International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(Research Article)

A user selection algorithm for downlink MU-MIMO systems using product of singular values of effective channels

Mohammed Ali Al-Shuraifi *, Watheq Naser Hussein, Maithem Hussein Rasheed and Bashar Abid Hamza

Department of Energy and Renewable Energies, College of Engineering / Al Musayab, University of Babylon, Iraq.

International Journal of Science and Research Archive, 2024, 13(01), 2286–2295

Publication history: Received on 19 January 2023; revised on 05 October 2024; accepted on 08 October 2024

Article DOI: https://doi.org/10.30574/ijsra.2024.13.1.0073

Abstract

User selection plays a crucial role when aiming to improve channel throughput in multiuser multiple- input multiple-output downlink systems with block diagonalization linear precoding. While an optimal group of users can be found by exhaustively searching all possible combinations of users, the process becomes prohibitively complex when there is a large number of users. In this paper, we propose a greedy suboptimal user selection algorithm, which iteratively selects a user to maximize the product of the singular values of the effective channels from a set of unselected users. The proposed algorithm is based on the iterative precoder design method, whereby interuser interference is perfectly cancelled with lower complexity than with the singular value decomposition-based precoding technique. Moreover, to avoid frequent use of singular value decomposition, the proposed algorithm applies QR decomposition to the selected channel matrices in order to obtain singular values, which are equivalent to the product of diagonal elements in the upper triangular matrix. Simulation results show that, under a high SNR regime, the proposed algorithm outperforms several other greedy algorithms and can provide the same performance as a capacity-based algorithm for both correlated and uncorrelated channels with significantly reduced complexity.

Keywords: Multiuser multiple-input multiple-output (MU-MIMO); User selection; Singular values; Block diagonalization

1. Introduction

In modern wireless communications, significant attention has been directed toward multiuser multipleinput multiple-output (MU-MIMO) systems due to their capability of improving system throughput [1] [2]

. In the case that channel state information (CSI) is available at the base station (BS), interuser interference (IUI) can be precancelled using several efficient methods. Dirty paper coding (DPC) provides optimal IUI cancellation, but its high complexity during coding and decoding makes its application to large multiple antenna systems unrealistic [3] [4] . For practical implementation, zero-forcing beamforming (ZF-BM) and block diagonalization (BD) techniques are proposed instead of DPC as suboptimal preprocessing techniques for MU-MIMO systems [5] . In ZF-BM, where each user has one receive antenna, the transmitted signal is multiplied by a precoding matrix which represents the pseudo-inverse of other users' channels [6] . On the other hand, for users with multiple receive antennas, BD designs each user's precoding matrix to be in the null space of other users' channels. Consequently, BD preeliminates IUI from users and breaks down the overall MU-MIMO channel into several independent parallel single user MIMO (SU-MIMO) downlink channels [7] .

The nullspace-based precoding matrix imposes the constraint that a BS must communicate with con- current users which have a total number of receive antennas less than that of transmit antennas for that BS. When there is a large number of users, the BS may select a subset for communication in order to increase the total sum rate capacity of the

* Corresponding author: Mohammed Ali Al-Shuraifi

system. Optimum users are obtained by exhaustively searching over all possible users combinations, which thus involves high complexity, in particular, when there is a large number of users.

To reduce the complexity of user selection under the BD technique, considerable research effort has been devoted to reducing the complexity of precoding stage. Regarding which, the conventional precoding design method which applies the singular value decomposition (SVD) iteratively to cancel IUI requires high computational burden. Alternatively, an iterative precoder design method is introduced by [8] to alleviate the computational demand caused by repeated SVD. For user selection, one strategy is to design a greedy suboptimal algorithm, whereby one user that maximizes a specific performance metric is selected at each iteration. Many greedy suboptimal user selection algorithms are proposed, which are based on various selection metrics. A capacity-based algorithm (c-algorithm) is proposed in [9] , which selects a user to maximize the average sum rate of the system at each iteration. Despite the high level of performance that the c-algorithm can provide, it requires high complexity due to frequent use of SVD. Another approach to user selection under BD is proposed by [10] , which utilizes both backward and forward projection in order to select the most orthogonal user channels optimally. This approach needs to find null space and spatial correlation among users at each iteration, which raises the complexity of selection for large number of users. Moreover, [11] proposes a low-complexity algorithm that greedily selects users to maximize the channel volume which can be found by calculating the product of diagonal elements of the upper triangular matrix R produced by performing QR factorization to the channel matrix. Another low complexity algorithm which is based on the product of squared row norms of effective channels is proposed by [8] to select an optimal set of users for BD systems. However, these low complexity user selection algorithms have a low burden of computation, but performance degradation is unavoidable. Under a high SNR regime, [12] proposes a user selection algorithm based on the product of the eigenvalues of effective channels and the idea of principle angles between subspaces. This algorithm provides good performance, but its complexity depends on the maximum number of users that can be simultaneously served by BS and total number of users in the system.

