Adaptive Virtual MIMO Single Cluster Optimization in a Small Cell

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***Abstract*—Adaptive Virtual MIMO optimized in a single cluster of small cells is shown in this paper to achieve near Shannon channel capacity when operating with partial or no Channel State Information. Although, access links have enormously increased in the recent years, the operational system complexity remains linear regardless of the number of access nodes in the system proposed.**

Adaptive Virtual MIMO optimized in a single cluster performs a theoretical information spectral efficiency, almost equal to that of the upper bounds of a typical mesh network, up to 43 bits/s/Hz at a SNR of 30dB while the BER performance remains impressively low hitting the 10^{-6} at an SNR of about 13 dB when the theoretical upper bound of an ideal small cell mesh network achieves the 10^{-6} at a SNR of 12.5 dB. In addition, in a sub-optimum channel condition, the channel capacity and BER performance of the proposed solution is shown to drastically delay saturation even for the very high SNR.

***Index Terms*—Adaptive Multiuser Detection, MIMO, Small Cell, Single Cluster, Inter-cell Interference, Partial Channel State Information.**

I. Introduction

Wireless and mobile communication networks have been massively transformed in the past decade. The constantly increasing number of data hungry devices have forced cellular network providers to often deliver data traffic in excess of 95% of the time. At the same time M2M and IoT have significantly changed the number of devices in a network while the access radio communication macro-cells are expected to be proved short in providing for the demand in due time. The industry and research community now recognise that channel capacity gains can only be achieved by spectrum reuse. Based on this principle Small Cells have been introduced increasing the dimensionality of the cellular networks providing short range connectivity for a large number of devices. In addition, with the growing demand for large data, new ways to increase bandwidth efficiency are necessary.

Multiple antenna systems benefit from spatial diversity resulting in spectral efficiency increase [1][2][3][4]. Spacing between the antennas within a single communication node is normally expected larger than half-wavelength [5], however due to the small physical dimensions of the access devices this is not always possible and when it is, the number of antennas on a single communication node will be small. This limitation is solved by the use of virtual antenna arrays as shown in [6]. Finally, centralized multiuser detection schemes as proposed in [7], are satisfactorily capable to keep intra-cell interferers under precise power control but the inter-cell interference is fully out of their control.

From this point on the term *cooperative* wireless communication system will refer to a fully interference controllable cooperative system where all communication terminals have full knowledge of:

- The channel statistics,
- The exact number of users K

while no unknown interfering nodes K_i will transmit in the area ($K_i = 0$). This is an ideal channel condition which is without a doubt very unlikely to happen in actual deployments and is used in this paper for comparison purposes only. Therefore, the term *sub-cooperative* wireless communication system will refer to an interference non-controllable cooperative system where the communication terminals have only limited or often no knowledge of:

- the statistics of the channel
- the exact number of users K
- the number of interfering nodes K_i, where ($K_i \neq 0$)

A sub-optimum yet more realistic system as described above will be considered throughout this paper.

Adaptive Virtual MIMO (AV-MIMO) in a Single Cluster Optimization (SCO) is shown in this paper to be used with small cells to increase spectral efficiency in the local cluster without the need of multiple antennas on each individual access device. Instead AV-MIMO-SCO makes use of the Adaptive Multiuser Detection (AMUD) as shown in [8][9] to utilize multiple communication nodes equipped with a single-antenna into a multi-antenna node equivalent to this of a Virtual Antenna Array (VAA) as shown in [10][11]. An AV-MIMO system is inherently (at the physical layer) responding to a time variable nature of the VAA [10] environment. Apart from backhauling, the small cell acts as a simple access device and is not always in the formation of the Adaptive Virtual Antenna Array (AVAA).

