Bit Error Rate Minimizing Antenna Selection in Zero-Forcing Precoded MU-MIMO Systems.

Dailys Arronde Pérez and Raimundo Sampaio-Neto

***Abstract*— This work focuses on the downlink of a Zero-Forcing (ZF) precoded multiuser multiple-input multiple-output (MU-MIMO) systems where the Base Station (BS) and the users stations (UE$_s$) transmit and receive information symbols, respectively, by selected subset of their antennas. An optimal transmit antenna selection procedure is proposed aiming at the maximization of the detection signal-to-noise ratio and consequent minimization of the detection error probability. A suboptimal search algorithm able to deliver a performance close to the one resulting from the optimal exhaustive search selection is proposed. The receive antenna selection is also performed using a similar optimization criterion. BER performance results, obtained via simulation and semi-analytical approaches, are presented for different scenarios.**

***Keywords*— MU-MIMO, transmit and receive antenna selection, sub-optimal selection algorithm.**

I. INTRODUCTION

MIMO technology is closely linked to the evolution of wireless communication systems, since it is considered one of the most suitable solutions to achieve the promising transmission rates, making an efficient use of the spectrum and energy in the fifth-generation (5G) networks. The use of a very large number of antennas at the base station (BS) to achieve more dramatic diversity gains leads to the so called massive MIMO systems that has been extensively studied in the last decade. An comprehensive overview from various perspectives on the topic is provided in [1]- [2]. The main drawback for the implementation of this technology is the hardware complexity and cost, that scale with the number of antennas. In order to overcome this problem, antenna selection technique, at the transmitter and receiver sides, was proposed in [3]. The basic idea is to use a reduced number of Radio Frequency (RF) chains and choose the best subset of all the antennas combinations. This leads to a notable reduction of implementation's cost and complexity.

Prior works consider an approach to receive antenna selection for capacity maximization as a convex optimization problem. In [4] an alternative approach that reachs near-optimal performance is proposed and the selection problem is formulated as a combinatorial optimization problem. In [5] a Generalized Pre-coding aided Spatial Modulation (GPSM) system for downlink MU-MIMO is considered.

Recent works address the problem of transmit antenna selection in massive MU-MIMO systems. A norm-and-correlation-based selection algorithm for energy efficiency maximization to decide the transmit RF chain configuration under the total power constraint in millimeter wave channel is proposed in [6]. An antenna selection scheme for Large-but-Finite MIMO networks, using Genetic Algorithm is addressed in [7], which can be applied with different amount of channel state information (CSI), various data communication models and objective functions.

In this paper we analyze the downlink of a ZF precoded MU-MIMO system where each terminal, BS and user's stations transmit and receive information symbols, respectively, by selected subsets of their antennas. A general model to describe the system and expressions that relate the energy spent in transmission with the energy available for detection at each user are presented. An optimal transmit antenna selection criteria is proposed, aiming at the maximization of the detection signal-to-noise ratio and consequent minimization of the detection error probability. Another contribution of this paper is the suboptimal antenna selection algorithm, that executing iterative searches (ITES) find a near-optimal subset of antennas, and can be employed with different precoding methods and channel models. Receive antenna selection is also performed, using a similar optimization criterion. In both cases, the base station is responsible for carrying out the selection procedure. BER performance results, obtained via simulation and semi-analytical approaches, are presented for different scenarios.

II. SYSTEM AND SIGNAL MODEL

We consider the downlink of a MU-MIMO system, where the base station (BS) is equipped with N_T transmit antennas serving K user stations (UE$_s$), each one with N_R antennas, where $KN_R \leq N_T$. Assuming transmission over flat fading channels and detection in presence of additive noise, the received signal by all users is expressed in a $[KN_R \times 1]$ vector $\mathbf{y} = [\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_K]^T$

