This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE ICC 2010 proceedings

Multi-antenna Downlink Broadcast using Compressed-Sensed Medium Access

Linda M. Davis
Inst. for Telecommunications Research
University of South Australia
linda.davis@unisa.edu.au

Stephen V. Hanly, Paul Tune
Dept. Electrical & Electronic Engineering
University of Melbourne
{s.hanly,lsptune}@ee.unimelb.edu.au

Sibi Raj Bhaskaran
Dept. Electrical Engineering
Indian Institute of Technology, Mumbai
bsraj@ee.iitb.ac.in

***Abstract*—In this paper, we propose a method for user selection and channel estimation using compressed sensing. In particular, we consider a multiple-input multiple-output (MIMO) downlink broadcast scenario. We establish that full channel state information (and not just channel quality) for each self-selecting user can be obtained at the basestation via compressed sensing with no increase in overhead for the uplink feedback channel. We demonstrate the new method as a medium access technique for MIMO downlink broadcast with transmitter precoding and linear receiver processing.**

***Index Terms*—compressed sensing, broadcast, user selection, scheduling, channel estimation, MIMO.**

I. Introduction

Consider the wireless communication scenario in which a large number of mobile users are being serviced by a single basestation. When the number of users is greater than the number of service slots available, the basestation must select a subset of users, taking into consideration the channel conditions, user demand and fairness.

In the present paper we consider the downlink, and assume multiple antennas at both the base station and mobile: the MIMO broadcast channel. Let the basestation transmitter have N_t antennas. There are K mobile users in the system, each with N_r receive antennas. We focus on the case where the number of antennas at the basestation is relatively small compared with the number of users in the cell. The basestation is tasked with selection and scheduling K_s users in each slot. Since the number of degrees of spatial freedom in the downlink is $\min(N_t, K)$, the basestation employing full diversity can transmit to at most $K_s = N_t$ selected users simultaneously.

Ideally, the process of user selection has knowledge of the downlink channel state information (CSI) from all users and employs a centralized user-selection algorithm. A common approach is to obtain CSI from user estimates fed back via the uplink channel, requiring a large signalling overhead, proportional to K. Various limited feedback schemes have been proposed, for example, using channel quality information (CQI) based on signal to interference plus noise ratio (SINR) [2], channel direction information (CDI) [3], and quantized channel state information [4], [5].

A recent and promising alternative was presented in [6], where a distributed self-selection procedure was combined with compressed sensing to identify a set of users ($K_{ss} \geq K_s$) with simultaneous access to a single-input single-output (SISO) broadcast channel. Recognising that the selected set is much smaller than the set of all users, the proposed technique reduces the overhead for obtaining CSI via the feedback channel, proportional to $K_{ss} \ll K$. In the proposed scheme of [6], the CQI was obtained for K_{ss} users via compressed sensing, and the CSI for the subset of $K_s \leq K_{ss}$ basestation selected users was then requested from those users.

In this paper, we extend the work of [6] in two ways. Firstly, we establish that compressed sensing can obtain full CSI (not just CQI) from each of the self-selecting users in a TDD system. Using compressed sensing, the basestation simultaneously obtains the set of target users and their channel estimates. Secondly, we make the non-trivial extension to MIMO systems, and demonstrate how this new compressed-sensed medium access technique can be used in combination with transmitter precoding and beamforming for the multiuser MIMO broadcast channel.

Our proposed multi-user selection and MIMO broadcast scheme has four phases: user self-selection (Section II); compressed-sensing for user detection and channel estimation (Section III); transmitter refinement of the set of selected users and calculation of precoding vectors (Section IV); and, data communication (Section V).