An AV-MIMO-SCO sub-cooperative system achieves a normalized information spectral efficiency of 28.75 bits/s/Hz at a SNR of 30dB and a BER of 10^{-6} at a SNR of about 25.75 dB in a cooperative environment. In a sub-cooperative environment (with 4 unknown interferers), the sub-cooperative AV-MIMO-SCO system putting through a system channel capacity of 25 bits/s/Hz at a SNR of 30 dB where the cooperative system does not exceed the 15.5 bits/s/Hz. In the sub-cooperative environment, the AV-MIMO-SCO achieves a BER of 10^{-6} at a SNR of about 28.5 dB while the cooperative system saturates at a BER of 10^{-3} at a SNR of 30 dB.

II. Communication Protocol

For simplicity, the coverage of a cluster should be considered the transmission coverage of the small cell while S_k number of users operate within the cluster.

1. Phase I: Constant Operation All users broadcast a training sequence message with length of M data symbols. Upon reception of the neighbors' training sequences and by means of Minimum Mean Square Error (MMSE) estimation [12] [9], nodes get to increase statistical knowledge of the channel with each neighbor node in the cluster.

2. Phase II: AVAA formation By means of a very small data packet sent with the training sequence, the source node informs the destination node of its intention to send data packets. From the constant operation shown in $PhaseI$ source and destination nodes activate the neighbor nodes that provided them with the best MMSE during the latest training sessions and they form the local AVAAs as shown in Fig.1 (source and destination communication nodes in black).

3. Phase II: AV-MIMO operation The source node forms a short range (low power) broadcast channel and distributes information packets to the nodes contributing to the transmit AVAA. The M transmit AVAA nodes form a $N \times M$-dimensional MIMO channel with the N receive AVAA nodes. The information packets are spread and transferred to the receiver AVAA through the MIMO channel.

4. Phase IV: Information recovery The receiver AVAA forwards the received information packets to the destination node in a single-cast low power operation. At the destination node the channels are de-correlated using AMUD [12] [9] forming an unbiased estimator for the information packets.

III. System Model

The system is similar to this in [6] with a total of K operational nodes. The nodes "recruited" by the source and destination are denoted in gray in Fig.1. This forms a $M \times N$ AV-MIMO system where

$$\sum_{k=2}^{K}(M,N) \leq K$$

where M is the dimension of the transmitter AVAA, N is the dimension of the receiver AVAA and K is the total number of nodes within the system.

The signal at every output of the communications channel of the system follows the standard linear type

$$\mathbf{y} = \mathbf{Hx} + \mathbf{n} \tag{1}$$

where $\mathbf{x}$ is the information signal, $\mathbf{H}$ is a composite channel, $\mathbf{n}$ is the noise vector and $\mathbf{y}$ is the signal at the destination node.

The recruited nodes on each side along with the source and destination nodes respectively, team up to form an $M \times N$ AVAA system.

The linear system model with respect to Fig. 1 and by assuming negligible noise within the local cluster:

$$\mathbf{y}_1 = \mathbf{A}_0\mathbf{x} + \mathbf{n}_0 \tag{2}$$

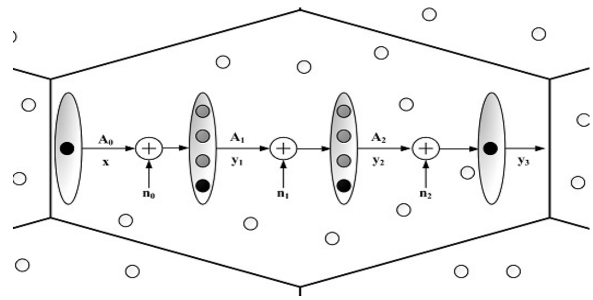

Fig. 1. General system model of AV-MIMO

where $\mathbf{x}$ is the original information vector, $\mathbf{A}_0$ is the broadcast channel of the transmit AVAA, $\mathbf{n}_0$ is the noise vector and $\mathbf{y}_1$ is the signal vector at the receiver AVAA.

