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SINR loss and user selection in massive MU-MISO systems with ZFBF

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Separating highly correlated users can reduce the loss caused by spatial correlation (SC) in multiuser multiple-input multiple-output (MU-MIMO) systems. However, few accurate analyses of the loss caused by SC have been conducted. In this study, we define signal-to-interference-plus-noise ratio (SINR) loss to characterize it in multiuser multiple-input single-output (MU-MISO) systems, and use coefficient of correlation (CoC) to describe the SC between users. A formula is deduced to show the accurate relation between SINR loss and CoC. Based on this relation, we propose a user selection method that utilizes CoC to minimize the average SINR loss of users in massive MU-MISO systems. Simulation results verify the correctness of the relation and show that the proposed user selection method is very effective at reducing the loss caused by SC in massive MU-MISO systems.

KEYWORDS
coefficient of correlation, multiuser multiple-input single-output, signal-to-interference-plus-noise ratio loss, spatial correlation, user selection

1 | INTRODUCTION

Multiuser multiple-input multiple-output (MU-MIMO) plays a major role in MIMO systems [1,2]. Compared with single-user MIMO (SU-MIMO), MU-MIMO can serve a group of users rather than just one user at the same time-frequency resource [3]. This indicates that user selection involves selecting user groups in MU-MIMO systems. Because of the requirement of forming these groups, the complexity of user selection is increased, particularly when the number of users is large [4,5]. Although an exhaustive search can find a very good result of user grouping, its complexity is extremely high. To address this problem in MU-MIMO systems, methods of user selection have been investigated in recent years to obtain appropriate user groups.

Spatial correlation (SC) is a key factor of user selection in MU-MIMO systems. This is because users in the same group are affected by the correlation between them. An improper selection of users may lead to a great loss caused by SC. Therefore, considering SC is necessary. A few metrics already exist that characterize SC between users. One key metric widely used in user selection is the normalized inner product, also known as coefficient of correlation (CoC) [1,6–8]. This metric is particularly applicable to time division duplex (TDD) systems, where base stations can quickly obtain downlink channel information according to channel reciprocity.

There are primarily two types of user selection methods that use CoC as the SC metric to reduce the loss. In [9–11], thresholds of CoC are set to obtain semi-orthogonal users for user selection. To avoid performance loss, only semi-orthogonal users can be served in the same group. In addition, many studies use metrics to estimate the loss caused by SC [12–16]. In these studies, the average of correlation values (ACV) or sum of correlation values (SCV) between users are widely used. In general, the main idea of user selection using CoC is to separate the highly correlated users into different groups. In other words, users in the same group should have small correlation values to reduce their losses caused by SC. Note that these methods based on CoC are also usable in massive MIMO systems because scenarios exist in which some users are highly correlated [12,17,18].

However, although the aforementioned idea of separating highly correlated users by CoC is widely used to reduce loss, it is mainly proposed based on two-user cases and intuitive observation. For example, the authors in [14] consider that when two users are strongly correlated, eliminating the interference between them requires considerable power. Thus, users with high values of SC should not be served together. In [19], the authors consider that in order to achieve a good performance using zero-forcing beamforming (ZFBF), the selected users should be nearly orthogonal to reduce the loss caused by SC. In previous works, although CoC has been widely used to reduce the loss, practically no research exists on the accurate loss caused by CoC, particularly in cases with more than two users. Furthermore, most studies use the average or sum of CoC to estimate the effect of correlation on user performance [12–16]. For example, the authors in [16] consider that the sum of CoC should be calculated to estimate the SC effect, but they do not show the reason for it. Therefore, whether the average or sum of CoC is the best metric to reduce the loss must be further investigated.

Based on the previous analysis, to reduce further the loss of each user in MU-MIMO systems, the analysis of accurate loss caused by CoC is necessary. In this study, signal-to-interference-plus-noise ratio (SINR) loss is defined to characterize the loss in downlink multiuser multiple-input single-output (MU-MISO) systems. We then derive a formula to show how SC affects user performance. Furthermore, a user selection method based on the approximate relation between SINR loss and SC in massive MISO systems is investigated. The main contributions of this study are summarized as follows:

1. SINR loss is defined to denote the loss caused by SC in MU-MISO systems with ZFBF. This value can also be regarded as the percentage of loss of the desired signal power. We give a formula to show the relation between SINR loss and CoC. Note that there is no limitation on the channel model in the formula.
2. In addition to the independent and identically distributed (i.i.d.) model, the 3D MIMO model is also considered. In 3D MIMO model, some users may still have high values of SC, even if the number of antennas at the base station is high.
3. Two approximate expressions are proposed to denote the relation between SINR loss and CoC in massive MISO systems.
4. A user selection method for massive MU-MISO systems is proposed to minimize average SINR loss, which is based on the approximate relation between SINR loss and CoC. Compared with the ACV or SCV used in many studies, the metric used in this method is more reasonable and effective at reducing the loss in MU-MISO systems.

The remainder of this paper is organized as follows. The system model is described in Section 2. In Section 3, the SINR loss is defined, and a formula is derived to show the relation between SINR loss and CoC. Two expressions are proposed in Section 4 to denote the approximate relation between SINR loss and CoC in massive MISO systems, and a user selection method for massive MISO systems is proposed in Section 5 to reduce the loss. Simulation results are presented in Section 6. Section 7 concludes the study.

Notations: Uppercase and lowercase bold letters denote matrix and vector, respectively. det(·), $(\cdot)^H$, $(\cdot)^{-1}$, $(\cdot)^*$, $\|\cdot\|$, $|\cdot|$ and card(·) denote the determinant, conjugate transpose, inverse matrix, adjugate matrix, norm, absolute value, and cardinality, respectively. $\mathbf{X}_{i,j}$ represents the entry from the ith row and jth column of $\mathbf{X}$, and $\mathbf{X}_{(\tilde{i},\tilde{j})}$ represents the block obtained by deleting the ith row and jth column of $\mathbf{X}$.