II. User Self-Selection

As in [6], the users first independently self-select based on their own channel conditions. We now consider the general MIMO case for user k. The $N_r \times 1$ received vector for a symbol transmitted in slot n is given by

$$\mathbf{r}_k = \mathbf{H}_k \mathbf{x} + \mathbf{n}_k \tag{1}$$

The $N_r \times N_t$ channel matrix $\mathbf{H_k}$ contains complex coefficients representing flat-fading channels, $\mathbf{x}$ is the $N_t \times 1$ transmitted (broadcast) vector and $\mathbf{n}_k$ is the noise at the receiver for user k, assumed to be complex white Gaussian with variance $\sigma_n^2 \mathbf{I}$. We assume that the channels between the transmitter antennas and the receiver antennas are iid Rayleigh flat-fading with $E[||h_{k,ij}||^2] = 1$ for all paths $i = 1, \ldots, N_t$; $j = 1, \ldots, N_r$.

For the SISO case presented in [6], i.e. $N_t = N_r = 1$, users self-select by comparing their channel quality with a threshold τ_k. The channel quality for the SISO case is in effect the signal to noise ratio: $\text{CQI}_k \triangleq \frac{P}{\sigma_n^2}||h_{k,11}||^2$, where P is the transmitter

978-1-4244-6404-3/10/$26.00 ©2010 IEEE

power. In Section II-A, we extend this to the MIMO setting, with a channel quality test based on predicted SINR.

A. MIMO Channel Quality Indicator

In this section we derive a CQI for the MIMO broadcast channel. If user k is selected, the transmitted vector will be

$$\mathbf{x} = \sqrt{p_k}\tilde{\mathbf{w}}_k d_k + \sum_{j=1, j\neq k}^{K_s} \sqrt{p_j}\tilde{\mathbf{w}}_j d_j \tag{2}$$

where p_k the power allocated to user k and $\tilde{\mathbf{w}}_k$ is the unit-norm beamforming vector for user k. The data symbol for user k is denoted d_k. At the receiver of user k, linear processing is applied to obtain

$$r_k = \sqrt{p_k}\tilde{\mathbf{u}}_k^\dagger \mathbf{H}_k \tilde{\mathbf{w}}_k d_k + \tilde{\mathbf{u}}_k^\dagger \mathbf{H}_k \sum_{j=1, j\neq k}^{K_s} \sqrt{p_j}\tilde{\mathbf{w}}_j d_j + \tilde{\mathbf{u}}_k^\dagger \mathbf{n}_k \tag{3}$$

where $\tilde{\mathbf{u}}_k$ is the unit-norm receive vector and $(\cdot)^\dagger$ denotes complex conjugate transpose.

Ultimately, once the base station has obtained CSI from all the users, it selects users and computes precoding (i.e. beamforming) vectors. However, at the self-selection stage, users do not have prior knowledge of who will be selected, nor the channel state of any other users but themselves. We seek a CQI based on SINR that can be calculated by each user with only their own channel information, $\mathbf{H}_k$.

The strategy we adopt is to assume that the basestation will be able to select a set of users with orthogonal MISO channels $\mathbf{v}_k^\dagger = \tilde{\mathbf{u}}_k^\dagger \mathbf{H}_k$. With zero-forcing (ZF) precoding, $\tilde{\mathbf{w}}_k$ for orthogonal users is given by the CDI , $\tilde{\mathbf{v}}_k$ (i.e. normalized $\mathbf{v}_k$), and the SINR for user k is independent of $\tilde{\mathbf{w}}_j$, $j \neq k$. The optimal receiver combiner, $\tilde{\mathbf{u}}_k$, can then be shown to be the dominant left singular vector of $\mathbf{H}_k$, and the resulting SINR is $\text{SINR}_k = \dfrac{p_k}{\sigma_n^2}\lambda_k$ where λ_k is the maximum eigenvalue of the positive definite matrix $\mathbf{H}_k\mathbf{H}_k^\dagger$. We will use the SINR as computed here as the channel quality indicator for user k. We will denote the average transmit SNR by $\gamma = P/\sigma_n^2$, and user k's proportion of the total power, P, by $\tilde{p}_k$, and then we write

$$\text{CQI}_k = \tilde{p}_k \gamma \lambda_k. \tag{4}$$

We now have a method for each user to determine their CQI. During pilot symbol transmission from the basestation, the user estimates its channel matrix $\mathbf{H}_k$ and signal to noise ratio p_k/σ_n^2. From $\mathbf{H}_k\mathbf{H}_k^\dagger$, the maximum eigenvalue, λ_k, is obtained, and the CQI_k is calculated according to (4).