The broadcast channel $\mathbf{A}_0$ is represented by a diagonal matrix of Zero Mean Circular Symmetric Complex Guassian (ZMCSCG) Independent and Identically Distributed (i.i.d.) random variable coefficients with variance of 1 [1]:

$$\mathbf{A}_0 = diag\left[\alpha_1 \;\; \alpha_2 \;\; \cdots \;\; \alpha_M\right] \tag{3}$$

where all sub-channels of $\mathbf{A}_0$ are orthogonal to each other. The source and destination nodes are always participating to the formed AVAA.

The linear system model with respect to Fig. 1, by assuming that noise influences the transmission and by equation 2:

$$\mathbf{y}_2 = \mathbf{S}\mathbf{A}_1\mathbf{y}_1 + \mathbf{n}_1$$

$$\mathbf{y}_2 = \mathbf{S}\mathbf{A}_1(\mathbf{A}_0\mathbf{x} + \mathbf{n}_0) + \mathbf{n}_1 \tag{4}$$

where $\mathbf{A}_1$ is the MIMO channel, $\mathbf{S}$ is the CDMA spreading codes matrix, $\mathbf{n}_1$ the noise vector and $\mathbf{y}_2$ is the signal at the receiver AVAA.

For the MIMO channel shown in Fig. 1, M active transmitters and N active receivers are assumed where $M \leq n_t$ and $N \leq n_r$. The MIMO channel $\mathbf{A}_1$ is a $(N \times M)$ matrix with ZMCSCG i.i.d. random variables where coefficients have a variance of 1 as follows:

$$\mathbf{A}_1 = \begin{bmatrix} \beta_{1,1} & \beta_{1,2} & \dots & \beta_{1,M} \\ \beta_{2,1} & \beta_{2,2} & \dots & \beta_{2,M} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{N,1} & \beta_{N,2} & \cdots & \beta_{N,M} \end{bmatrix} \tag{5}$$

Information packets are forwarded to the destination node through $\mathbf{A}_2$ MISO channel.

The linear model with respect to Fig. 1 will be

$$\mathbf{y}_3 = \mathbf{A}_2\mathbf{y}_2 \;\; + \mathbf{n}_2$$

$$\mathbf{y}_2 = \mathbf{A}_2\mathbf{S}\mathbf{A}_1\mathbf{A}_0\mathbf{x} + \mathbf{A}_2\mathbf{n}_1 \tag{6}$$

where $\mathbf{A}_2$ is the MISO channel and $\mathbf{y}_3$ is the signal at the destination node. $\mathbf{A}_2$ is a MISO diagonal matrix with ZMCSCG i.i.d. random variables with unit variance coefficients [1] as follows:

$$\mathbf{A}_2 = diag\left[\gamma_1 \;\; \gamma_2 \;\; \cdots \;\; \gamma_M\right] \tag{7}$$

For the purpose of analysis the following parameters are set:

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{N} \tag{8}$$

where,

$$\mathbf{H} = \mathbf{A}_2\mathbf{S}\mathbf{A}_1\mathbf{A}_0 \tag{9}$$

$$\mathbf{N} = \mathbf{A}_2\mathbf{n}_1 \tag{10}$$

IV. Mean Square Error Analysis

In order to simplify calculations in the estimation of the overall system channel capacity a set of definitions have been introduced in [6].

$Definitions$:

1) Autocovariance matrix $\mathbf{R} = \mathcal{E}\left\{\mathbf{y}\mathbf{y}^H\right\}$
2) Crosscorrelation vector $\mathbf{p} = \mathcal{E}\left\{x_k^*\mathbf{y}\right\}$
3) Filter output statistic $\hat{x}_k(\mathbf{w}) = \mathbf{w}^H\mathbf{y}$

where $\mathcal{E}(\bullet)$ typify the expectation function, $(\bullet)^H$ represents the Hermitian matrix (complex conjugate and transpose) and x_k is the training sequence of the k^{th} user where $k \leq K$. Finally, $\mathbf{y}$ is the signal received at the destination node and $\mathbf{w}$ introduce the matched filter coefficients.