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{1}$$

where $\mathbf{H} = [\mathbf{H}_1^T, \mathbf{H}_2^T, \ldots, \mathbf{H}_K^T]^T$, $\mathbf{H} \in \mathbb{C}^{KN_R \times N_T}$ is the channel matrix for all users, with $\mathbf{H}_k \in \mathbb{C}^{N_R \times N_T}$ representing the channel matrix that connects the BS with the kth user and $\mathbf{n}$ is a $[KN_R \times 1]$ noise vector. Perfect channel state information (CSI) is assumed at the transmitter. The vector $\mathbf{x} \in \mathbb{C}^{N_T \times 1}$ contains the information transmitted by the N_T antennas at the BS. In MU-MIMO systems is necessary to employ a precoding technique to decouple the information conveyed to the different users and mitigate the multiuser interference (MUI). Then the transmit vector $\mathbf{x}$ can be expressed

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as

$$\mathbf{x} = \mathbf{P}\mathbf{s}, \tag{2}$$

where $\mathbf{P} = [\mathbf{P}_1, \mathbf{P}_2, \ldots, \mathbf{P}_K]$, $\mathbf{P} \in \mathbb{C}^{N_T \times KN_R}$ is the precoding matrix and the information symbols for all users are organized into the $\mathbf{s} = [\mathbf{s}_1^T, \mathbf{s}_2^T, \ldots, \mathbf{s}_K^T]^T$ vector. Each entry $\mathbf{s}_k \in \mathbb{C}^{N_R \times 1}, k = 1, 2, \ldots, K$ represents the kth user information vector, to be precoded by the matrix $\mathbf{P}_k \in \mathbb{C}^{N_T \times N_R}$. Conveniently for our analyses, the $\mathbf{s}_k$ vectors are represented by

$$\mathbf{s}_k = \sqrt{E_k}\tilde{\mathbf{s}}_k = \sqrt{E_s}\sqrt{\varepsilon_k}\ \tilde{\mathbf{s}}_k, \tag{3}$$

where E_k is the energy of the information symbols sent to user k, $E_s = 1/K \sum_{k=1}^{K} E_k$ is the average energy of the transmitted information symbols, $\varepsilon_k = E_k/E_s$ and $\tilde{\mathbf{s}}_k \in \mathbb{C}^{N_R \times 1}$ contains statistically independent symbols with zero mean and variance 1 in all its entries, taken from the modulation constellation $\mathcal{C} = \{c_1, c_2, \ldots, c_M\}$, where M is the order of the modulation. Then (2) can be written as

$$\mathbf{x} = \sqrt{E_s}\mathbf{P}\boldsymbol{\mathcal{E}}^{1/2}\ \tilde{\mathbf{s}}, \tag{4}$$

where $\boldsymbol{\mathcal{E}}$ is a diagonal matrix containing the vectors $\boldsymbol{\epsilon}_k = \varepsilon_k\mathbf{u},\ k = 1, 2, \ldots, K$, in its main diagonal, $\mathbf{u}$ is a $[N_R \times 1]$ unit vector and $\tilde{\mathbf{s}} = [\tilde{\mathbf{s}}_1^T, \tilde{\mathbf{s}}_2^T, \ldots, \tilde{\mathbf{s}}_K^T]^T$, then $\mathbb{E}[\tilde{\mathbf{s}}] = 0$ and $\mathbb{E}\left[\tilde{\mathbf{s}}\tilde{\mathbf{s}}^H\right] = \mathbf{I}_{KN_R}$.

A. Energy Relations

The mean energy expended by the BS at each transmission is

$$E_T = \mathbb{E}[\|\mathbf{x}\|^2] = \mathrm{Tr}\{\mathbb{E}[\mathbf{x}\mathbf{x}^H]\}, \tag{5}$$

where Tr$\{\mathbf{A}\}$ denote the trace of matrix $\mathbf{A}$.We then have from (4) that

$$\begin{aligned} E_T =& \mathrm{Tr}\left\{E_s\mathbf{P}\boldsymbol{\mathcal{E}}^{1/2}\mathbb{E}\left[\tilde{\mathbf{s}}\tilde{\mathbf{s}}^H\right]\boldsymbol{\mathcal{E}}^{1/2}\mathbf{P}^H\right\} \\ =& \mathrm{Tr}\left\{E_s\boldsymbol{\mathcal{E}}\mathbf{P}^H\mathbf{P}\right\} = E_s\gamma, \end{aligned} \tag{6}$$