B. Thresholds for Self-Selection

Thresholds for self-selection may be set by the basestation and adapted based on system or individual link performance. For simplicity of exposition in this paper, we consider a common threshold τ for all users. The desired target for the number of self-selected users is K_s. Recognising that the number of self-selected users, K_{ss}, will be random, the user threshold must be set such that $K_{ss} > K_s$ with high probability, yet retain the property $K_{ss} \ll K$. In the case that $K_{ss} > K_s$, the basestation can refine the set of selected users, as discussed in Section IV.

To find the threshold, we define the desired fraction of users (sparsity) as $\xi = K_{\text{tar}}/K$. We seek the threshold τ such that

$$\Pr\left(\text{CQI}_k \tilde{p}_k \gamma \lambda_k > \tau\right) = \xi. \tag{5}$$

and for this, we need the distribution of the maximum eigenvalue, λ_k of the matrix $\mathbf{H}_k\mathbf{H}_k^\dagger$.

For the independent Rayleigh fading case, in which the entries of $\mathbf{H}_k$ are independent, identically distributed, zero mean, complex Gaussians, the cumulative distribution function of λ_k is known [7]. Indeed, $\mathbf{H}_k\mathbf{H}_k^\dagger$ is in this case a central, complex Wishart matrix, and with $m = \min\{N_r, N_t\}$, $n = \max\{N_r, N_t\}$, the cumulative distribution function of λ_k is given by

$$\Pr\left(\lambda_k \leq x\right) = \frac{\det(\Phi(x))}{\prod_{q=1}^{m}(n-q)!(m-q)!} \tag{6}$$

where $\Phi(x)$ is a m by m Hankel matrix, with (i,j)-th element $\gamma(n-m+i+j-1, x)$, and where $\gamma(s,x)$ is the lower incomplete Gamma function. We can use this result to obtain a τ for any target proportion of users $\xi = K_{\text{tar}}/K$ via a bisection search.

We note that the distribution of λ_k is particularly simple when $m = 1$, as is the case when either $N_t = 1$ (SIMO) or $N_r = 1$ (MISO). In both these cases, the distribution is Erlang(1, n), with $n = N_r$ in the SIMO case and $n = N_t$ in the MISO case, respectively, i.e.

$$\Pr\left(\lambda_k > x\right) = \exp(-x) \sum_{q=0}^{n-1} \frac{x^q}{q!} \tag{7}$$

and this reduces to the well known exponential distribution in the SISO case.

We will use this theoretical basis, (6) and (7), to set our threshold, τ. We note however, that a practical system might favour an adaptive approach to setting the threshold based on the number of self-selecting users as determined by the basestation.

III. Compressed Sensing for User Detection and Channel Estimation

Here we follow the key idea of [6], using compressed sensing to detect the set of K_{ss} self-selected users. We further demonstrate that for the same overhead, compressed sensing can be used directly to estimate the full CSI for the equivalent MISO channel $\mathbf{v}_k$ (and not just the CQI as in [6]) for each of the self-selected users. Due to the sparsity of the self-selected set, compressed sensing reduces the overhead in using the uplink to do this from $\mathcal{O}(K)$ to $\mathcal{O}(\log K)$.