As shown in [6], at the destination node, the error is given by

$$J(\mathbf{w}) = \mathcal{E}\left\{\left|x_k - \hat{x}_k(\mathbf{w})\right|^2\right\} \tag{11}$$

where, expanding equation (11) yields

$$J(\mathbf{w}) = \mathcal{E}\left\{x_k^*(x_k - \hat{x}_k(\mathbf{w}))\right\} - \mathcal{E}\left\{\hat{x}_k^*(\mathbf{w})(x_k - \hat{x}_k(\mathbf{w}))\right\}$$

$Lemma$ 1 : For MMSE $\mathcal{E}\left\{\hat{x}_k^*(\mathbf{w})(x_k - \hat{x}_k(\mathbf{w}))\right\} = 0$ where the expectation of $\hat{x}_k(\mathbf{w})$ is orthogonal to the error.

$Proof$:

$$\mathcal{E}\left\{\left(\mathbf{w}^H\mathbf{y}\right)^*\left(x_k - \mathbf{y}^H\mathbf{w}\right)\right\} = \mathcal{E}\left\{\mathbf{w}^H\mathbf{y}x_k^*\right\} - \mathcal{E}\left\{\mathbf{w}^H\mathbf{y}\mathbf{y}^H\mathbf{w}\right\}$$

Since $\mathbf{w}$ is constant, then

$$\mathcal{E}\left\{\left(\mathbf{w}^H\mathbf{y}\right)^*\left(x_k - \mathbf{y}^H\mathbf{w}\right)\right\} = \mathbf{w}^H\mathcal{E}\left\{\mathbf{y}x_k^*\right\} - \mathbf{w}^H\mathcal{E}\left\{\mathbf{y}\mathbf{y}^H\right\}\mathbf{w}$$

$$\mathcal{E}\left\{\left(\mathbf{w}^H\mathbf{y}\right)^*\left(x_k - \mathbf{y}^H\mathbf{w}\right)\right\} = \mathbf{w}^H\mathbf{p} - \mathbf{w}^H\mathbf{R}\mathbf{w} \tag{12}$$

$Corollary$ 1 : For the MMSE $\mathbf{w}$ is given by $\mathbf{w} = \mathbf{R}^{-1}\mathbf{p}$. By substitution

$$\mathbf{w}^H\mathbf{p} - \mathbf{w}^H\mathbf{R}\mathbf{w} = 0$$

So, for MMSE $\mathcal{E}\left\{\hat{x}_k^*(\mathbf{w})(x_k - \hat{x}_k(\mathbf{w}))\right\} = 0$.
When $\mathbf{w} = \mathbf{R}^{-1}\mathbf{p}$, it is clear that

$$J(\mathbf{w}) = \mathcal{E}\left\{x_k^*\left(x_k - \hat{x}_k(\mathbf{w})\right)\right\} \tag{13}$$

Given Lemma 1 $J(\mathbf{w}) = \sigma_x^2 - \mathbf{w}^H\mathbf{p}$, therefore,

$$J(\mathbf{w}) = \sigma_e^2 = \sigma_x^2 - \mathbf{p}^H\mathbf{R}^{-1}\mathbf{p} \tag{14}$$

where σ_e^2 is the error variance. $J(\mathbf{w})$ is the error function, where the Minimum Mean Square Error is for $\mathbf{w} = \mathbf{R}^{-1}\mathbf{p}$.

V. AMUD with Least Mean Squares

The Least Mean Square (LMS) algorithm as well known to converge to the MMSE within a small arbitrary constant [9]. The LMS is given as:

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \alpha e_k^*\mathbf{y} \tag{15}$$

where e_k^* is the complex conjugate of the instantaneous error while α is the step size shown in [9] [6] to be bounded by:

$$0 < \alpha < \frac{2}{\lambda_{max}}$$

$$\sum_{i=1}^{2G+1}\frac{\alpha\lambda_i}{2 - \alpha\lambda_i} < 1$$

where λ_i is the i^{th} eigenvalue of the autocorrelation matrix $\mathbf{R}$, λ_{max} is the maximum eigenvalue, $2G+1$ is the number of filter coefficients and G is the length of the spreading sequence.