In this paper, we propose a greedy suboptimal user selection algorithm, which utilizes the product of singular values of effective channels as a selection metric in MU-MIMO downlink systems under the assumption of a high SNR regime. The main motivation behind the proposed algorithm is to reach the performance achieved by the capacity-based algorithm as well as to reduce the computational load during the user selection process. To achieve high performance, we have designed our selection metric to express the capacity of BD in a high SNR regime. In terms of complexity, the QR decomposition (QRD) has been used to obtain the product of the singular values instead of SVD so as to reduce the computational effort at each selection step. Further, the proposed algorithm applies the iterative precoder design method, which requires a small concatenated matrix size in order to cancel IUI.

The rest of this paper is organized as follows. A MU-MIMO system with block diagonalization is presented in section 2 and section 3 introduces the proposed user selection algorithm with their also being analysis of its computational complexity. Simulation results are presented in section 4 and finally, section 5 provides the conclusion.

Notation: Bold uppercase and lowercase letters denote matrices and vectors, respectively; HH and

N (H) are Hermitian and null space of matrix H, respectively; for a M × N matrix H, we denote by δ(H) the product of the singular values of H. Furthermore, null(H) denotes the matrix whose columns form an orthonormal basis of N (H).

2. MU-MIMO system with block diagonalization

2.1. System Model

Consider a single-cell downlink MU-MIMO system with N_t transmit antennas at the base station BS and K users which have an equal number of receive antennas N_r. The channels are assumed to be independent and identically distributed (i.i.d) flat fading channels. The channel propagation from BS to the kth user is given as $H_k \in C^{N_r \times N_t}$, under the assumption of perfect channel information at the transmitter by using either time-division duplexing (TDD) or frequency-division duplexing (FDD) communication mode. Each user's channel H_k is assumed to be independent of other users' channels and has full rank, $rank(H_k) = min(N_r, N_t)$ with $N_t > N_r$. Consequently, the overall system channel, $H = [H_1^H H_2^H \dots H_K^H]$, ascertains a full rank matrix.

Let S ⊂ {1, 2, ..., K} denotes a set of users which can be served simultaneously by the BS. For the kth user, a symbol vector $X_k \in C^{N_r \times 1}$ is transmitted with an input covariance matrix and a total transmit power. $P = \sum_{k=1}^{K} trace\ (Q_k)$Then, the transmitted signal is multiplied by a precoding matrix $W_k \in C^{N_t N_r}$ and transmitted to users. Thus, the kth user receives [13]

$$y_k H_k W_k H x_k + \sum_{j=1, j\neq k}^{|S|} H_k W_j H x_j + Z_k$$

where zk ∈ CNr y1 denotes the Additive White Gaussian Noise (AWGN) with (0,σ^2)

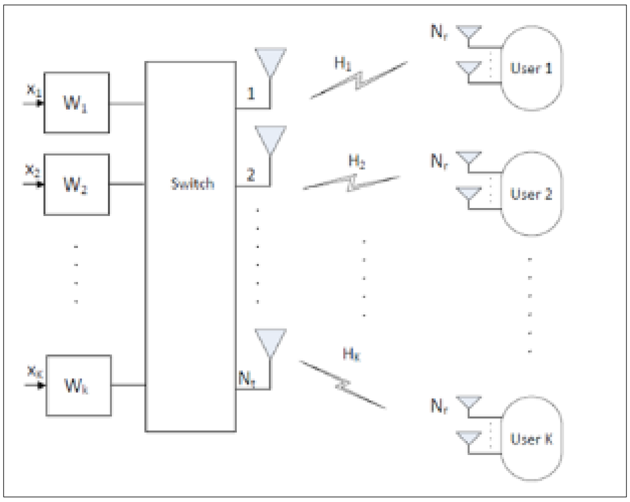

Figure 1 Proposed model for a MU-MIMO system with BD precoding technique

2.2. Iterative Precoder Design method

Block diagonalization serves to cancel the IUI of a MU-MIMO channel and decompose it into parallel SU-MIMO channels. For user k, the precoder matrix has to satisfy the condition

$$\boldsymbol{H_j W_k = 0}, \forall \boldsymbol{j \neq k} \text{ .... (2)}$$

W_k must be a unitary matrix, i.e., $W_k \cup (N_t, N_r)$, so as to satisfy the total transmitted power. Moreover, W_k can be broken down into two matrices F and Λ, i.e., $W_k = F_k \Lambda_k$, where F_k is designed to nullify the IUI and Λ_k in order to optimize the data rate [14] . Therefore, F_k is designed to lie in the intersection of all other users' nullspaces except user k, i.e., M $(\tilde{H}_k)$, where

$$\boldsymbol{\tilde{H}_k = \left[H_1^H, \dots H_{k-1}^H, H_k^H, \dots, H_{|S|}^H\right]^H}$$