Each user in the system is assigned a unique signature sequence vector $\mathbf{a}_k$ of length N_{obs}, and we use sequences generated by iid Bernoulli($\frac{1}{2}$) process with values ± 1. Each user knows its sequence, and the basestation knows the $N_{\text{obs}} \times K$ matrix of user sequences $\mathbf{A}$ with the k-th column given by $\mathbf{a}_k$. The choice of N_{obs} is discussed in [8]. The set

of self-selecting users signal the basestation on the uplink by transmitting their signature sequences, using their combining vector $\tilde{\mathbf{u}}_k$ as a beamformer. Those users whose CQI did not meet the threshold test transmit nothing. Thus, assuming a TDD system, N_{obs} observations are generated at each of the N_t basestation antennas, according to the $N_t N_{\text{obs}} \times 1$ model

$$\mathbf{y} = \sum_{k=1}^{K_{ss}} \mathbf{v}_k \otimes \mathbf{a}_k + \mathbf{z} \tag{8}$$

where $\otimes$ indicates a Kronecker product and $\mathbf{z}$ is the observation noise vector with variance σ_z^2. We note that the uplink channel has phase reversal and is comprised of the beamformer $\mathbf{u}_k$ and the uplink channel $\mathbf{H}_k^\dagger$, viz. $\mathbf{v}_k = \mathbf{H}_k^\dagger \tilde{\mathbf{u}}_k$. Separating the observations for each antenna, we have

$$\begin{aligned} \mathbf{y}_t &= \sum_{k=1}^{K_{ss}} \mathbf{a}_k v_{k,t} + \mathbf{z}_t & (9)\\ &= \mathbf{A}\left(\mathbf{s}.\mathbf{v}_t\right) + \mathbf{z}_t & (10)\\ &= \mathbf{A}\mathbf{x}_t + \mathbf{z}_t & (11) \end{aligned}$$

where $\mathbf{s}$ is a $K \times 1$ selection vector with ones for self-selecting users and zeros otherwise, and $\mathbf{v}_t$ is the vector of complex channel coefficients corresponding to the t-th element of each users effective channel $\mathbf{v}_k$. The $K \times 1$ vector $\mathbf{x}_t = (\mathbf{s}.\mathbf{v}_t)$ therefore contains the t-th channel coefficient for each user k if they self-selected, and zero otherwise. This is a sparse vector which can be obtained by compressed-sensing techniques such as ℓ_1 minimization. Separating the real and imaginary parts

$$\hat{\mathbf{x}}_{t,\Re} = \arg \min_{\mathbf{x}_{t,\Re} \in R^K} ||\mathbf{x}_{t,\Re}||_{\ell_1} \text{ subject to } \mathbf{A}\mathbf{x}_{t,\Re} = \mathbf{y}_{t,\Re} \tag{12}$$

$$\hat{\mathbf{x}}_{t,\Im} = \arg \min_{\mathbf{x}_{t,\Im} \in R^K} ||\mathbf{x}_{t,\Im}||_{\ell_1} \text{ subject to } \mathbf{A}\mathbf{x}_{t,\Im} = \mathbf{y}_{t,\Im} \tag{13}$$

and so $2N_t$ minimizations (i.e. real plus imaginary for each Tx antenna) are required to detect the self-selected users and estimate their equivalent channels.

As in [6], we favour use of an ℓ_2 minimization with a penalty term favoring solutions with low ℓ_1 norms, specifically the gradient projection algorithm for sparse reconstruction (GPSR) [9]. This algorithm not only offers relatively fast performance (compared with current and easily accessible ℓ_1 minimization algorithms), but also avoids the need for initialization. The optimization is of the form

$$\hat{\mathbf{x}}_{\text{GPSR}} = \arg \min_{\mathbf{x} \in R^K} \frac{1}{2}||\mathbf{y} - \mathbf{A}\mathbf{x}||_2^2 + \kappa||\mathbf{x}||_{\ell_1} \tag{14}$$

where κ is a non-negative parameter.

The output from the GPSR optimization will be a vector low in ℓ_1 norm. Since we seek only those users whose CQI meets the threshold test, we refine the estimate of $\mathbf{x}$ by applying the same (or slightly looser threshold to allow for estimation error) threshold, thus enforcing the sparsity on $\hat{\mathbf{x}}$.