As shown in [9] a steady state MSE for the LMS algorithm can be given by:

$$e(\infty) = \frac{J(\mathbf{w})}{1 - \sum_{i=1}^{2M+1}\frac{\alpha\lambda_i}{2-\alpha\lambda_i}} \tag{16}$$

Given that α is relatively small, the steady state error is almost equivalent to $J(\mathbf{w})$.

VI. Channel Capacity

A. MIMO Capacity Upper Bound

Channel capacity is defined in [13] as the maximum data rate assuming Gaussian input signalling with vanishingly small error probability. The factor $\frac{1}{2}$ is removed from the capacity formula and this notation is kept throughout the paper whereas all logarithms are base 2, i.e. $\log_2(\bullet)$, unless differently stated.

The MIMO channel capacity formula is found in [1][14]:

$$C = log\left|\mathbf{I}_r + \hat{\mathbf{H}}\mathbf{Q}\hat{\mathbf{H}}^H\right| \tag{17}$$

where $\mathbf{Q} = \mathcal{E}\left|\mathbf{x}\mathbf{x}^{\mathcal{H}}\right|$ and $tr(\mathbf{Q}) \leq P$. For simplicity it is assumed that$\mathbf{H}$ will be the system's composite channel.

B. MMSE Capacity Analysis

The AV-MIMO-SCO system capacity is calculated according to equation (18).

$Lemma$ 2 : The capacity of the AV-MIMO-SCO system with a bank of MMSE filters is shown in [8] to be given by

$$C = I_{max}(x_k; \hat{x}_k(\mathbf{w})) = log\left(\frac{\mathcal{E}\left\{x_k^2\right\}}{\mathcal{E}\left\{e^2\right\}}\right) = log\left(\frac{1}{\sigma_e^2}\right) \tag{18}$$

where x_k is $N(0, \sigma^2)$.

$Proof$: As per Lemma 1, when a signal vector with $\mathbf{w}_{opt}$ coefficients is chosen to minimize mean error, the error signal is orthogonal to the symbol estimate ($\mathcal{E}\left\{\hat{x}_k^*(\mathbf{w})(x_k - \hat{x}_k(\mathbf{w}))\right\} = 0$). Now if $x_1, x_2, ..., x_k$ are ZM-CSCG i.i.d. random variable coefficients, then:

1) $\hat{x}_k(\mathbf{w})$ is also Gaussian

2) $(\hat{x}_k(\mathbf{w}) - x_k)$ is Gaussian with zero mean

Lemma 3 : [13] Given that $p(x)$ follows a Gaussian distribution, then the maximum entropy $H(x) = \sigma_x log\left(\sqrt{2\pi e}\right)$.

Lemma 4 : [15] The entropy of two independent random variables α and β:

$$H(\alpha|\beta) = H(\alpha) \tag{19}$$

Lemma 5 : [15] For any two independent random variables α and β

$$H(\alpha, \beta|\beta) = H(\alpha|\beta) \tag{20}$$

Considering Lemmas 1-5, the mutual information is given by:

$$I(x_k; \hat{x}_k(\mathbf{w})) = H\left(x_k\right) - H\left(x_k|\hat{x}_k(\mathbf{w})\right)$$

From Lemma 5

$$I(x_k; \hat{x}_k(\mathbf{w})) = H\left(x_k\right) - H\left(x_k - \hat{x}_k(\mathbf{w})|\hat{x}_k(\mathbf{w})\right)$$

$$I_{max}(x_k; \hat{x}_k(\mathbf{w})) = log(\sigma_x^2) - log(\mathcal{E}(n_e^2))$$

From Lemma 2 and considering a signal power normalized to unit energy, $\sigma_x^2 = 1$

$$I_{max}(x_k; \hat{x}_k(\mathbf{w})) = C = log\left(\frac{1}{\sigma_e^2}\right) \tag{21}$$

By substitution of 14 to 21

$$C = log\left(\frac{1}{1 - \mathbf{p}^H \mathbf{R}^{-1} \mathbf{p}}\right) \tag{22}$$

$$0 \leq \mathbf{p}^H \mathbf{R}^{-1} \mathbf{p} < 1$$

for standard MMSE approach [7] where autocovariance matrix $\mathbf{R}$ and crosscorrelation vector $\mathbf{p}$ are defined in Section IV.