An iterative method is proposed in [8] to design F_k, which applies the QR decomposition instead of SVD to compute the nullspace matrix. To illustrate the iterative precoder design method, let us consider finding the precoding matrix for user 1, which is denoted by $\boldsymbol{F_1^{(n)}}$ at the nth iteration. Initially, we set $\boldsymbol{F_1^{(n)} = I_{n_t}}$ At step two, $\boldsymbol{F_1^{(2)} = N(H_2)}$. After the nth iteration, we obtain $\boldsymbol{F_1^{(n)}}$ such that $\boldsymbol{H_k F_1^{(n)} = 0}$ for all $\boldsymbol{1 < k \leq n}$ In each step $\boldsymbol{F_1^{(n)}}$ can be found from$\boldsymbol{F_1^{(n-1)}}$ in a recursive way, as follows

$$\boldsymbol{F_1^{(n)} = F_1^{(n-1)} G_1^{(n)}} \text{ ....(4)}$$

where $\boldsymbol{G_1^{(n)}}$ is in $\boldsymbol{N(H_n F_1^{(n-1)}}$)))In the same way, we can obtain other users' precoder matrices recursively. Note that from (4), the effective channel for user 1 can be found $\boldsymbol{\tilde{H}_1^{(n)} = \tilde{H}_1^{(n-1)} G_1^{(n)}}$In general, we can obtain the effective channel for user k form that in (n — 1)th iteration as follows

$$\boldsymbol{\tilde{H}_k^{(n)} = \tilde{H}_k^{(n-1)} G_k^{(n)}}$$

$$= \boldsymbol{\tilde{H}_k^{(n-1)} N(H_n F_k^{(n-1)}} \text{ ....(5)}$$

To ensure nullity of $\widetilde{\boldsymbol{H}}_{\mathbf{k}}$, the number of transmit antennas must be larger than the total number of receive antennas of users that are simultaneously communicating with BS, that is

$$\boldsymbol{N_t} > \sum_{\boldsymbol{k+1}}^{|\boldsymbol{S}|} \boldsymbol{N_{r,k}}$$

where Nr,k denotes the number of receive antennas of user k.

When the total number of users K is larger than the number of simultaneously supportable users, $\hat{K}$, i.e., K> $\hat{K}$, , we need to find the set of users $S \subset \{1, 2, ..., K\}$ that can maximize the total throughput of the system. The optimal subset of users can be obtained by exhaustively searching for all possible user combinations, i.e., $|\boldsymbol{S}| = \boldsymbol{C}_{\boldsymbol{K}}^{\hat{\boldsymbol{k}}}$, but this becomes prohibitive when the number of users is large, i.e., $\mathbf{K} \gg \hat{\mathbf{K}}$. Conceptually, it is necessary to find suboptimal user selection methods for realistic use with acceptable efficiency,

3. Proposed user selection algorithm

In this section, we propose a greedy user selection algorithm, where the product of the singular values of the effective channel matrices is considered as our selection metric. For low complexity, the singular values can be obtained efficiently using QR decomposition rather than SVD. In each iteration, the effective channels of selected users are updated recursively using the (n — 1)th previous effective channels to eliminate the interference induced by the new selected user.

3.1. Extracting the singular values using QR Decomposition

The singular values of a matrix can be computed using the conventional SVD method. The key weakness of SVD is that it is considered data dependent and hence, it requires expensive calculations to obtain the diagonal elements of the singular values. In contrast, QRD can be used efficiently to extract the product of the singular values instead of SVD and with lower complexity. Without loss of generality, assume matrix A ∈ Cpyq with p < q, then A can be written as

$$\boldsymbol{A^H} = \boldsymbol{Q}\begin{bmatrix}\boldsymbol{R_1}\\ \mathbf{0}\end{bmatrix}$$

where $\boldsymbol{Q} \in \boldsymbol{C}^{q\times q}$ has orthonormal column vectors, and $\boldsymbol{R_1} \in \boldsymbol{C}^{p\times p}$ is the upper triangular matrix. Note that in order to get the actual product of the singular values for matrix A, we have used the hermitian matrix A^H instead of A in (7). Then, it is possible to obtain the product of the singular values, δ, as

$$\boldsymbol{\delta} = \left|\prod_{\boldsymbol{i+1}}^{\boldsymbol{p}} \boldsymbol{ru}\right| = \left|\prod_{\boldsymbol{i+1}}^{\boldsymbol{p}} \boldsymbol{\sigma i}\right| \quad \dots\dots..(\mathbf{8})$$

where r_{ii} are the entries of the diagonal of R_1, and σ_i represent the singular values of matrix A

3.2. Proposed Algorithm

In this subsection we briefly summarize the proposed algorithm of user selection, which is based on the user selection algorithm proposed by [8] , but with different selection metric. Algorithm 1 outlines the main operations of the proposed algorithm, where the sets of remaining and selected users are denoted

by Ψ and ϒ, respectively. Let F(n) denote the precoding matrix of the jth selected user at the nth iteration. Z denotes the orthonormal basis of the null space of the rows of previously selected users, which can be obtained by applying th Gram-Schmidt Orthogonalization (GCO) procedure on the null space of the rows of earlier selected channel matrices. Initially, the algorithm selects the first user that maximises the product of the singular values δ(Hk) for k ∈ Ψ, k = {1, 2, ..., K}. We set the initial precoding matrix of the first selected user to be the identity matrix and at the nth iteration, the algorithm selects a new user a

$$un = \arg\max_{j\in\Psi}\left(\underbrace{\sigma(\bar{H}_j)}_{term1}\underbrace{\prod_{k\in Y}\sigma(\bar{H}_k)}_{term2}\right)$$

where,

- term1: constitutes the product of the singular values for the effective channel of the user currently under investigation. (line 8 in Algorithm 1)
- term2: constitutes the product of the singular values for the updated effective channels of all previously selected users. (line 11 in Algorithm 1)

More specifically, when there is a new user under investigation, the algorithm takes into consideration the following. It calculates the precoding matrix of this investigated user and its effective channel (line 7 and line 8 in Algorithm 1, respectively). Next, the algorithm temporarily updates first the precoder matrix of each of the previously selected users so as to cancel the interference caused by the investigated user and then their effective channels (lines 9-12 in Algorithm 1). After that, according to (9), a user that yields the maximum product of the singular values of effective channels is selected from set Ψ (line 13 in Algorithm 1). After a new user is selected, Z and $\boldsymbol{F_k^{(n)}}$ must be updated accordingly. The selection process repeats until the required number of users K^ is obtained.