IV. Transmitter Refined User Selection and Precoding

Following the distributed self-selection and compressed-sensed detection and estimation, the basestation can identify a set of $\hat{K}_{ss}$ users and their channel estimates. From this set, $K_s < \hat{K}_{ss}$ users are selected for transmission. Precoding vectors can then be calculated, which are optimal for the effective MISO channels. The basestation notifies the users as to whether they have been selected, and transmission of data commences. Selected user k demodulates her data using the linear receiver $\tilde{\mathbf{u}}_k^\dagger$.

The refinement of the set of selected users from $\hat{K}_{ss}$ to K_s is the traditional user selection problem. In our compressed-sensed scheme, the complexity of the task is vastly reduced as the transmitter no longer needs to consider all K users, only $\hat{K}_{ss}$. The aim is to select the subset of users to maximize system utility, and for this paper, we consider the total throughput, i.e. the system sum capacity in bps/Hz. However, even for a moderate number of self-selected users, a brute force exhaustive search may be infeasible. Suboptimal selection algorithms have been proposed in the literature including random selection, greedy user selection (GUS) [10], orthogonal and semi-othogonal user selection (SUS) [1].

In the simulations that follow, we will adopt SUS refinement of the selected user set. This algorithm starts with a single user, and greedily adds users whose channels are semi-orthogonal to those already selected. Semi-orthogonality between user j and user k is defined by

$$|\hat{\mathbf{v}}_j^\dagger \hat{\mathbf{v}}_k| \leq \epsilon \tag{15}$$

where ϵ is a design parameter that dictates the maximum spatial correlation allowed between the channels as estimated at the basestation. There is, of course, a trade-off between the number of users self-selecting and the achievable orthogonality of the selected users. Effectively then, we have a tradeoff between the uplink bandwidth together with the complexity of compressed-sensed channel estimation, and the sum-rate performance of the system.

Our simulations apply ZF precoding, calculated for the selected user set by $\mathbf{W}^\dagger = \left(\tilde{\mathbf{V}}^\dagger \tilde{\mathbf{V}}\right)^{-1} \tilde{\mathbf{V}}^\dagger$, where the set of CDIs uses the estimates from compressed sensing $\tilde{\mathbf{V}} = [\tilde{\hat{\mathbf{v}}}_1 \ldots \tilde{\hat{\mathbf{v}}}_{K_s}]$.

V. Compressed-sensed Medium Access Simulations

Through simulation, we demonstrate our new compressed-sensed medium access technique for multi-antenna downlink broadcast. In particular, we investigate:

- *A.* the distribution of the number of self-selected users, K_{ss}
- *B.* channel estimation performance; and,
- *C.* sum-rate capacity for the complete user-selection and multi-antenna broadcast scheme

We will consider three systems of interest: a SISO system with $N_t = 1$, $N_r = 1$, a MISO system with $N_t = 4$, $N_r = 1$ and a MIMO system with $N_t = 4$, $N_r = 2$. In all simulations, the number of users in the system is $K = 512$, and the target number of self-selecting users is $K_{\text{tar}} = 20$, and so the desired sparsity is $\xi \approx 0.04$.

We use the analysis in Section II-B to set thresholds for self-selection. Specifically, the distribution functions in the SISO and MISO scenarios are exponential(1) and Erlang(1,4) in $x =$

(τ/γ), respectively. In the MIMO scenario, we evaluate (6) for $N_t = 4,\ N_r = 2$ to obtain:

$$\Pr\big(\lambda_k \le x\big) = 4\left(1-\exp(-x)\sum_{q=0}^{2}\frac{x^q}{q!}\right) * \left(1-\exp(-x)\sum_{q=0}^{4}\frac{x^q}{q!}\right) - 3\left(1-\exp(-x)\sum_{q=0}^{3}\frac{x^q}{q!}\right)^2. \quad (16)$$

To obtain the threshold, τ, for the MISO and MIMO scenarios, we use a bisection search on (7) or (16), respectively. The SISO threshold can be explicitly computed from the exponential distribution.

