the gains achievable through beam selection come at the expense of the increased feedback required to convey the SINR information from the users to the base station during the training period. As an example, for the case of 50 users, the capacity gain shown in Fig. 9 is obtained at a cost of $M^{\mathrm{opt}} = 4$ SINR feedbacks per user according to Fig. 5.

TABLE I
COMPARISON OF VARIOUS OPPORTUNISTIC MIMO TECHNOLOGIES

Technique	**OBF (Opportunistic Beamforming) [32]**	**OBF-S (Opportunistic Beamforming with Selection) [35]**	**OSDMA (Opportunistic Space Division Multiple Access) [7]**	**OSDMA-S (Opportunistic Space Division Multiple Access with Beam Selection)**
Amount of required feedback per user[1]	Q bits	MQ bits	($\log_2$B+Q) bits	M($\log_2$B+Q) bits
Relative sum capacity gain over OBF[2]	-	8 %	40 %	60 %
Pros	Significantly reduced feedback.	Provides meaningful multiuser diversity gain even for a small number of users.	Exploits both multiuser diversity gain and multiplexing gain.	Provides significant multiuser diversity gain and multiplexing gain even for a small number of users.
Cons	Marginal gain for a small number of users. No multiplexing gain.	No multiplexing gain.	Multiuser diversity gain becomes marginal for a small number of users.	Increased feedback due to training.

Notes) 1. Assume that Q bits are required for quantizing SINR or data rate (R_m).
2. Relative capacity gain is computed for the condition that $K=10$, $N_t=4$, SNR = 5 dB, and $\tau/L=2\%$.

Note that the system parameters τ/L and N_t can be adjusted to maximize the sum capacity for a given constraint on the training overhead. For example, consider a system with $U=10$ users, $N_t=B=4$ transmit antennas, and $Q=12$ bits used to quantize the SINR information. Under these conditions, from Fig. 5, we observe that the optimal numbers of minislots for the case of $\tau/L=2\%$, 5%, and 10% are $M^{\rm opt}=5$, 2, and 1, respectively. Note that for all three scenarios, the training overhead is fixed to $M^{\rm opt}\tau/L=10\%$, enabling a fair comparison between different cases. In these three cases, the feedback overhead in Table I is 20, 8, and 4 bits, respectively, while the normalized sum capacity is 3.6, 3.2, and 2.9 bits/s/Hz, respectively, as shown in Fig. 7. Hence, for a fixed constraint on the training overhead, we can increase the capacity at the expense of larger feedback overhead.

Fig. 9 also shows the capacity of different OBF techniques. We observe that OSDMA-S provides significant capacity gains over OBF, especially for a large number of users, due to SDMA. Interestingly, for $U=3$, our proposed technique has the same performance as OBF-S due to the adverse effect of the interference, while yielding 20% and 30% gains over conventional OBF and OSDMA, respectively. Table I provides an overall comparison among OBF, OBF-S, OSDMA, and OSDMA-S.

D. Discussion on Different Channel Models

In this paper, we assume an uncorrelated Rayleigh fading channel in the time domain. We observe that larger performance gains are expected from the proposed method in temporally correlated channels (with Doppler effect), consistent with the results shown in [32] for OBF scheme. Both opportunistic beamforming and opportunistic SDMA are designed to produce artificial channel fluctuations to amplify the multiuser diversity gain under opportunistic scheduling. These intentional channel fluctuations are more effective in the context of channels with small variations. That is, the multiuser diversity gain will be larger in Rician fading channels (with large K-factor) or slow fading Rayleigh channels. For example, it is shown in [32] that opportunistic beamforming is more effective in Rician fading channels than that in Rayleigh fading channels. Similar results are expected for the OSDMA scheme. In future work, we will evaluate the gains attainable from OSDMA as a function of the Doppler frequency of the channel.

V. CONCLUSION

We presented a novel transmission scheme for the MIMO broadcast channel. This scheme combines OSDMA without training with beam selection, yielding gains in sum capacity for any number of users. Our technique generalizes both conventional OBF by enabling parallel transmission to multiple users, and OSDMA without training by using beam selection to yield capacity benefit. The main advantage of the proposed system is that it provides throughput gains with a small feedback overhead, even for a small number of active users. We first computed the theoretical sum capacity of our scheme, accounting for the penalty due to training overhead. We used this capacity expression to derive the optimal number of minislots used for training. Finally, we compared the performance of our scheme against conventional OBF and OSDMA transmission techniques, showing up to 20% capacity gains over OSDMA without training, and a 100% gain (for a large number of users) over conventional OBF.

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