2 | SYSTEM MODEL

We consider a downlink MU-MISO system with ZFBF. As shown in Figure 1, M antennas exist at the base station (BS). K single-antenna users are selected from N active users to form a group. Users in the same group are affected by the correlation between them. We assume that the BS knows the downlink channel matrix of all users through channel reciprocity in TDD systems [1,10].

2.1 | Received signal

The received signals in the system can be expressed as:

$$\mathbf{y} = \mathbf{H}\mathbf{W}_{\text{norm}}\mathbf{P}\mathbf{x} + \mathbf{n}, \quad (1)$$

where $\mathbf{y}$ is the vector of received signals of size $K \times 1$, $\mathbf{H}$ is the downlink channel matrix of size $K \times M$, $\mathbf{W}_{\text{norm}}$ is the column-normalized precoding matrix of size $M \times K$, $\mathbf{P}$ is the

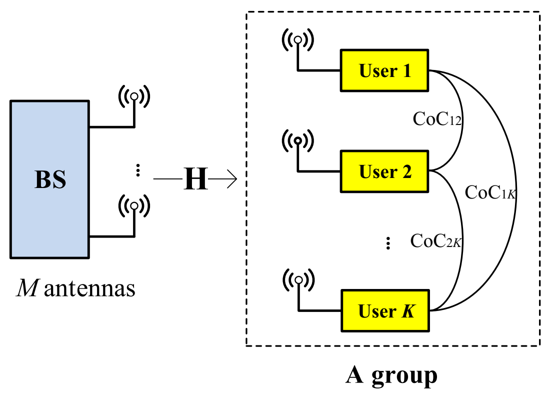

FIGURE 1 System model

diagonal matrix of transmit power with diagonal elements equal to $\left[\sqrt{p_1}, \dots, \sqrt{p_k}, \dots, \sqrt{p_K}\right]$, $\mathbf{x}$ is the vector of data symbols of size $K \times 1$, and $\mathbf{n}$ is the vector of additive zero-mean white Gaussian noise with variance σ_n^2. Because ZFBF is used, the non-normalized precoding matrix $\mathbf{W}$ can be expressed as

$$\mathbf{W} = \mathbf{H}^H(\mathbf{H}\mathbf{H}^H)^{-1} = (\mathbf{w}_1, \dots, \mathbf{w}_k, \dots, \mathbf{w}_K), \quad (2)$$

where $\mathbf{w}_k$ is the non-normalized precoding vector of user k. The column-normalized precoding matrix $\mathbf{W}_{\text{norm}}$ is given by

$$\mathbf{W}_{\text{norm}} = \left(\frac{\mathbf{w}_1}{\sqrt{\mathbf{w}_1^H\mathbf{w}_1}}, \frac{\mathbf{w}_2}{\sqrt{\mathbf{w}_2^H\mathbf{w}_2}}, \dots, \frac{\mathbf{w}_K}{\sqrt{\mathbf{w}_K^H\mathbf{w}_K}} \right). \quad (3)$$

According to (1), (2), and (3) the received signal of user k can be expressed as

$$y_k = \sum_{i=1}^{K} \frac{\sqrt{p_i}\mathbf{h}_k\mathbf{w}_i}{\sqrt{\mathbf{w}_i^H\mathbf{w}_i}} x_i + n_k = \frac{\sqrt{p_k}\mathbf{h}_k\mathbf{w}_k}{\sqrt{\mathbf{w}_k^H\mathbf{w}_k}} x_k + n_k, \quad (4)$$

where $\mathbf{h}_k$ is the channel vector of user k of size $1 \times M$. Note that in (4), $\mathbf{h}_k\mathbf{w}_i = 0$ $(i \neq k)$. This is because perfect channel state information at the transmitter (CSIT) is assumed and the multiuser interference at each user is eliminated [20].

2.2 | SINR

Based on (4) and the analysis in [20], the SINR of user k with transmit power p_k can be expressed as

$$\text{SINR}_k = \frac{p_k}{(\mathbf{w}_k^H\mathbf{w}_k)\sigma_n^2}. \quad (5)$$

According to (2), we have

$$\mathbf{W}^H\mathbf{W} = \left(\mathbf{H}^H(\mathbf{H}\mathbf{H}^H)^{-1}\right)^H \mathbf{H}^H(\mathbf{H}\mathbf{H}^H)^{-1} = \left((\mathbf{H}\mathbf{H}^H)^{-1}\right)^H. \quad (6)$$

Thus, $\mathbf{w}_k^H\mathbf{w}_k$ can be obtained by

$$\mathbf{w}_k^H\mathbf{w}_k = \left((\mathbf{H}\mathbf{H}^H)^{-1}\right)_{k,k}, \quad (7)$$

where $((\mathbf{H}\mathbf{H}^H)^{-1})_{k,k}$ is the entry from the kth row and kth column of $(\mathbf{H}\mathbf{H}^H)^{-1}$. When we combine (5) and (7) SINR_k can be expressed as [21]

$$\text{SINR}_k = \frac{p_k}{\sigma_n^2\left((\mathbf{H}\mathbf{H}^H)^{-1}\right)_{k,k}}. \quad (8)$$

2.3 | CoC

CoC is widely used as a metric of SC. The value of SC between user i and j can be expressed as [17]

$$|\rho_{ij}| = \frac{\left|\mathbf{h}_i\mathbf{h}_j^H\right|}{\|\mathbf{h}_i\|\|\mathbf{h}_j\|}, \quad (9)$$

where $|\rho_{ij}|$ is a value between 0 and 1. A large value of $|\rho_{ij}|$ means that the channel vectors of user i and j are highly correlated, and a small value means the channel vectors of the two users are nearly orthogonal. ρ_{ij} can be expressed as

$$\rho_{ij} = \frac{\mathbf{h}_i\mathbf{h}_j^H}{\|\mathbf{h}_i\|\|\mathbf{h}_j\|}. \quad (10)$$

3 | LOSS CAUSED BY SC

In this section, SINR loss is defined to express the percentage loss caused by SC in MU-MISO systems. We then provide a formula to show the relation between SINR loss and SC. Four parts are used to analyze this problem. Part 1 defines the SINR loss. Part 2 shows the process of simplification. Part 3 shows the relation between SINR loss and CoC. Part 4 gives two examples of the relation.