with γ given by

$$\gamma = \mathrm{Tr}\left\{\boldsymbol{\mathcal{E}}\mathbf{P}^H\mathbf{P}\right\} = \sum_{k=1}^{K}\varepsilon_k\mathbf{u}^T\mathbf{g}_k, \tag{7}$$

where the column vectors $\mathbf{g}_k$ are given by

$$[\mathbf{g}_1^T, \mathbf{g}_2^T, \ldots, \mathbf{g}_K^T]^T = \mathbf{d}\left(\mathbf{P}^H\mathbf{P}\right), \tag{8}$$

with $\mathbf{d}(\mathbf{A})$ denoting the vector whose entries are the main diagonal elements of matrix $\mathbf{A}$. Considering (6), and since $E_k = E_s\varepsilon_k$, we can express the relation between the energy of symbols conveyed to user k and E_T as

$$E_k = E_T\frac{\varepsilon_k}{\gamma}. \tag{9}$$

B. Zero Forcing Precoding

Zero Forcing (ZF) is a linear precoding technique extensively studied in MU-MIMO systems, since completely remove the MUI by applying the right pseudoinverse of channel matrix, then the precoding matrix is given by

$$\mathbf{P}_{ZF} = \mathbf{H}^H(\mathbf{H}\mathbf{H}^H)^{-1}. \tag{10}$$

Applying (10) into the signal model described by (1) and (2) we have

$$\mathbf{y} = \mathbf{H}\mathbf{P}_{ZF}\mathbf{s} + \mathbf{n} = \mathbf{s} + \mathbf{n}, \tag{11}$$

and the signal received by user k is

$$\mathbf{y}_k = \sqrt{E_k}\tilde{\mathbf{s}}_k + \mathbf{n}_k. \tag{12}$$

C. Maximum Likelihood (ML) detection

Here we consider that the noise vector in (1) is a complex white Gaussian noise (AWGN), hence the optimal ML detection of the signal vector $\mathbf{s}_k$ provides the estimate

$$\hat{\mathbf{s}}_k = \underset{\mathbf{s}_k \in \mathcal{C}}{\operatorname{argmin}} \left\|\mathbf{y}_k - \sqrt{E_k}\tilde{\mathbf{s}}_k\right\|^2. \tag{13}$$

Since the symbols sent to each user are assumed statistically independent, decoupled detection may be employed, which treats the separate ML detection of the N_R modulated symbols. The advantage is that only $N_R \times M$ hypothesis need to be tested, instead of the M^{N_R} required if joint detection is implemented, thus the complexity reduction is noteworthy.

III. Transmit Antenna Selection

To model the transmit antenna selection, we assume that BS is equipped with N_{ta} RF chains ($N_{ta} < N_T$). At each transmission, the most suitable subset with N_{ta} active antennas should be selected, thus we have a total of $S_t = \binom{N_T}{N_{ta}}$ possibles combinations containing N_{ta} out of N_T antennas.

Each set is depicted by a column vector $\mathbf{p} \in \mathbb{R}^{N_T}$, whose elements take the values 1 or 0, if the antenna is activated or not respectively. For instance, let $N_T = 5$ and $N_{ta} = 3$, resulting $S_t = 10$ possible sets, represented by the patterns $\boldsymbol{\Gamma} = \{\mathbf{p}_1, \mathbf{p}_2 \ldots \mathbf{p}_{10}\}$. Pattern $\mathbf{p}_1 = [11100]^T$ indicates that antennas 1, 2 and 3 are selected for transmission, while antennas 4 and 5 are deactivated. For each subset, we have a corresponding $\mathbf{H}_{(\mathbf{p})} \in \mathbb{C}^{KN_R \times N_{ta}}$ that represents the sub-channel matrix of $\mathbf{H}$ obtained by selecting the columns indexed by $\mathbf{p}$. Consequently the S_t sub-matrices $\mathbf{H}_{(\mathbf{p})} \in \mathbb{C}^{KN_R \times N_{ta}}$ are given by