3.3. Computational Complexity Analysis

In this subsection, we investigate the computational complexity of Algorithm 1 and compare it with that of various suboptimal user selection algorithms. This complexity is calculated by the number of flops as

Algorithm 1 User selection using the product of the singular values

- Ψ = {1,2,…,K}, Y=∅
- select the first user $\boldsymbol{u_1} = \mathbf{arg}\max_{\boldsymbol{k\in\Psi}} \boldsymbol{\delta(H_k)}$
- Set the precoding matrix of $\boldsymbol{u_1}$: $\boldsymbol{F_{u_1}^{(1)} = I_{N_t}}$
- Let $\mathbf{Z} = \mathbf{null}\ (\boldsymbol{H_{u_1}})$
- Update $\boldsymbol{\Psi = \Psi - u_1 Y = Y + u_1, n = 2}$
- for $\boldsymbol{j \in \Psi}$ do
- Set $\boldsymbol{F_j = Z}$
- Calculate the effective channel matrices $\boldsymbol{\bar{\bar{H}}_j^{(n)} = H_j F_j}$
- for $\boldsymbol{k \in Y\ do}$
- Set $\boldsymbol{F_{temp} = F_k^{(n-1)} \times null\ (H_j F_k^{(n-1)})}$
- Update the effective channel matrices $\boldsymbol{\bar{\bar{H}}_k^{(n)} = H_k F_{temp}}$
- end for
- Select the new user as : $\boldsymbol{u_n} = \mathbf{arg}\max_{\boldsymbol{k\in\Psi}} \left(\boldsymbol{\delta}(\bar{H}_j^{(n)}) \prod_{k\in Y} \boldsymbol{\delta}(\boldsymbol{\bar{H}_k^{(n)}})\right)$
- Update the intersection of the null space of all previously selected users : $\boldsymbol{Z = Z \times null(H_{u_n} Z)}$
- for $\boldsymbol{k \in y\ do}$
- Update $\boldsymbol{F_k^{(n)} = F_k^{(n-1)} \times null\ (H_{u_n} F_k^{(n-1)})}$
- end for
- Update : $\boldsymbol{\Psi = \Psi - u_1 Y = Y + u_1, n = 1}$
- end for in [9] and a flop is defined as a real floating point operation. For example, real addition, multiplication, or division is calculated as one flop. For complex numbers, an addition and a multiplication operation involve two and six flops, respectively. Multiplication of the two matrices A∈C^(p×a) and B∈C^(a×q) requires 8paq flops. Moreover, the complexity of the QRD operation for a matrix H∈C^(p×q) is approximated by q^2 (4p-q) , as in [8] .

Table 1 Comparison of the complexity order for different user selection algorithms

Algorithm	**Complexity order**
c-algorithm [9]	$\boldsymbol{O}(\boldsymbol{K}\widehat{\boldsymbol{K}}^{2}\boldsymbol{N}_t^3)$
psrn-algorithm [8]	$\boldsymbol{O}(\boldsymbol{K}\widehat{\boldsymbol{K}}\boldsymbol{N}_t^3)$
pe-algorithm [12]	$\boldsymbol{O}(\boldsymbol{K}\widehat{\boldsymbol{K}}\boldsymbol{N}_t^3)$
v-algorithm [11]	$\boldsymbol{O}(\frac{\boldsymbol{K}}{\boldsymbol{4}}\widehat{\boldsymbol{K}}\boldsymbol{N}_t^3)$
proposed algorithm	$\boldsymbol{O}(\boldsymbol{K}\widehat{\boldsymbol{K}}\boldsymbol{N}_t^3)$

Specifically, the proposed algorithm of user selection has the following complexity analysis:

- To select the first user, we need $\boldsymbol{4KN_r^2(3N_t - N_r)}$ flops.
- To find the null space of the first user via QRD operation, we require $\boldsymbol{4KN_r^2(3N_t - N_r)}$ flops
- For each $j \in \Psi$, $n \geq 2$, we need
  - $\boldsymbol{8N_rN_t(N_t - (n-1)N_r) flops\ for\ \overline{H}_j^{(n)}}$;
  - $\boldsymbol{16N_rN_t(N_t - (n-2)N_r) + 4N_r^2\ (3N_t - (n-1)N_r)\ flops\ forF_{temp}}$;
  - $\boldsymbol{8N_r(N_t - (n-1)N_r)(N_t - (n-2)N_r) flops\ for\ \overline{H}_k^{(n)}}$;
- To select a new user, we need $\boldsymbol{4N_r^2\ (3N_t - (n-1)N_r)\ flops}$
- To update the null space Z, we need $\boldsymbol{16N_rN_t(N_t - (n-2)N_r) + 4N_r^2\ (3N_t - (n-1)N_r)\ flops}$
- Finally, for each k ∈ Y, we need $\boldsymbol{16N_rN_t(N_t - (n-2)N_r) + 4N_r^2\ (3N_t - (n-1)N_r)\ flops}$
- to update the precoder $\boldsymbol{F_k^{(n)}}$