3.1 | SINR loss

SINR loss is defined in this part. To denote it, we first investigate SINR_k when the channels of other users are orthogonal to k $(|\rho_{ki}| = 0, \forall i \neq k)$. This is the SINR of user k, which has no loss caused by SC, and we use $\text{SINR}_{k,\text{ort}}$ to represent it. In (8), the SINR of user k in the ordinary case with perfect CSIT is already given. In an orthogonal case, this expression can be further simplified. We use $\mathbf{H}_{k,\text{ort}}$ to denote the channel matrix in the orthogonal case. Because of the orthogonality, the entries in the kth row and kth column of matrix $\mathbf{H}_{k,\text{ort}}\mathbf{H}_{k,\text{ort}}^H$ are all equal to 0 except $(\mathbf{H}_{k,\text{ort}}\mathbf{H}_{k,\text{ort}}^H)_{k,k}$. Based on the Laplace expansion and cofactor introduced in [22], $((\mathbf{H}_{k,\text{ort}}\mathbf{H}_{k,\text{ort}}^H)^{-1})_{k,k}$ can be expressed as

$$\begin{aligned}\left((\mathbf{H}_{k,\text{ort}}\mathbf{H}_{k,\text{ort}}^H)^{-1}\right)_{k,k} &= \frac{\left((\mathbf{H}_{k,\text{ort}}\mathbf{H}_{k,\text{ort}}^H)^*\right)_{k,k}}{\det\left(\mathbf{H}_{k,\text{ort}}\mathbf{H}_{k,\text{ort}}^H\right)} \\ &= \frac{\det\left((\mathbf{H}_{k,\text{ort}}\mathbf{H}_{k,\text{ort}}^H)_{(\bar{k},\bar{k})}\right)}{\mathbf{h}_k\mathbf{h}_k^H\det\left((\mathbf{H}_{k,\text{ort}}\mathbf{H}_{k,\text{ort}}^H)_{(\bar{k},\bar{k})}\right)} \\ &= \frac{1}{\mathbf{h}_k\mathbf{h}_k^H},\end{aligned} \quad (11)$$

where $(\mathbf{H}_{k,\text{ort}}\mathbf{H}_{k,\text{ort}}^H)_{(\bar{k},\bar{k})}$ represents the block obtained by deleting the kth row and kth column of the matrix, and $(\cdot)^*$ is the adjugate matrix. Therefore, when the channels of other users are orthogonal to user k, $\text{SINR}_{k,\text{ort}}$ can be expressed as:

$$\text{SINR}_{k,\text{ort}} = \frac{p_k}{\sigma_n^2\left((\mathbf{H}_{k,\text{ort}}\mathbf{H}_{k,\text{ort}}^H)^{-1}\right)_{k,k}} = \frac{p_k\mathbf{h}_k\mathbf{h}_k^H}{\sigma_n^2}. \quad (12)$$

This SINR can be regarded as the upper bound of the performance of user k. No loss is caused by SC in this case. Combining $\text{SINR}_{k,\text{ort}}$ and SINR_k, we define the SINR loss caused by SC. We use L_k to denote the SINR loss of user k, and it can be expressed as

$$L_k = \frac{\text{SINR}_{k,\text{ort}} - \text{SINR}_k}{\text{SINR}_{k,\text{ort}}} = \frac{\mathbf{h}_k\mathbf{h}_k^H - \frac{1}{((\mathbf{HH}^H)^{-1})_{k,k}}}{\mathbf{h}_k\mathbf{h}_k^H}. \quad (13)$$

When the channels of other users are orthogonal to user k, L_k is equal to zero. This means that no loss of user k occurs when this user is being served with other users. When the channels are non-orthogonal, L_k shows the loss caused by SC.

Compared with the average and sum of SC used in many studies, the metric L_k is more reasonable to denote the loss in MU-MIMO systems. It provides an accurate method for calculating the loss. Note that although this metric represents the SINR loss caused by SC, according to (13), L_k can also represent the loss of the desired signal power.

3.2 | Simplified form of SINR loss

In this part, we investigate the expression of $((\mathbf{HH}^H)^{-1})_{k,k}$ and obtain a simplified form of L_k. These are shown in (20) and (22), respectively. For simplicity, we use $\mathbf{A}$ to represent the Hermitian matrix $\mathbf{HH}^H$. Because $\mathbf{A}$ is a square matrix, it can be expressed as

$$\mathbf{A} = \begin{pmatrix} \mathbf{A}_{1,1} & \mathbf{r}_{\tilde{1}} \\ \mathbf{c}_{\tilde{1}} & \mathbf{A}_{(\tilde{1},\tilde{1})} \end{pmatrix}, \quad (14)$$

where $\mathbf{A}_{k,k}$ is the entry from the kth row and kth column of $\mathbf{A}$, $\mathbf{r}_{\tilde{k}}$ refers to the kth row of $\mathbf{A}$ without the kth entry, $\mathbf{c}_{\tilde{k}}$ denotes the kth column of $\mathbf{A}$ without the kth entry, and $\mathbf{A}_{(\tilde{k},\tilde{k})}$ represents the block obtained by deleting the kth row and kth column of $\mathbf{A}$. Because an even number of interchanges will not affect the determinant value, the determinant of $\mathbf{A}$ can be expressed as

$$\det(\mathbf{A}) = \det\begin{pmatrix} \mathbf{A}_{1,1} & \mathbf{r}_{\tilde{1}} \\ \mathbf{c}_{\tilde{1}} & \mathbf{A}_{(\tilde{1},\tilde{1})} \end{pmatrix} = \det\begin{pmatrix} \mathbf{A}_{k,k} & \mathbf{r}_{\tilde{k}} \\ \mathbf{c}_{\tilde{k}} & \mathbf{A}_{(\tilde{k},\tilde{k})} \end{pmatrix}. \quad (15)$$