$$\mathbf{H}_{(\mathbf{p})} = \mathbf{H}\mathbf{U}_{(\mathbf{p})}, \tag{14}$$

where $\mathbf{U}_{(\mathbf{p})} \in \mathbb{C}^{N_T \times N_{ta}}$ is obtained from $\mathbf{I}_{N_T}$, suppressing its ith column, when the ith component of vector $\mathbf{p}$ is zero. The matrix $\mathbf{U}_{(\mathbf{p})}$ fulfills the properties $\mathbf{U}_{(\mathbf{p})}^T\mathbf{U}_{(\mathbf{p})} = \mathbf{I}_{N_{ta}}$ and $\mathbf{U}_{(\mathbf{p})}\mathbf{U}_{(\mathbf{p})}^T = \mathbf{D}(\mathbf{p})$, where $\mathbf{D}(\mathbf{p})$ is a diagonal matrix with the elements of vector $\mathbf{p}$ on its main diagonal. Then, the expression of the zero forcing precoding matrix for a given pattern $\mathbf{p}$ can be expressed as

$$\begin{aligned} \mathbf{P}_{(\mathbf{p})} =& \mathbf{H}_{(\mathbf{p})}^H\left[\mathbf{H}_{(\mathbf{p})}\mathbf{H}_{(\mathbf{p})}^H\right]^{-1} \\ =& \mathbf{U}_{(\mathbf{p})}^T\mathbf{H}^H\left[\mathbf{H}\mathbf{D}(\mathbf{p})\mathbf{H}^H\right]^{-1}. \end{aligned} \tag{15}$$

From (9) and (12) it results evident that, for a fixed energy distribution $\varepsilon_k, k = 1, 2, \ldots, K$ and a given energy E_T available at the transmitter, maximizing the detection energy E_k at the receivers is equivalent to minimizing the factor γ

given by (7) and (8). Hence the optimization problem can be rewritten as

$$\min_{\mathbf{p}\in\mathbf{\Gamma}} \gamma_{(\mathbf{p})}, \tag{16}$$

where $\gamma_{(\mathbf{p})}$ is given by

$$\gamma_{(\mathbf{p})} = \sum_{k=1}^{K} \varepsilon_k \mathbf{u}^T \mathbf{g}_{k(\mathbf{p})}, \tag{17}$$

with

$$\begin{aligned}[\mathbf{g}_{1}{}_{(\mathbf{p})}^{T}, \mathbf{g}_{2}{}_{(\mathbf{p})}^{T}, \ldots, \mathbf{g}_{K}{}_{(\mathbf{p})}^{T}]^T =& \mathbf{d}\left(\mathbf{P}_{(\mathbf{p})}^{H}\mathbf{P}_{(\mathbf{p})}\right) \\ =& \mathbf{d}\left(\left[\mathbf{H}\mathbf{D}(\mathbf{p})\mathbf{H}^H\right]^{-1}\right).\end{aligned} \tag{18}$$

A. *Proposed Suboptimal Search Algorithm ITES*

Given the channel matrix $\mathbf{H}$ and the normalized energy distribution $\varepsilon_k, k = 1, 2, \ldots, K$, the subset of antennas that minimize $\gamma_{(\mathbf{p})}$ can be obtained by exhaustive search, i.e. testing all possible patterns $\mathbf{p}$. However, as the number of transmit antennas and available RF chains grow, the search complexity, that includes the inversion of large dimension matrices for each tested configuration pattern $\mathbf{p}$, increases dramatically. In this paper, we propose a sub-optimal search algorithm, described in Algorithm 1. ITES (Iterative Search) is based on a pilot-symbols allocation algorithm for OFDM systems proposed in [8]. It starts the algorithm by considering an initial pattern $\mathbf{p}_{init}$, randomly selected from the set $\mathbf{\Gamma}_{S_t}$, and its associated metric γ_{init}. The vectors $\boldsymbol{\alpha}_i$ and $\boldsymbol{\delta}_j$ index the able and unable antennas respectively. The algorithm generate new patterns by moving the active antennas positions independently, thus we have a new pattern for each possible position, e.i. each element $\mathbf{p}^{\alpha_i \to \delta_j}$ of de set Ω_i is generated by deactivating the ith antenna and activating the jth. The set Ω_i is composed by N_d new patterns and we find the one that results in the best value of γ. Then the optimum pattern is saved in $\mathbf{p}_{otm}$ for the next cycle. Note that each iteration implies $N_a \times N_d$ trials of antenna assignments. The process continues until no improvements in γ calculation are found, i.e. the algorithm stops when two consecutive iterations return the same pattern.