The total number of flops, ψ, of the proposed algorithm becomes

$$\boldsymbol{\psi} \approx \boldsymbol{4KN_r^2\ (3N_t - N_r) + 4KN_r^2\ (3N_t - N_r)} +$$

$$\sum_{n=2}^{\widehat{K}} \times \{\boldsymbol{8N_rN_t(N_t - (n-1)N_r)}$$

$$+(n-1)[16N_rN_t(N_t - (n-2)N_r)$$

$$4N_r^2\ (3N_t - (n-1)N_r\ )$$

$$+8N_r(N_t - (n-1)N_r)(N_t - (n-2)N_r)]$$

$$+4nN_r^2\ (3N_t - (n-1)N_r) - N_r)\}$$

$$+16N_rN_t(N_t - (n-2)N_r)$$

$$+4nN_r^2\ (3N_t - (n-1)N_r)$$

$$+(n+1)[16N_rN_t(N_t - (n-2)N_r)$$

$$+4nN_r^2\ (3N_t - (n-1)N_r)]$$

$$\approx O(K\widehat{K}\ \ N_t^3) \ldots\ldots\ldots\ (10)$$

Note that to simplify the above equation, we have assumed $\widehat{\boldsymbol{K}}\boldsymbol{N_r} \approx \boldsymbol{N_t}$. A comparison of the complexity order for different user selection algorithms is listed in Table I. Evidently, the proposed algorithm has a complexity order less than the c-algorithm and the same as the psrn-algorithm and pe-algorithm, while the v-algorithm has the lowest complexity order.

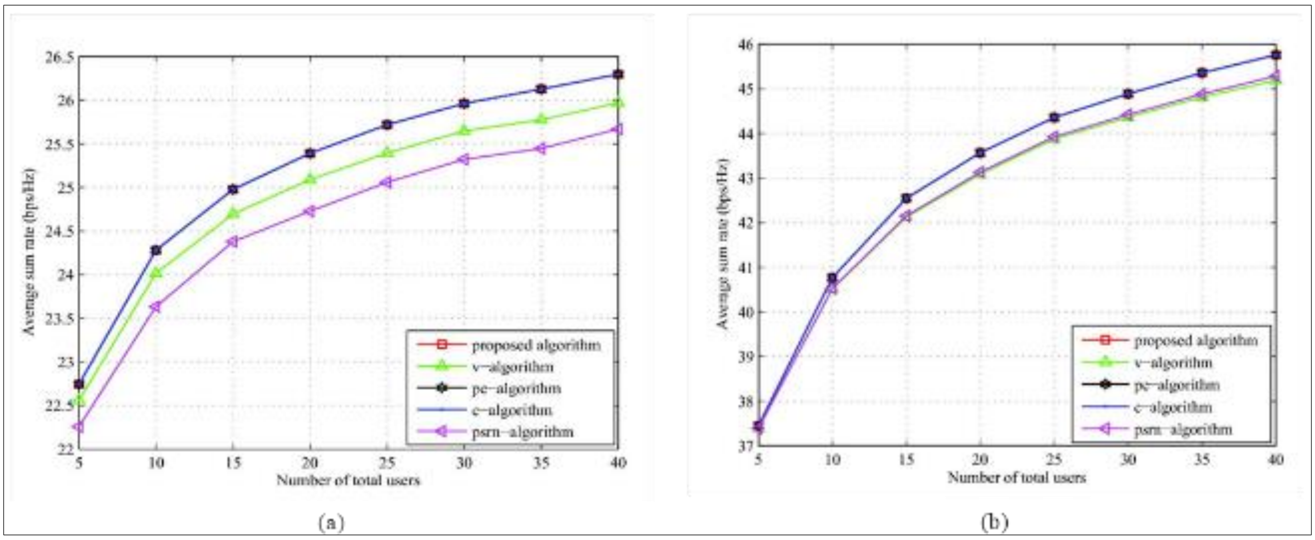

Figure 2 Average sum rate of different user selection algorithms when SNR=20 dB, ρ = 0. (a) Nt = 4, Nr = 2, (b) Nt = 8, Nr = 2

3.4. Simulation results

To evaluate the performance of the proposed user selection algorithm, we compare it with the following algorithms:

- Capacity-based algorithm (c-algorithm) [9] ;
- Product of the squared row norms of the effective channel matrices-based algorithm (psrn-algorithm) [8] ;
- Volume-based algorithm (v-algorithm) [11] ;
- Product of the eigenvalues of effective channel matrices from the angle between subspaces (pe- algorithm) [12] ;

The numerical results have been averaged over 5,000 independent quasi-static fading channel realizations. Further, the simulation assumed both uncorrelated and correlated channels.