Based on the block determinant and Schur complement explained in [22], the determinant of $\mathbf{A}$ is given by

$$\det(\mathbf{A}) = \det\left(\mathbf{A}_{(\tilde{k},\tilde{k})}\right)\det\left(\mathbf{A}_{k,k} - \mathbf{r}_{\tilde{k}}\left(\mathbf{A}_{(\tilde{k},\tilde{k})}\right)^{-1}\mathbf{c}_{\tilde{k}}\right). \quad (16)$$

In addition, $\mathbf{A}^{-1}$ can be expressed as [22]

$$\mathbf{A}^{-1} = \frac{\mathbf{A}^*}{\det(\mathbf{A})}, \quad (17)$$

where $\mathbf{A}^*$ is the adjugate matrix of $\mathbf{A}$. Based on (17) and the properties of the adjugate matrix introduced in [22], $(\mathbf{A}^{-1})_{k,k}$ can be expressed as

$$(\mathbf{A}^{-1})_{k,k} = \frac{\det\left(\mathbf{A}_{(\tilde{k},\tilde{k})}\right)}{\det(\mathbf{A})}. \quad (18)$$

Combining (16) and (18) we get

$$\det\left(\mathbf{A}_{(\tilde{k},\tilde{k})}\right)\det\left(\mathbf{A}_{k,k} - \mathbf{r}_{\tilde{k}}\left(\mathbf{A}_{(\tilde{k},\tilde{k})}\right)^{-1}\mathbf{c}_{\tilde{k}}\right) = \frac{\det(\mathbf{A}_{(\tilde{k},\tilde{k})})}{(\mathbf{A}^{-1})_{k,k}}, \quad (19)$$

Therefore, $1/(\mathbf{A}^{-1})_{k,k}$ can be simplified as

$$\frac{1}{(\mathbf{A}^{-1})_{k,k}} = \det\left(\mathbf{A}_{k,k} - \mathbf{r}_{\tilde{k}}\left(\mathbf{A}_{(\tilde{k},\tilde{k})}\right)^{-1}\mathbf{c}_{\tilde{k}}\right). \quad (20)$$

Because $(\mathbf{A}_{k,k} - \mathbf{r}_{\tilde{k}}(\mathbf{A}_{(\tilde{k},\tilde{k})})^{-1}\mathbf{c}_{\tilde{k}})$ is a 1×1 matrix, the determinant of this matrix can be expressed as

$$\det\left(\mathbf{A}_{k,k} - \mathbf{r}_{\tilde{k}}(\mathbf{A}_{(\tilde{k},\tilde{k})})^{-1}\mathbf{c}_{\tilde{k}}\right) = \mathbf{A}_{k,k} - \mathbf{r}_{\tilde{k}}\left(\mathbf{A}_{(\tilde{k},\tilde{k})}\right)^{-1}\mathbf{c}_{\tilde{k}}. \quad (21)$$

Note that $\mathbf{h}_k\mathbf{h}_k^H$ is equal to $\mathbf{A}_{k,k}$. Thus, combining (13), (20), and (21), L_k can be expressed as

$$L_k = \frac{\mathbf{A}_{k,k} - \frac{1}{(\mathbf{A}^{-1})_{k,k}}}{\mathbf{A}_{k,k}} = \frac{\mathbf{r}_{\tilde{k}}\left(\mathbf{A}_{(\tilde{k},\tilde{k})}\right)^{-1}\mathbf{c}_{\tilde{k}}}{\mathbf{A}_{k,k}}, \quad (22)$$

where $\mathbf{A}$ is equal to $\mathbf{HH}^H$. Taking $k = 1$ as an example, L_1 can be expressed as

$$L_1 = \frac{\mathbf{r}_{\tilde{1}}\left(\mathbf{A}_{(\tilde{1},\tilde{1})}\right)^{-1}\mathbf{c}_{\tilde{1}}}{\mathbf{A}_{1,1}} = \frac{\mathbf{r}_{\tilde{1}}\left((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})}\right)^{-1}\mathbf{c}_{\tilde{1}}}{\mathbf{h}_1\mathbf{h}_1^H}, \quad (23)$$

where $\mathbf{r}_{\tilde{1}}$ and $\mathbf{c}_{\tilde{1}}$ are given by

$$\mathbf{r}_{\tilde{1}} = \mathbf{c}_{\tilde{1}}^H = \left(\mathbf{h}_1\mathbf{h}_2^H, \mathbf{h}_1\mathbf{h}_3^H, \ldots, \mathbf{h}_1\mathbf{h}_K^H\right). \quad (24)$$

3.3 | Relation between loss and SC

In this part, we use CoC to express L_k, and the result is finally shown in (33). For simplicity, we first take $k = 1$ as an example to investigate the relation. The $((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})})^{-1}$ in (23) can be expressed as [22]:

$$\left((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})}\right)^{-1} = \frac{\left((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})}\right)^*}{\det\left((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})}\right)}. \quad (25)$$

In (25), two parts must be analyzed: the adjugate matrix $((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})})^*$ and the determinant $\det((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})})$. To obtain the entries of the adjugate matrix in (25), we use $(-1)^{i+j}d_{i,j}$ to denote the cofactor of $(\mathbf{HH}^H)_{(\tilde{1},\tilde{1})}$, where $d_{i,j}$ is the determinant obtained by deleting the ith row and jth column of $(\mathbf{HH}^H)_{(\tilde{1},\tilde{1})}$. Then, the entry from the ith row and jth column of $((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})})^*$ can be expressed by $(-1)^{i+j}d_{j,i}$ [22].