ITES can be implemented for different scenarios and precoding schemes. Moreover, as will be seen in the following, it reaches results near the optimal solution with significantly less implementation complexity.

Algorithm 1: Iterative Search Algorithm (ITES)

Input: $\mathbf{p}_{init}, \gamma_{init}$
Output: $\mathbf{p}_{otm}$
Initialization: $\mathbf{p}_{otm} = \mathbf{p}_{init}$, $\gamma^{in} = \gamma_{init}$
$\boldsymbol{\alpha}_i \to$ index the N_a active antennas
$\boldsymbol{\delta}_j \to$ index the $N_d = (N_T - N_a)$ deactive antennas
do
  $\gamma^{out} = \gamma^{in}$
  for $i = 1$ **to** N_a **do**
    $\mathbf{p} = \mathbf{p}_{otm}$
    $\Omega_i = \left\{\mathbf{p}^{\alpha_i \to \delta_j}\right\}_{j=1}^{N_d}$
    $\mathbf{p} = \min_{\mathbf{p}\in\mathbf{\Omega}_i} \gamma_{(\mathbf{p})}$
    if $\gamma_{(\mathbf{p})} < \gamma^{in}$ **then**
      $\gamma^{in} = \gamma_{(\mathbf{p})}$
      $\mathbf{p}_{otm} = \mathbf{p}$
    else
    end
    update the vector $\boldsymbol{\delta}_j$ for the next cycle
  end
  keep the best pattern $\mathbf{p}_{otm}$ for the next iteration
while ($\gamma^{in} < \gamma^{out}$);

IV. RECEIVE ANTENNA SELECTION

To evaluate the receive antenna selection, we consider that each user is equipped with N_R receive antennas and only N_{ra} RF chains ($N_{ra} < N_R$). The total number of combinations containing N_{ra} out of N_R antennas is given by $S_r = \binom{N_R}{N_{ra}}$. The most appropriate set of N_{ra} antennas is selected by the transmitter to receive the information symbols, i.e. the BS selects the set that maximizes the detection energy at each UE and must notify the users which of the S_r possible patterns is chosen for transmission, in order to guarantee the correct signal detection. In the receiving antenna selection case, the signal vector conveyed to user k is expressed by

$$\mathbf{s}_k = \sqrt{E_k}\mathbf{D}(\mathbf{q}_k)\tilde{\mathbf{s}}_k = \sqrt{E_s}\sqrt{\varepsilon_k}\ \mathbf{D}(\mathbf{q}_k)\tilde{\mathbf{s}}_k, \tag{19}$$

where the N_R-dimensional vector $\mathbf{q}_k$ has N_{ra} entries 1 and the remaining are zero. Its non-zero entries indicate the information bearing (IB) antennas to which the receiver N_{ra} RF chains are to be connected. Here the relation (6) assumes the form

$$E_T = E_s \mathrm{Tr}\left\{\boldsymbol{\mathcal{E}}\mathbf{D}(\mathbf{q}_{all})\mathbf{P}_{ZF}^{H}\mathbf{P}_{ZF}\right\} = E_s\gamma_r, \tag{20}$$

where $\mathbf{q}_{all} = [\mathbf{q}_1^T, \mathbf{q}_2^T, \ldots, \mathbf{q}_K^T]^T$ and the γ_r factor is given by

$$\gamma_r = \mathrm{Tr}\left\{\boldsymbol{\mathcal{E}}\mathbf{D}(\mathbf{q}_{all})\mathbf{P}_{ZF}^{H}\mathbf{P}_{ZF}\right\} = \sum_{k=1}^{K} \varepsilon_k {\mathbf{q}_k}^T \mathbf{g}_k, \tag{21}$$

where vectors $\mathbf{g}_k, k = 1, \ldots, K$ obtained according to (8) and (10) are given by

$$[\mathbf{g}_1^T, \mathbf{g}_2^T, \ldots, \mathbf{g}_K^T]^T = \mathbf{d}\left(\mathbf{P}_{ZF}^{H}\mathbf{P}_{ZF}\right) = \mathbf{d}\left(\left[\mathbf{H}\mathbf{H}^H\right]^{-1}\right). \tag{22}$$