VII. Simulation System Model

SNR term, as used throughout this paper, denotes the signal to thermal noise power ratio. For the Bit Error Probability results, normalized (unit energy) BPSK modulated signal is used. The CDMA spreading sequences are random Bernoulli (antipodal) sequences with a spreading factor of 32. The propagation / fading channels are modeled as normalized (unit energy) ZMCSCG i.i.d. random variables.

The total number of access nodes within the small cell cluster is arbitrarily set to 30 (i.e. $K = 30$). The number of access nodes at the transmit and receive AVAAs is set to 4 (i.e. $M = N = 4$). The source and destination nodes are by default (as shown in the methodology) one of the four access nodes in each AVAA. Therefore, by means of MMSE estimation, the source and destination nodes activate 3 access nodes each to form their AVAAs. Hence, we end up with a virtual 4×4 virtual MIMO communication system.

When the environment is sub-cooperative, i.e. an uncontrolled form of interference present in the system, each interferer is modeled as Gaussian random variable with variance set to 0.1 (assuming that the system bandwidth is ubiquitous). This means that each interferer has precisely one tenth of the transmit power of the AVAA. The results assume 4 independent interferers. It is well known that the AMUD techniques are able to mitigate Multiple Access Interference and thus AV-MIMO remains tolerant to many concurrent transmissions [9][16][17][18].

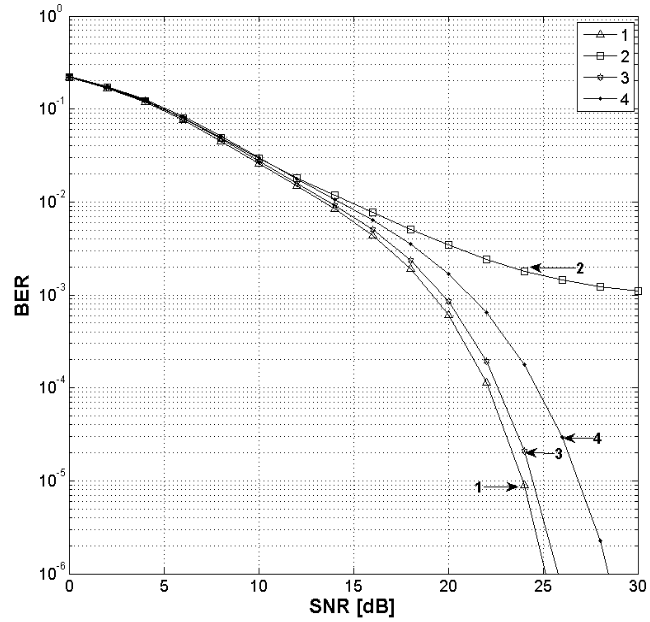

Fig. 2. BER Comparison - MSE user selection.

1) Cooperative Upper Bound - No interference.
2) Sub-Cooperative Upper Bound - Four interferers at 10% intercell power.
3) Cooperative AV-MIMO-SCO - No interferer.
4) Sub-Cooperative AV-MIMO-SCO - Four interferers at 10% intercell power.