To analyze the determinant $\det((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})})$, we introduce $\mathbf{C}$ to denote the correlation matrix of users, which can be expressed as

$$\mathbf{C} = \begin{pmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1K} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{K1} & \rho_{K2} & \cdots & \rho_{KK} \end{pmatrix}. \tag{26}$$

According to [22], if a row or column of $\mathbf{A}$ is multiplied by α, the determinant of the new matrix is equal to $\alpha \det(\mathbf{A})$. By analyzing the entries of $\mathbf{C}$, we find that if we multiply every row i in $\mathbf{C}$ by $\sqrt{\mathbf{h}_i\mathbf{h}_i^H}$ and every column j in $\mathbf{C}$ by $\sqrt{\mathbf{h}_j\mathbf{h}_j^H}$, the new matrix is equal to $\mathbf{HH}^H$. This shows that the relation between $\det(\mathbf{HH}^H)$ and $\det(\mathbf{C})$ can be expressed as

$$\det\left(\mathbf{HH}^H\right) = \mathbf{h}_1\mathbf{h}_1^H\,\mathbf{h}_2\mathbf{h}_2^H \cdots \mathbf{h}_K\mathbf{h}_K^H \det(\mathbf{C}). \tag{27}$$

As in the analysis of (27), $\det((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})})$ can be expressed as

$$\det\left((\mathbf{HH}^H)_{(\tilde{1},\tilde{1})}\right) = \mathbf{h}_2\mathbf{h}_2^H \cdots \mathbf{h}_K\mathbf{h}_K^H \det\left(\mathbf{C}_{(\tilde{1},\tilde{1})}\right). \tag{28}$$

When we combine (23) and (28), and the analysis of the cofactor, L_1 can be expressed as

$$L_1 = \frac{\sum_{i,j\in\{2,\ldots,K\}} \left((-1)^{i+j}\mathbf{h}_1\mathbf{h}_i^H\mathbf{h}_j\mathbf{h}_1^H d_{j-1,i-1}\right)}{\mathbf{h}_1\mathbf{h}_1^H\mathbf{h}_2\mathbf{h}_2^H \cdots \mathbf{h}_K\mathbf{h}_K^H \det\left(\mathbf{C}_{(\tilde{1},\tilde{1})}\right)}. \tag{29}$$

Furthermore, we can obtain that

$$\begin{aligned} &\frac{\sum_{i,j\in\{2,\ldots,K\}} \left((-1)^{i+j}\mathbf{h}_1\mathbf{h}_i^H\mathbf{h}_j\mathbf{h}_1^H d_{j-1,i-1}\right)}{\mathbf{h}_1\mathbf{h}_1^H\mathbf{h}_2\mathbf{h}_2^H \cdots \mathbf{h}_K\mathbf{h}_K^H} \\ &= \sum_{i,j\in\{2,\ldots,K\}} \left(\frac{(-1)^{i+j}\mathbf{h}_1\mathbf{h}_i^H\mathbf{h}_j\mathbf{h}_1^H d_{j-1,i-1}\sqrt{\mathbf{h}_i\mathbf{h}_i^H}\sqrt{\mathbf{h}_j\mathbf{h}_j^H}}{\mathbf{h}_1\mathbf{h}_1^H\sqrt{\mathbf{h}_i\mathbf{h}_i^H}\sqrt{\mathbf{h}_j\mathbf{h}_j^H}\mathbf{h}_2\mathbf{h}_2^H \cdots \mathbf{h}_K\mathbf{h}_K^H}\right) \\ &= \sum_{i,j\in\{2,\ldots,K\}} \left((-1)^{i+j}\rho_{1i}\rho_{j1}\frac{d_{j-1,i-1}\sqrt{\mathbf{h}_i\mathbf{h}_i^H}\sqrt{\mathbf{h}_j\mathbf{h}_j^H}}{\mathbf{h}_2\mathbf{h}_2^H \cdots \mathbf{h}_K\mathbf{h}_K^H}\right). \end{aligned} \tag{30}$$

Based on the analysis of (27), we can also obtain

$$d_{j-1,i-1} = \frac{\mathbf{h}_2\mathbf{h}_2^H \cdots \mathbf{h}_K\mathbf{h}_K^H}{\sqrt{\mathbf{h}_i\mathbf{h}_i^H}\sqrt{\mathbf{h}_j\mathbf{h}_j^H}} \det\left(\left(\mathbf{C}_{(\tilde{1},\tilde{1})}\right)_{(\widetilde{j-1},\widetilde{i-1})}\right). \tag{31}$$

When we combine (29), (30), and (31) , L_1 can be expressed as

$$L_1 = \frac{\sum_{i,j\in\{2,\ldots,K\}} \left[(-1)^{i+j}\rho_{1i}\rho_{j1}\det\left(\left(\mathbf{C}_{(\tilde{1},\tilde{1})}\right)_{(\widetilde{j-1},\widetilde{i-1})}\right)\right]}{\det\left(\mathbf{C}_{(\tilde{1},\tilde{1})}\right)}. \tag{32}$$

The calculation of L_k is the same as that of L_1. L_k can be expressed as

$$\begin{aligned} L_k &= \frac{\sum_{i,j\in\{1,\ldots,K\}\backslash\{k\}} \left[(-1)^{x+y}\rho_{ki}\rho_{jk}\det\left(\left(\mathbf{C}_{(\tilde{k},\tilde{k})}\right)_{(\tilde{x},\tilde{y})}\right)\right]}{\det(\mathbf{C}_{(\tilde{k},\tilde{k})})}, \\ x &= \begin{cases} j, & j<k \\ j-1, & j>k \end{cases}, \quad y = \begin{cases} i, & i<k \\ i-1, & i>k \end{cases}. \end{aligned} \tag{33}$$

This is the most important formula we obtain in this study. It shows the accurate loss caused by SC. Note that there is no limitation on the channel model in the formula.