As pointed out in the previous section, by minimizing γ_r the detection signal-to-noise ratio of all users are maximized. In order to minimize γ_r we consider the independent minimization of the terms in the summation (21), since they are all positive and each one is associated to a single user. Among the S_r possible choices of pattern $\mathbf{q}$, the one that results in minimal $\mathbf{q}^T\mathbf{g}_k$ is selected for user k. This is done by simply setting to one the elements of $\mathbf{q}$, in positions corresponding to the smaller values of $\mathbf{g}_k$ entries.

A. *Notification*

As mentioned before, to guarantee correct detection the UE receiver must connect its N_{ra} RF chains to the correct set of N_{ra} IB antennas. Since the IB pattern selected by the BS may change according to the variations of the channel, information regarding the pattern selection has to be periodically sent to the

UE receiver (UE notification) where a very reliable retrieval of this information has to be performed. To implement the UE notification we consider a frame transmission scheme, where signals informing the index of the selected pattern are sent to the users during the notification period, preceding the user data frame. The antenna pattern used during the notification period is fixed and known a priori by the receivers. Moreover by sending the same notification information several times, it is possible to further reduce the notification error probability. The UE receiver accumulates the signal vectors received during the notification period and performs detection using the resulting summation signal. With this procedure, if F_{not} is the number of repeated transmissions adopted, a detection signal-to-noise gain of $10\log_{10}(F_{not})$ dB is obtained.

V. Numerical Results

In this section, numerical results are presented to evaluate the bit-error-rate (BER) performance of the considered systems in different scenarios. The curves are obtained after N_{CR} independent realizations of the channel matrix $\mathbf{H}$. The entries of $\mathbf{H}$, are complex independent circularly symmetric gaussian random variables with zero mean and unity variance. The noise vector in (1) is a complex zero-mean gaussian vector with circularly symmetric components and covariance matrix $\mathbf{K_n} = \sigma_n^2\mathbf{I}$. Results are expressed in terms of the signal-to-noise ratio

$$\text{SNR}_{\text{dB}} = 10\log_{10}\left(\frac{E_T}{\sigma_n^2}\right) \quad , \tag{23}$$

and QPSK modulation is assumed. From (9) we have that the detection signal-to-noise ratio per receive antenna is

$$\frac{E_k}{\sigma_n^2} = \frac{E_T}{\sigma_n^2}\frac{\varepsilon_k}{\gamma} = SNR\frac{\varepsilon_k}{\gamma}. \tag{24}$$

Therefore, with ML detection performed by the UE receivers it results that for a given channel realization and antenna pattern selection the user k conditional bit-error-rate is given by

$$\text{BER}_k(\gamma) = \text{Q}\left(\sqrt{\frac{E_k}{\sigma_n^2}}\right) = \text{Q}\left(\sqrt{\frac{SNR}{\gamma}\varepsilon_k}\right), \tag{25}$$

where Q(.) is the Q-function defined as

$$\text{Q}(x) = \frac{1}{2\pi}\int_x^\infty \exp\left(-\frac{\beta^2}{2}\right)d\beta \tag{26}$$

and the user k BER performance is

$$\text{BER}_k = \mathbb{E}\left[\text{Q}\left(\sqrt{\frac{SNR}{\gamma}\varepsilon_k}\right)\right]. \tag{27}$$

In a semi-analytical approach we approximate (27) by

$$\text{BER}_k \cong \frac{1}{N_{CR}}\sum_{i=1}^{N_{CR}}\text{Q}\left(\sqrt{\frac{SNR}{\gamma_i}\varepsilon_k}\right). \tag{28}$$

We note that (25) and the approximation (28), with $\gamma_{(p)}$ given by (17) and (18), are applicable to the case of transmit antenna selection but they can be used in the receive antenna selection case, with γ_r given by (21) and (22), only if error free