A. Distribution of number of self-selected users

Figure 1 shows the distribution for the number of self-selecting users K_{ss} for a downlink channel with $\gamma_{\text{dB}} = 5$dB for each of a SISO, MISO and MIMO system example with 1000 realizations. Table I summarises chosen system parameters for each system together with indicative values of K_{ss} as shown in Figure 1.

$\xi \approx 0.04$	SISO	MISO	MIMO
N_t	1	4	4
N_r	1	1	2
τ/γ	3.2	8.1	10.8
$K_{ss,\text{min}}$	8	8	5
$K_{ss,\text{ave}}$	19.96	20.13	20.67
$K_{ss,\text{max}}$	35	34	34

TABLE I
SYSTEM PARAMETERS FOR SELF-SELECTION, INDICATIVE VALUES OF K_{ss}

We note that $K_{\text{tar}} = 20$ was sufficient to ensure that $K_{ss} > K_s = N_t$ in each of these examples. Analysis of the tail of the distribution allows for appropriate choice for K_{tar} as indicated for the SISO case in [6].

B. Channel estimation performance

Using the same system parameters as given in Table I, we investigated the channel estimation performance of the compressed-sensing at the basestation. For these simulations the number of observations was chosen to be $N_{\text{obs}} = 100 = 5 * K_{\text{tar}}$, and the total number of users K was assumed known at the basestation. The uplink channel included additive noise at the basestation, with the uplink channel strength (in dB) defined by $10\log_{10}\left(\frac{1}{\sigma_z^2}\right)$ at equation (8). We employed the GPSR algorithm [9] with $\kappa = 1$ for estimation at the basestation.

Figure 2a) shows a comparison of the actual channel coefficients for each user (shown in red) with the compressed-sensed estimates (shown in blue) for the 4×1 MISO system with 0 dB uplink. The real part is shown, and similar performance was observed for the imaginary parts. The upper subfigure shows the raw estimates and the lower subfigure shows the same estimates where a threshold has been used to remove those belonging to users whose total channel strength falls below a given SNR threshold. The threshold applied in this example was 0.5 times that used for self-selection. Figure 2b) shows the channel estimate mean square error (MSE) as a function of uplink dBs.

C. Self-selection and sum-rate performance

Here we investigate the self-selection performance and demonstrate the sum-rate (bps/Hz) performance of our complete compressed-sensed medium access scheme with equal power users. Following [3], the orthogonality parameter was chosen to be $\epsilon = 0.25$. We used SUS refinement and ZF precoding, and selected users applied linear combining given by the dominant left singular vector of their channel $\mathbf{H}_k$.

For the 5 dB downlink, Figure 3a), shows the comparison of the SINR achieved by the system for user k and the CQI originally calculated by user k in self-selecting. Ideally, $\text{CQI}_k \approx \text{SINR}_k$, and divergence from this can be seen for the MISO and MIMO cases, resulting from a combination of channel estimation error, and non-orthogonal channels.

Figure 3b) shows the significant advantage of multiple antennas at basestation (MISO case, red x), and the smaller advantage of increasing the number of antennas at the receiver.

VI. CONCLUSIONS

In this paper, we have outlined the background, motivation and key aspects of a novel compressed-sense medium access scheme for the multiuser MIMO broadcast scenario. Importantly we have shown that compressed sensing can be used for channel estimation on the uplink. We have provided analysis for setting of self-selecting thresholds and insights into user selection, precoding, receiver combining and system throughput. Our ongoing research is focused on the tradeoff of sum-rate performance against the uplink bandwidth and complexity of compressed-sensed channel estimation.