3.4 | Relation in simple cases

We take $k = 1$ as an example. According to (33), when two users exist in a group, L_1 is given by

$$L_1 = \frac{\rho_{12}\rho_{21}}{\rho_{22}} = |\rho_{12}|^2 = L_2. \tag{34}$$

Note that $L_1 = L_2$ in (34), which means that the SINR losses of these two users are the same in two-user scenarios. When three users exist in a group, L_1 can be calculated by:

$$\begin{aligned} L_1 &= \frac{\rho_{12}\rho_{21}\rho_{33} + \rho_{13}\rho_{31}\rho_{22} - \rho_{12}\rho_{31}\rho_{23} - \rho_{13}\rho_{21}\rho_{32}}{\rho_{22}\rho_{33} - \rho_{23}\rho_{32}} \\ &= \frac{|\rho_{12}|^2 + |\rho_{13}|^2 - 2\,\mathrm{Re}(\rho_{12}\rho_{31}\rho_{23})}{1 - |\rho_{23}|^2}, \end{aligned} \tag{35}$$

where $\rho_{ii} = 1$, the imaginary part of $(\rho_{12}\rho_{31}\rho_{23} + \rho_{13}\rho_{21}\rho_{32})$ equals 0, and $\mathrm{Re}(\rho_{12}\rho_{31}\rho_{23})$ is the real part of $\rho_{12}\rho_{31}\rho_{23}$.

4 | APPROXIMATE RELATION IN MASSIVE MU-MISO

Because of the complexity of (33) in massive MISO systems, two approximate expressions with low complexity are proposed to denote their relation in this section. The i.i.d and 3D MIMO models are both considered.

4.1 | Channel models

The i.i.d and 3D MIMO models have different characteristics of SC. In the i.i.d. model, the channel gains from transmit antennas to user antennas are assumed to be i.i.d. zero-mean complex Gaussian random variables with unitary variance [10]. This assumption is widely used in many studies [2]. One main characteristic of this model is that with the increase in the number of antennas at the base station, the channel vectors between users become nearly orthogonal.

However, the channel model of i.i.d. only considers non-line-of-sight (NLOS) communications. To investigate more practical scenarios, the 3D MIMO model is also investigated in this study. This model considers more practical factors such as the height and line-of-sight (LOS) communications [23,24]. Thus, some users may still have high correlation values in this model even if the number of antennas at the base station is high [25].

4.2 | Approximate relation between loss and SC

In this part, two low-complexity methods for estimating SINR loss in these two channel models are proposed.

We use $\hat{L}_k^{\text{i.i.d.}}$ and $\hat{L}_k^{\text{3D}}$ to denote the SINR loss of user k obtained in the i.i.d and 3D models, respectively. First, we investigate the estimation method used in the i.i.d. model.

Based on (33), (34), and (35), we obtain that one main factor affecting the SINR loss of user k is the SCs between user k and other users (ρ_{ki} and ρ_{ik}). This is the critical part in calculating L_k. Another essential part is the SCs among the other users, which is reflected by $\det(\mathbf{C}_{(\tilde{k},\tilde{k})})$ and $\det((\mathbf{C}_{(\tilde{k},\tilde{k})})_{(\tilde{x},\tilde{y})})$ in (33). Because of the characteristics of i.i.d. models in massive MIMO systems, the channel vectors between users are nearly orthogonal. Considering the extreme cases, we ignore the correlations between the other users in massive MIMO systems and thus assume $\rho_{ij}=0$ ($i \neq j \neq k$). We take $k=1$ as an example. In this case, the correlation matrix can be denoted as

$$\hat{\mathbf{C}}=\begin{bmatrix} \rho_{11} & \rho_{12} & \dots & \rho_{1K} \\ \rho_{21} & \rho_{22} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{K1} & 0 & \dots & \rho_{KK} \end{bmatrix}. \tag{36}$$

Combining (32) and (36), we obtain that

$$\begin{aligned}\hat{L}_1^{\text{i.i.d.}} &= \frac{\sum_{i,j\in\{2,\dots,K\}}\left[(-1)^{i+j}\rho_{1i}\rho_{j1}\det\left((\hat{\mathbf{C}}_{(\tilde{1},\tilde{1})})_{(\tilde{j}-1,\tilde{i}-1)}\right)\right]}{\det(\hat{\mathbf{C}}_{(\tilde{1},\tilde{1})})} \\ &= \sum_{i\in\{2,\dots,K\}}(\rho_{1i}\rho_{i1}) = \sum_{i\in\{2,\dots,K\}}|\rho_{1i}|^2\end{aligned}. \tag{37}$$

The calculation of $\hat{L}_k^{\text{i.i.d.}}$ is the same as that of $\hat{L}_1^{\text{i.i.d.}}$. Thus, $\hat{L}_k^{\text{i.i.d.}}$ in massive MIMO systems with i.i.d. models can be calculated by

$$\hat{L}_k^{\text{i.i.d.}} = \sum_{i\in\{1,\dots,K\}\backslash\{k\}}|\rho_{ki}|^2. \tag{38}$$