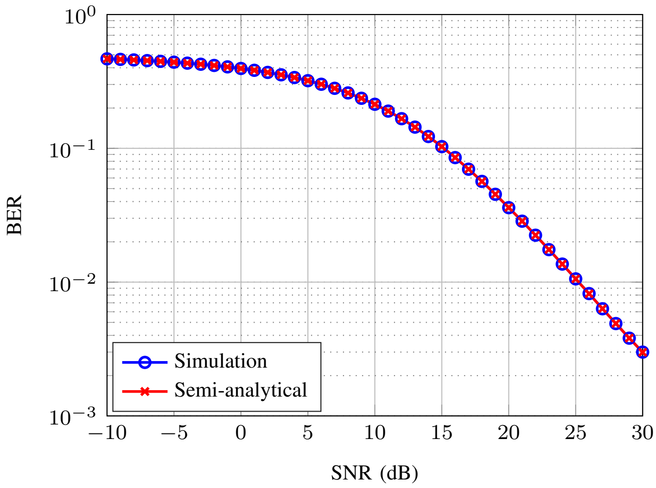

Fig. 1. BER vs. SNR(dB) for N_T = 8, N_R = 4 and K = 2.

notification is assumed. The results in this section consider an uniform user energy allocation ($\varepsilon_k = 1$, for all k).

Fig.1. compares the BER performance obtained with Monte Carlo simulation and with the semi-analytical approximation (28). In both cases the results are for N_{CR} = 1000 channel realizations, and in the Monte Carlo simulations a data frame of 1200 signal vectors are transmitted to each user per channel realization. Considering the coincidence of the BER results, the much less computation time consuming approximation (28) was used to generate the results presented in figures 2 and 3.

The results in Fig.2. are for transmit antenna selection and illustrate the BER performance when the BS is equipped with different number of antennas and RF chains. It is easily observed that the case of no selection with 10 available antennas gives the best performance, but it requires a RF chain connected to each transmit antenna. However, if we have 6 RF chains available a notable improvement in BER performance is obtained when BS is equipped with 10 antennas and the most suitable set of 6 antennas is selected for transmission when compared to the case of 6 fixed antennas. The results shown in Fig.3. correspond to a scenario with N_T = 20, N_{ta} = 6, K = 2 and N_R = 3 and illustrate the high gain in performance obtained with the proposed BER minimizing antenna selection approach when compared with a non-selective choice, where one of the possible S_t sets is randomly selected for each channel realization. Also in this figure are the BER results obtained with the use of the proposed suboptimal search algorithm (ITES) and with the Genetic Algorithm based search procedure proposed in [7]. The former resulted in a slight improvement in BER performance than the latter. To have a fair comparison, both algorithms use the same number of iterations to generate their results, i.e. we modify the stop condition of ITES so that it performs 3 iterations, same as GA. This change in the stop criteria was made only for comparative purposes. Note that with only 3 iteration ITES achieves a BER performance close to that obtained with the optimum exhaustive search, with a very significant lower complexity. For the considered scenario, the exhaustive search tested all

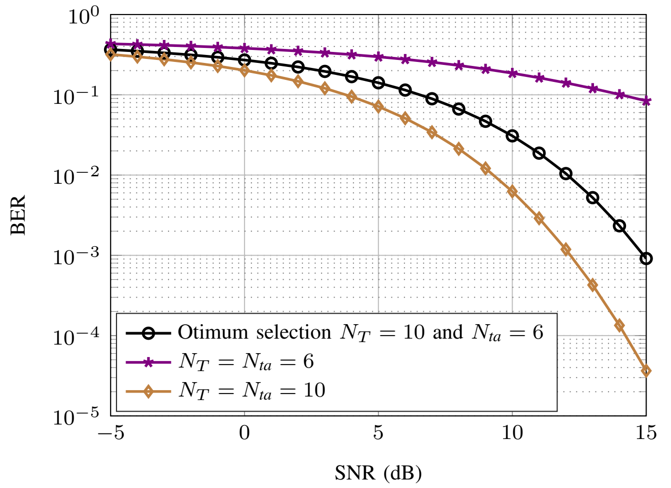

Fig. 2. BER vs. SNR(dB) for transmit antenna selection considering different number of antennas and RF chains available at BS, N_R = 3 and K = 2.