In Fig. 2 the average sum rate of different user selection algorithms is plotted against the number of total users K for $\rho = 0$ (uncorrelated channels), and SNR =20 dB. It can be seen that for two different antenna scenarios, the proposed algorithm outperforms the v-algorithm and the psrn-algorithm and has the same result as the c-algorithm and pe-algorithm. More specifically, the c-algorithm achieves high performance over other suboptimal user selection algorithms, because its selection metric corresponds directly to the sum rate capacity of the BD channel. Similarly, at high SNR, the throughput of an individual user is an increasing function of the product of the eigenvalues of the effective channels [9] . Hence, taking in consideration the relation between SVD and the eigendecomposition, the proposed selection metric can achieve almost similar performance to the c-algorithm under a high SNR regime. Also, we observe that the psrn-algorithm achieves better performance in Fig. 2(b), which is because the number of effective transmit antennas has increased that lead to increase the product of squared row norms of the effective channels [8] .

In Fig 3, we validate the performance results of different user selection algorithms under a highly correlated MIMO channel ($\rho = 0.95$) and at high SNR. We model the MIMO channel matrix according to the Kronecker model as $\boldsymbol{H_k} = \Omega_{\boldsymbol{k.r}}^{\frac{1}{2}} \boldsymbol{H_{k,iid}} \Omega_{\boldsymbol{k.t}}^{\frac{1}{2}}$ where $H_{k,iid}$ is an independent and identically distributed complex Gaussian distribution with zero mean and unit variance and $\Omega_{\boldsymbol{k.t}}^{\frac{1}{2}}$ denotes $N_t \times N_t$ transmit covariance matrix, i.e., $\Omega_{\boldsymbol{k,t}} = \Omega_{\boldsymbol{k.t}}^{\frac{H}{2}}$ **[15]**. $\Omega_{\boldsymbol{k,r}}^{\frac{1}{2}}$ is the correlation matrix for the receive antennas and here assumed as the identity matrix (i.e., the receive antennas elements are uncorrelated)

[16] . Under this assumption, the MIMO channel has a transmit correlation only and the above model can be written as $\boldsymbol{H_k} = \boldsymbol{H_{k,iid}} \Omega_{\boldsymbol{k.t}}^{\frac{1}{2}}$ Simulation results are generated using the exponential correlation model, i.e., $[\Omega_{\boldsymbol{k,t}}]_{\boldsymbol{i,j}} = \boldsymbol{p_k^{|i-j|}}$. where $[]_{\boldsymbol{i,j}}$ is the entry of matrix $\Omega_{\boldsymbol{k,t}}$ with index (i,j), and ρ_k is the correlation coefficient for user k defined as $\boldsymbol{pk} = \boldsymbol{pe^{j\emptyset k}}$ with $\emptyset_{\boldsymbol{k}}$ is i.i.d. and uniformly distributed over $[\boldsymbol{0}, \boldsymbol{2\pi}]$ [17] [18] . Clearly, the results shown in Fig 3 indicate that

the proposed algorithm outperforms the v-algorithm and the psrn-algorithm, with almost similar performance to the c-algorithm and the pe- algorithm. In addition, we notice that the proposed algorithm is less affected by channel correlation than the v-algorithm and the psrn-algorithm, with almost similar performance to the c-algorithm and the pe- algorithm. In addition, we notice that the proposed algorithm is less affected by channel correlation than the psrn-algorithm and the volume-algorithm for the same number of transmit antennas, which is expected since the proposed performance metric corresponds directly to the data rate of BD in high SNR scenario. However, as the channel correlation increases, the instantaneous channels of the users tend to be more dependent (i.e., quasi-identical) and, as a result, the sum rate is reduced due to loss in the spatial degrees of freedom. [19] –[21]

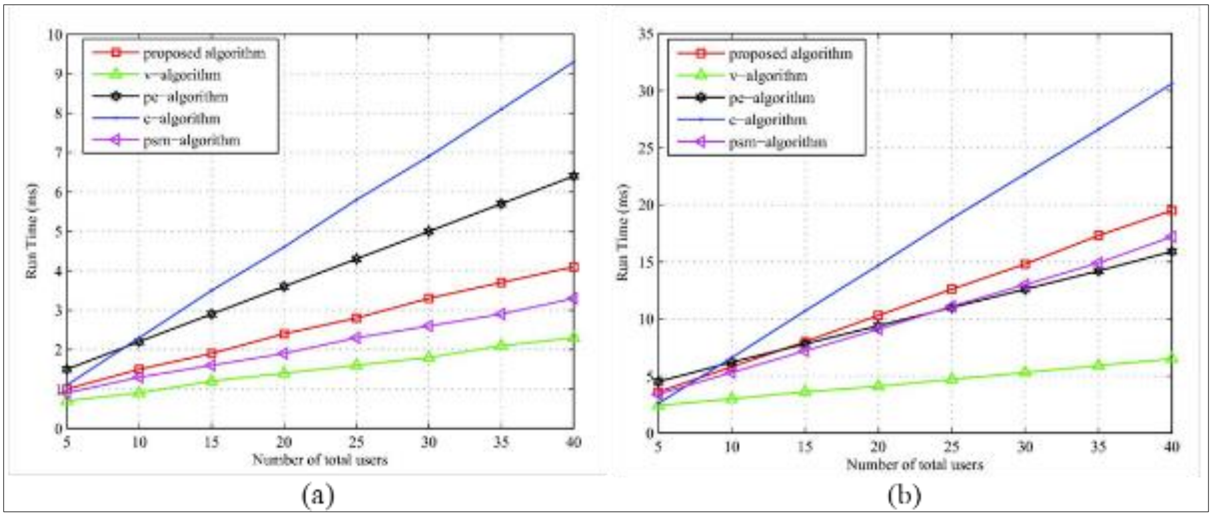

Figure 3 Run time of different user selection algorithms when SNR=20 dB, ρ = 0. (a) Nt = 4, Nr = 2 (b) Nt = 8, Nr = 2