Because of the characteristics of 3D MIMO such as LOS communications, some users may still not be nearly orthogonal when the number of antennas at the base station increases. In other words, we cannot use $\rho_{ij}=0$ ($i \neq j \neq k$) for simplification in the 3D MIMO model. According to (34), we know that the percentage of the remaining SINR of a user in two-user cases can be expressed as $(1-|\rho_{12}|^2)$. Inspired by this, we propose the following method to estimate the SINR loss in 3D MIMO systems, which can be expressed as

$$\hat{L}_k^{\text{3D}} = 1-\prod_{i\in\{1,\dots,K\}\backslash\{k\}}\left(1-|\rho_{ki}|^2\right), \tag{39}$$

where the second term denotes the estimation value of the remaining SINR of user k. It considers the losses caused by each user in the group.

5 | USER SELECTION IN MASSIVE MU-MISO SYSTEMS

To reduce the loss caused by SC in MU-MISO systems, some methods have been proposed such as using the metric sum of CoC to select users. However, because no accurate analysis has been conducted on the loss caused by CoC, these methods may not be the best choices. In this section, a user selection method that minimizes the average SINR loss in massive MISO systems is proposed. We use L_{avg} to denote the average SINR loss, which can be expressed as

$$L_{\text{avg}} = \frac{1}{K}\sum_{k=1}^{K}L_k. \tag{40}$$

Compared with the methods using the average or sum of CoC, the average SINR loss is more reasonable to denote the effect of SC on MU-MISO systems. The objective of our method is to select K users from the user set $\dot{\mathbf{U}}$ and achieve the lowest average SINR loss. This problem can be denoted as

$$\begin{aligned}&\min_{\dot{\mathbf{S}}\subset\dot{\mathbf{U}}}\frac{1}{K}\sum_{s\in\dot{\mathbf{S}}}L_s \\ &\text{s.t. } \text{card}(\dot{\mathbf{S}})=K,\end{aligned} \tag{41}$$

where $\dot{\mathbf{S}}$ is the set of selected users. This problem can be solved by exhaustive search, but the computational complexity is extremely high. For example, when $K=40$ and $\text{card}(\dot{\mathbf{U}})=200$, the number of iterations is equal to $\binom{200}{40}$. Because of its high complexity, we propose a low-complexity method. We first investigate the average SINR loss in i.i.d. models, which can be expressed as

$$\begin{aligned}\hat{L}_{\text{avg}}^{\text{i.i.d.}} &= \frac{1}{K}\sum_{k=1}^{K}\hat{L}_k^{\text{i.i.d.}} = \frac{1}{K}\sum_{k=1}^{K}\left[\sum_{i\in\{1,\dots,K\}\backslash\{k\}}|\rho_{ki}|^2\right] \\ &= \frac{1}{K}\left[\sum_{i,j\in\{1,\dots,K\}}|\rho_{ij}|^2-K\right] \\ &= \frac{1}{K}(\|\mathbf{C}\|_F^2-K).\end{aligned} \tag{42}$$

According to (40), the average SINR loss with 3D models can be expressed as

$$\begin{aligned}\hat{L}_{\text{avg}}^{\text{3D}} &= \frac{1}{K}\sum_{k=1}^{K}\hat{L}_k^{\text{3D}} \\ &= \frac{1}{K}\sum_{k=1}^{K}\left[1-\prod_{i\in\{1,\dots,K\}\backslash\{k\}}\left(1-|\rho_{ki}|^2\right)\right] \\ &= 1-\frac{1}{K}\sum_{k=1}^{K}\left[\prod_{i\in\{1,\dots,K\}\backslash\{k\}}\left(1-|\rho_{ki}|^2\right)\right].\end{aligned} \tag{43}$$

Compared with (43), (42) has a simpler form for analysis. Therefore, we mainly utilize (42) to solve the problem in (41). According to (42), we know that to obtain the lowest average SINR loss, we must first obtain the smallest $\|\mathbf{C}\|_F^2$. In other words, we must find the group of users with the smallest value of $\sum_{i,j\in\{1,\ldots,K\}}|\rho_{ij}|^2$. Because $|\rho_{ij}|^2 = |\rho_{ji}|^2$ and $|\rho_{ii}|^2 = 1$, the problem in can be translated into finding the smallest value of $\|\mathbf{C}_{\text{up}}\|_F^2$, where $\mathbf{C}_{\text{up}}$ is the strictly upper triangular matrix obtained by $\mathbf{C}$, which can be expressed as

$$\mathbf{C}_{\text{up}} = \begin{bmatrix} 0 & \rho_{12} & \ldots & \rho_{1K} \\ 0 & 0 & \ldots & \rho_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 0 \end{bmatrix}. \quad (44)$$

If we analyze $\|\mathbf{C}_{\text{up}}\|_F^2$ from the perspective of each column, $\|\mathbf{C}_{\text{up}}\|_F^2$ can be calculated as:

$$\begin{aligned}\|\mathbf{C}_{\text{up}}\|_F^2 = &|\rho_{12}|^2 + (|\rho_{13}|^2 + |\rho_{23}|^2) \\ &+ (|\rho_{14}|^2 + |\rho_{24}|^2 + |\rho_{34}|^2) \\ &+ \cdots + (|\rho_{1K}|^2 + \cdots + |\rho_{(K-1)K}|^2).\end{aligned} \quad (45)$$

According to (45), we find that to obtain a small value of $\|\mathbf{C}_{\text{up}}\|_F^2$, we can add the user k who has the smallest $\sum_i |\rho_{ik}|^2$ to the group, where i represents the users existing in the group. For example, after the two users who have the smallest value of $|\rho|^2$ are chosen, the third user who has the smallest value of $(|\rho_{13}|^2 + |\rho_{23}|^2)$ is chosen. Then, the fourth user with the smallest value of $(|\rho_{14}|^2 + |\rho_{24}|^2 + |\rho_{34}|^2)$ is chosen. Based on this rule, we propose a user selection method, which is given as Algorithm 1.