REFERENCES

[1] T. Yoo, H. Jindal, A. Goldsmith, "On the optimality of multiantenna broadcast scheduling using zero-forcing beamforming," *IEEE J. Selected Areas in Communications*, vol. 24, no. 2, pp. 528-541, Mar. 2006.

[2] M. Sharif, B. Hassibi, "On the capacity of MIMO broadcast channels with partial side information," *IEEE Trans. Information Theory*, vol. 51, pp. 506-522, Feb. 2005.

[3] T. Yoo, N. Jindal, A. Goldsmith, "Multi-antenna downlink channels with limited feedback and user selection," *IEEE J. Selected Areas in Communications*, vol. 25, no. 7, pp. 1478-1491, Sep. 2007.

[4] F. Boccardi, H. Huang, M. Trivellato"Multiuser eigenmode transmission for MIMO broadcast channels with limited feedback," in *Proc. IEEE Int. Workshop on Signal Processing Advances for Wireless Communications (SPAWC)*, pp. 1-5, Jun. 2007.

[5] M. Trivellato, F. Boccardi, H. Huang, "On transceiver design and channel quantization for downlink multiuser MIMO systems with limited feedback," *IEEE J. Selected Areas in Communications*, vol. 26, no. 8, pp. 1494-1504, Oct. 2008.

[6] S. Bhaskaran, L. M. Davis, A. Grant, S. Hanly, P. Tune, "Downlink scheduling using compressed sensing," in *Proc. IEEE Information Theory Workshop (ITW)*, Volos, Greece, pp. 201-205, Jun. 2009.

[7] C. G. Khatri, "Distribution of the largest or the smallest characteristic root under null hypothesis concerning complex multivariate normal populations," *Annals of Mathematical Statistics*, Vol. 35, Dec. 1964, pp. 1807-1810.

[8] P. Tune, S. R. Bhaskaran, S. V. Hanly, "Number of measurements in sparse signal recovery in *Proc. IEEE Int. Symp. on Information Theory (ISIT)*, pp.16-20, Seoul, Korea, Jun. 2009.

[9] M. Figueiredo, R. Nowak, S. Wright "Gradient projection for sparse reconstruction: application to compressed sensing and other inverse problems," *IEEE J. Selected Topics in Signal Processing: Convex Optimization Methods for Signal Processing*, vol. 1, no. 4, pp. 586-598, 2007.

[10] G. Dimic, N. D. Sidiropoulos, "On downlink beamforming with greedy user selection: performance analysis and a simple new algorithm," *IEEE Trans. on Communications*, vol. 53, no. 10, pp. 3857-3868, Oct. 2005.

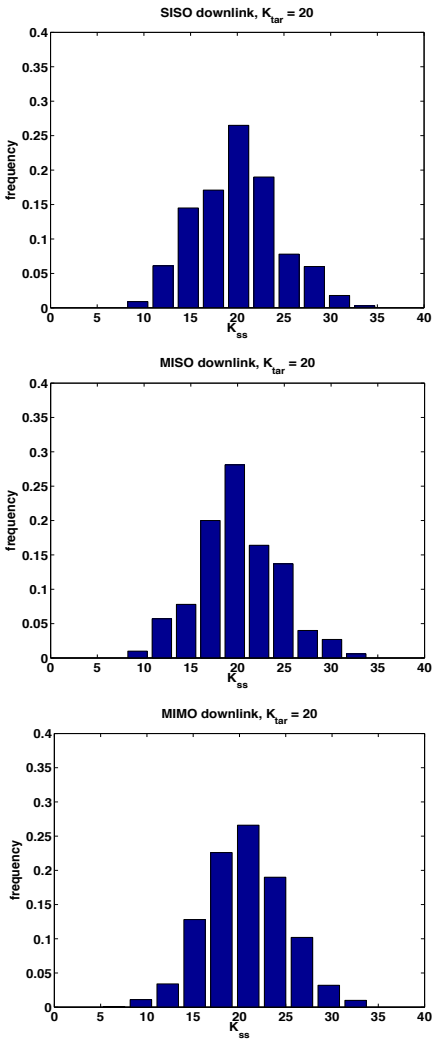


Fig. 1. Distribution of K_{ss} for SISO, MISO and MIMO systems, 5 dB downlink, $K_{\text{tar}} = 20$.