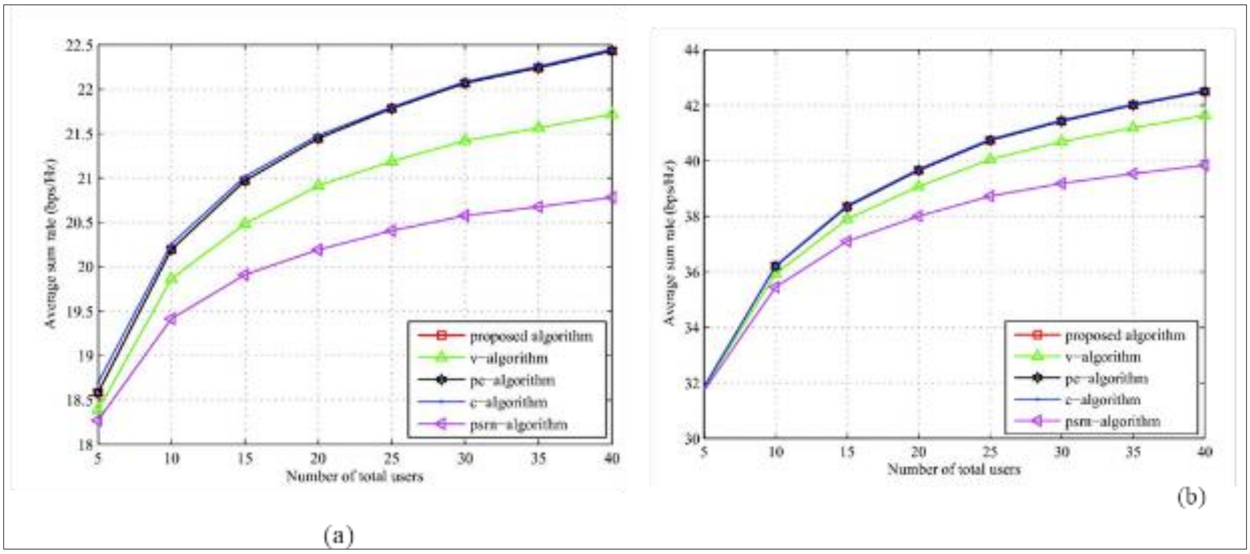

Figure 4 Average sum rate of different user selection algorithms when SNR=20 dB, $\rho = 0.95$. (a) $N_t = 4, N_r = 2$, (b) $N_t = 8, N_r = 2$

Fig. 4 plots a comparison of the elapsed CPU time of various user selection algorithms versus the number of total users for ρ = 0 (uncorrelated channels), and SNR =20 dB. These results are attained by 3.4 GHz Core i7 CPU PC. In the first scenario[Fig. 4(a)], where the maximum number of users that can be supported by BS is two, the simulation time results show that the proposed algorithm needs less run time than that of the pe-algorithm. In contrast, Fig. 4(b) presents the run time comparison when N_t = 8, N_r = 2. In this scenario, we observe that the running time of the proposed algorithm starts to be greater than that of the pe-algorithm when the number of total users exceeds a particular limit (in this case K = 15). In either way the proposed algorithm has less run time than the c-algorithmn, while the volume-based has the shortest run time. In summary, the proposed algorithm gives the same performance as the c-algorithm and pe-algorithm in high SNR as seen in Fig 2 and 3. In terms of complexity, the proposed algorithm has a shorter run time than the c-algorithm and pe-algorithm when the maximum number of simultaneously supportable users, $\widehat{\boldsymbol{K}}$ is two, but it becomes more dependant on the total number of users, K, to whom data is transmitted simultaneously by BS as seen in Fig. 4.

4. Conclusion

In this paper, a greedy suboptimal user selection algorithm for MU-MIMO downlink systems has been proposed. The key idea is that, for each iteration, the algorithm selects a user to maximize the product of the singular values of the effective channels from a set of unselected users. The singular values are extracted from the upper triangular matrix, which is obtained by applying QR decomposition to the selected channel matrices and hence, the use of SVD is avoided. Moreover, to alleviate the computational burden, the proposed algorithm relies on iterative precoder design rather than the conventional SVD-based precoding method in order to cancel IUI. From computational complexity analysis, we have demonstrated that the proposed scheme is approximately equivalent to the psrn-algorithm and pe-algorithm and has less complexity than that of the c-algorithm. More specifically, the algorithm has a shorter run time than the pe-algorithm and is close to the psrn-algorithm if the maximum number of users that can be simultaneously supported is two, but it becomes more dependant on the total number of users in the system when this figure is greater than two. In either case, the proposed algorithm has less run time than the c-algorithm. Furthermore, simulation results show that the proposed algorithm outperforms the psrn-