VIII. Numerical Results

As shown in Fig. 2 a BER of 10^{-6} is achieved for the cooperative theoretical upper bound system at a SNR of almost 25 dB where under the same conditions the AV-MIMO-SCO system achieves nearly the same performance with a BER of 10^{-6} at a SNR of 25.75 dB. There is a small outage (3%) due to the time delay spent to distribute data packets to all transmitting communication nodes, at the first burst. In the sub-optimum (sub-cooperative) environment a BER of 10^{-6} is obtained at a SNR of 28.5 dB by the the AV-MIMO-SCO system, which is a significant improvement over the theoretical upper bound system operating under the conditions of a sub-cooperative environment where the system saturates at a high BER. It is clearly shown that the AV-MIMO-SCO loses almost 15% of its energy but it is still proven more tolerant to inter-cell interference while the theoretical upper bound system cannot achieve a BER better than 10^{-3} at a SNR of 30 dB.

At the same time, as shown in Fig. 3 in a cooperative environment, a channel capacity of 29.3 bits/s/Hz is achieved at a SNR of 30 dB while under the same environment assumption, the AV-MIMO-SCO system achieves a spectral efficiency of 28.75 bits/s/Hz at the same SNR experiencing

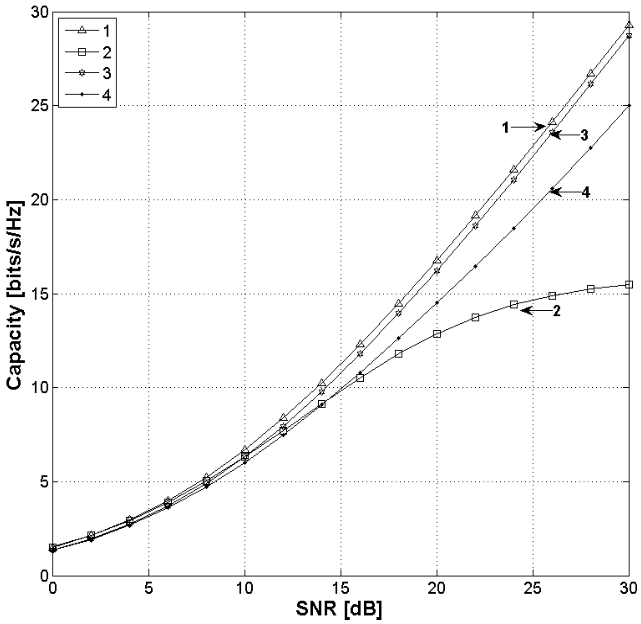

Fig. 3. Capacity Comparison - MSE user selection.

1) Cooperative Upper Bound (eq. 17) - No interference.
2) Sub-Cooperative Upper Bound (eq. 17) - Four interferers at 10% intercell power.
3) Cooperative AV-MIMO-SCO (eq. 22) - No interferer.
4) Sub-Cooperative AV-MIMO-SCO (eq. 22) - Four interferers at 10% intercell power.

an outage of almost 2%. In the sub-cooperative conditions the AV-MIMO-SCO system achieves a channel capacity of 25 bits/s/Hz outperforming the saturated cooperative by almost 10 bits/s/Hz at 30dB of SNR.

IX. Conclusion

The AV-MIMO-SCO system operating in a single cluster small cell enables interference to be controlled and allows results comparable to the theoretical upper bound for transmission of bid data. This is important factor for high spectral efficient cooperative systems, particularly when interference is unknown where traditional cooperative systems will fail. This is expatiated in the results where in sub-cooperative environments the cooperative MIMO system saturates in fairly high BER while spectral efficiency is approximately 10 bit/s/Hz (at SNR=30dB) less than the sub-cooperative AV-MIMO-SCO approach. It can be further noted that in a cooperative environment the two systems perform similarly, within 1 dB of SNR in BER and 0.5 bits/s/Hz in spectral efficiency.

Furthermore, the AV-MIMO-SCO system is a completely decentralized approach needless of a coordinating node to either cooperative and sub-cooperative mobile environments while it performs equally well under partial or no channel state information. Finally, due to it dependency on AMUD, AV-MIMO-SCO enable linear computational complexity when increasing the access nodes and unknown interferers of the overall system.

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