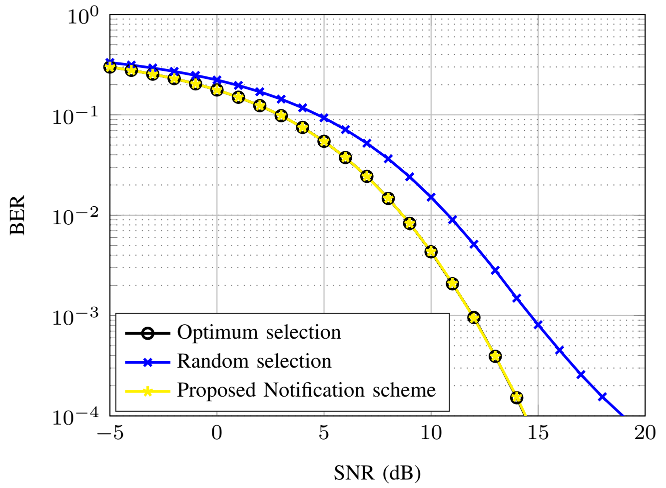

Fig. 4. BER vs. SNR(dB) for receive antenna selection with N_T = 10, N_{ra} = 2, N_R = 4 and K = 2.

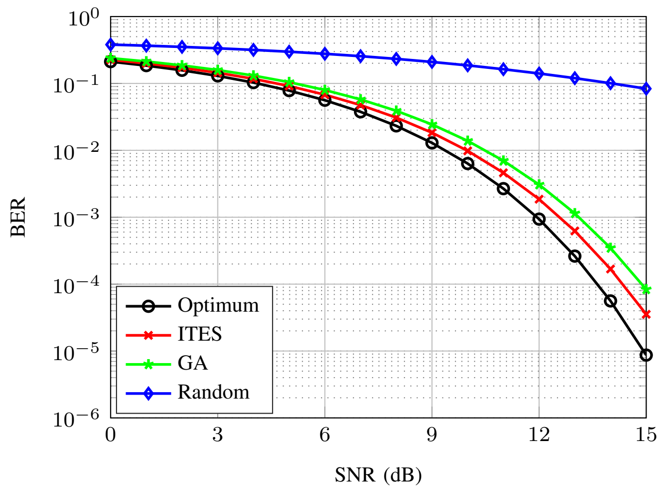

Fig. 3. BER vs. SNR(dB) for transmit antenna selection with N_T = 20, N_{ta} = 6, N_R = 3 and K = 2.

the 38760 possible antenna patterns, while the ITES and GA tested only 252 each.

In receive antenna selection case, the BS uses all its N_T antennas for transmission and, based on the minimization of γ_r, given in (21) and (22), selects the most suitable set of antennas for receiving data symbols. Fig.4 presents BER performance curves for a scenario with N_T = 10, N_R = 4, N_{ra} = 2 and K = 2, thus yielding a set of S_r = 6 possible antenna patterns that can be chosen to receive information symbols. BER curves assuming error-free user notification and incorporating the proposed notification method were generated using Monte Carlo simulations, where for each of the N_{CR} = 1000 channel realizations, 1200 data signal vectors followed by F_{not} = 10 notification signal vectors are transmitted to each user. The coincidence of the BER performance curves evidences the effectiveness of the adopted notification method. The results also evidence the high performance gains that can be obtained with the proposed receive antenna selection optimization method.

VI. Conclusions

This paper considered a BER minimizing approach to antenna selection in the downlink of MU-MIMO systems. We have developed a procedure to obtain the optimal transmit antenna set when a reduced number of RF chains is available at the BS. We have also introduced the ITES algorithm, that significantly reduces the search space and is able to achieve a BER performance close to the optimum exhaustive search selection. Similarly, a method to perform optimal receive antenna selection was proposed, and a notification procedure to inform the BS selections to the users' receivers was explored. Joint transmit and receive antenna selection is a natural extension and is currently in progress.

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