Algorithm and v-algorithm as well as providing performance that is the same as that of the c-algorithm and pe-algorithm under a high SNR regime, for both correlated and uncorrelated channels.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Lu, L., Lee, G., Swindlehurst, A., Ashikhmin, A., Zhang, R.: 'An overview of massive MIMO: benefits and challenges', IEEE J. Sel. Topics Signal Process., 2014, 8, (5), pp. 742-758

[2] Khomyat, T., Uthansakul, P., Uthansakul, M., Hee, S.: ' On the performance of the zero-forcing-space-time block coding multiple-input-multiple-output receiver with channel estimation error and error propagation', IET Commun., 2014, 8, (18), pp. 3381-3392

[3] Costa, M.: 'Writing on dirty paper', IEEE Trans. Inf. Theory, 1983, 29, (3), pp. 439-441

[4] Donghun, L.: 'Performance analysis of zero-forcing-precoded scheduling system with adaptive modulation for multiuser- multiple input multiple output transmission', IET Commun., 2015, 9, (16), pp. 2007 - 2012.

[5] Nguyen, D. H. N., Nguyen-Le, H., Le-Ngoc, T.: ' Block-diagonalization precoding in a multiuser multicell MIMO System: competition and coordination', IEEE Trans. Wireless Commun., 2014, 13, (2), pp. 968 - 981.

[6] Caire, G., Shamai, S.: 'On the achievable throughput of a multiantenna Gaussian broadcast channel', IEEE Trans. Inf. Theory, 2003, 49, (7), pp. 1691-1706

[7] Spencer, Q., Swindlehurst, A., Haardt, M.: 'Zero-forcing methods for downlink spatial multiplexing in multiuser MIMO channels', IEEE J. Sel. Topics Signal Process., 2004, 52, (2), pp. 461-471

[8] Tran, L-N, Bengtsson, M., Ottersten, B.: 'Iterative precoder design and user scheduling for block-diagonalized systems', IEEE Trans. Signal Process., 2012, 60, (7), pp. 3762-3739

[9] Shen, Z., Chen, R., Andrews, J., Heath, R.W., Evans, B.L.: 'Low complexity user selection algorithms for multiuser MIMO systems with block diagonalization', IEEE Trans. Signal Process., 2006, 54, (9), pp. 3658-3663

[10] Sigdel, S., Krzymien, W.A.: 'Simplified fair scheduling and antenna selection algorithms for multiuser MIMO orthogonal space-division multiplexing downlink', IEEE Trans. Veh. Technol., 2009, 58, (3), pp. 1329-1344

[11] Jin, L., Gu, X., Hu, Z.: 'Low-complexity scheduling strategy for wireless multiuser multiple-input multiple-output downlink system', IET Commun., 2011, 5, (7), pp. 990-995

[12] Nam, S., Kim, J., Han, Y.: ’A user selection algorithm using angle between subspaces for downlink MU-MIMO Systems’, IEEE Trans. Commun., 2014, 62, (2), pp. 616-624

[13] Cho, Y., Kim, J., Yang, W., and Kang, C.: MIMO-OFDM wireless communications with MATLAB, (WILEY Press, Singapore, 1st edn.2010)

[14] Fuchs, M., Galdo, G.D., Haardt, M.: ’Low-complexity space-time-frequency scheduling for MIMO systems with SDMA’, IEEE Trans. Veh. Technol., 2007, 56, (5), pp. 2775-2784.

[15] Kermoal, J.P., Schumacher, L., Pedersen, K.I., Mogensen, P.E.: ’A stochastic MIMO radio channel model with experimental validation’, IEEE J. Sel. Areas Commun., 2002, 20, (6), pp. 1211-1226

[16] kang, M., Alouini, M.S.: ’Capacity of correlated MIMO rayleigh channels’, IEEE Trans. Wireless commun., 2006, 5, (1), pp. 143-155

[17] Loyka, S.L.: ’Channel capacity of MIMO architecture using the exponential correlation matrix’, IEEE Commun. Lett., 2001, 5, (9), pp. 369-371

[18] Yu, K., Bengtsson, M., Ottersten, B., McNamara, D., Karlsson, P., Beach, M.: ’Second order statistics of NLOS indoor MIMO channels based on 5.2 GHz measurements’, IEEE GLOBECOM, 2001, 1, pp. 156-160

[19] Akhtar, J., Gesbert, D.: ’Spatial multiplexing over correlated MIMO channels with closed-form precoder’, IEEE Trans. Wireless Commun., 2005, 4, (5), pp. 2400-2409

[20] Chuah, C-N., Tse, D.N.C., Kahn, J.M., Valenzuela, R.A.: ’Capacity scaling in MIMO wireless systems under correlated fading’, IEEE Trans. Inf. Theory,, 2002, 48, (3), pp. 637-650

[21] Girnyk, M.A., Vehkapera, M., Rasmussen, L.K.: ’Large-system analysis of correlated MIMO multiple access channels with arbitrary signaling in the presence of interference’, IEEE Trans. Wireless commun., 2014, 13, (4), pp. 2060-2073