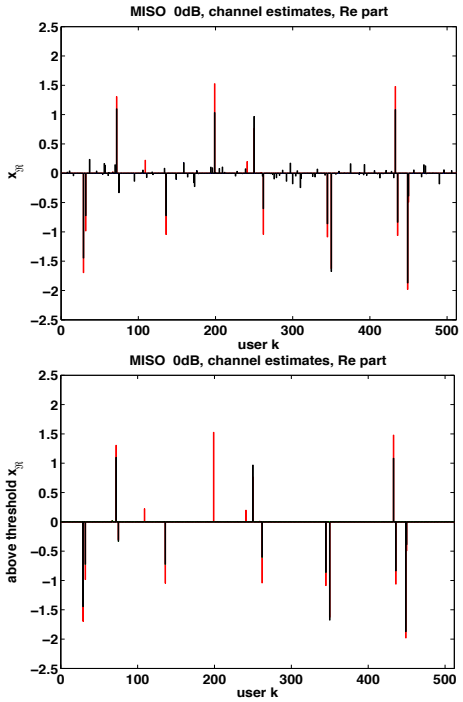


Fig. 2. a) Channel estimates MISO uplink 0dB, raw estimates and thresholded, real part, $t = 1$.

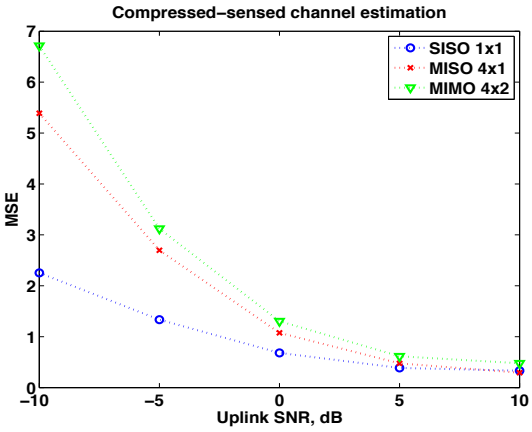


Fig. 2. b) Channel estimates mean square error, uplink dBs shown

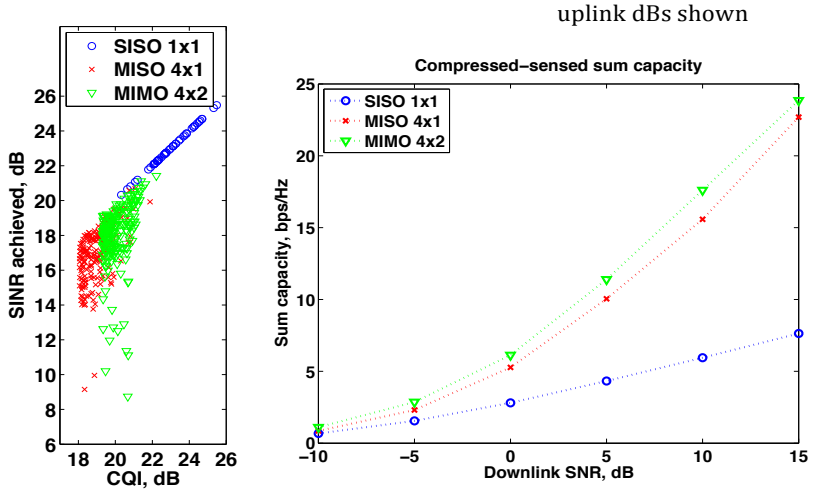


Fig. 3. a) Self-selection and b) sum-rate performance in compressed-sensed system