Algorithm 1 User Selection

1:	Calculate $|\rho|$ between all users
2:	$\dot{\mathbf{U}}$ is the user set and $\dot{\mathbf{S}} = \varnothing$
3:	Find the smallest value of $|\rho_{i,j}|^2$ $(i < j)$
4:	$\dot{\mathbf{S}} = \{i, j\}, \dot{\mathbf{U}} = \dot{\mathbf{U}} \backslash \{i, j\}$
5:	**while** card($\dot{\mathbf{S}}$) $< K$ **do**
6:	Find user $k \in \dot{\mathbf{U}}$ who has the smallest $\sum_{i\in\dot{\mathbf{S}}} |\rho_{ik}|^2$
7:	$\dot{\mathbf{S}} = \dot{\mathbf{S}} \cup \{k\}, \dot{\mathbf{U}} = \dot{\mathbf{U}} \backslash \{k\}$
8:	**end while**

The most important part of Algorithm 1 is the metric we use in Row 6, which refers to the sum of squares of correlation values (SSCV). For simplicity, we use SSCV to represent this algorithm. After SSCV is implemented, K users are chosen to be in a group, and a very small value of $\|\mathbf{C}_{\text{up}}\|_F^2$ can be obtained by this algorithm according to (45). In other words, this algorithm provides a good means of solving the problem in (41), which achieves a very small value of L_{avg}.

Note that in this study we focus on investigating user performance from the perspective of minimizing user loss caused by SC in a group, and Algorithm 1 tries to select the set of users that is least affected by SC. If we consider user fairness, we can separate all users into different groups, and the selection method can also be easily proposed based on Algorithm 1. For example, we can iteratively separate the two users having the largest correlation value into different blank groups. Then, the metric in Row 6 of Algorithm 1 can be used for the remaining users to select their appropriate groups. Note that the same user can be allocated to different groups for better fairness and performance if necessary.

6 | SIMULATION

6.1 | Simulation settings

Two channel models are used to generate channels: i.i.d. and 3D MIMO. In the i.i.d. model, the channel gains from transmit antennas to user antennas are assumed to be i.i.d. zero-mean complex Gaussian random variables with unitary variance [10]. This is a typical model for NLOS scenarios. To generate more practical channels in MIMO systems, we use the channel model of 3D MIMO, which is introduced in detail in [23]. A complete platform of 3D MIMO is established to generate the channels. The simulation settings are all based on 3GPP specifications [23], and Table 1 shows some of the key parameters. Users are randomly deployed in a 120° sector. The effects of LOS communications are considered in 3D urban macrocell (3D-UMa) scenarios [24]. The power for each user p_i is allocated equally in simulations, and σ^2 is set to −174 dBm/Hz [17].

6.2 | Simulation results

In this part, we show the simulation results of SINR loss and user selection. First, we verified the correctness of (33). Because it is the most important formula we derived in this study, the correctness of (33) is of great importance. To verify it, different channels were generated and different user numbers were tried. Numerical results show that the loss obtained by (33) had the same value of (13) with any number of K. This means that (33) shows the relation between SINR

TABLE 1 Parameters of 3D MIMO model

Parameter	Configuration
Channel model	3D-UMa
BS transmit power	46 dBm for 10 MHz
BS antenna number M	64, 128, 256, 512
BS antenna height	25 m
Carrier frequency	2 GHz
Inter-site distance (ISD)	500 m
Pathloss	3D-UMa
LOS probability	3D-UMa

loss and CoC correctly. We use Figure 2 to show this result visually. A 3D channel model was used to generate the channels, and K users were randomly selected from the user set of 200 users. From Figure 2, we can see that the SINR losses calculated by (13) and (33) were exactly the same, which shows the correctness of derivation.

Figure 3 shows the correlation values between different users in the i.i.d. and 3D models. Here, $\text{card}(\dot{\mathbf{U}}) = 200$, and all combinations of two users were simulated. Because of the characteristics of the i.i.d model in massive MIMO systems, we can see that nearly all of the users had low correlation values between each other. However, in the 3D channel model, some users may still have had high correlation values. This is because the user channels were no longer independent, and many factors such as LOS may have affected the correlation values.

Figure 4 shows the SINR loss in different cases. In Figure 4A, we investigated the SINR loss with a different number of users K in the i.i.d and 3D models. K users were randomly selected from the user set of 200 users. From Figure 4A, we can see that with the same number of users K and antennas M, the users in the 3D model could more easily obtain higher SINR losses caused by SC. This was because the correlation values between different users in the 3D model were higher, which is shown in Figure 3. In addition, we see that the SINR loss increased with the increase in the number of users K. When K increased, the loss of SINR could not be ignored even in the i.i.d. model. Figure 4B shows the SINR loss with different numbers of antennas M. We can see that with the increase in the number of antennas, SINR loss diminished. This was because the correlation values of users decreased. Furthermore, as shown in Figure 4B, the loss with the 3D model was greater than that with the i.i.d. model.

In Figure 5, we investigated the performance of our approximate expressions proposed for different channel models as described in Section 4. Forty users were randomly selected from the user set of 200 users, and the SINR losses of these 40 users were estimated by the two approximate relations. Figure 5A shows the performance of the two methods in the scenario with the i.i.d. model. From this figure, we can see that the proposed method for i.i.d. performed better. In addition, with the increase in the number of antennas, the proposed methods obtained smaller percentage errors. Figure 5B shows the performance of the two methods in the

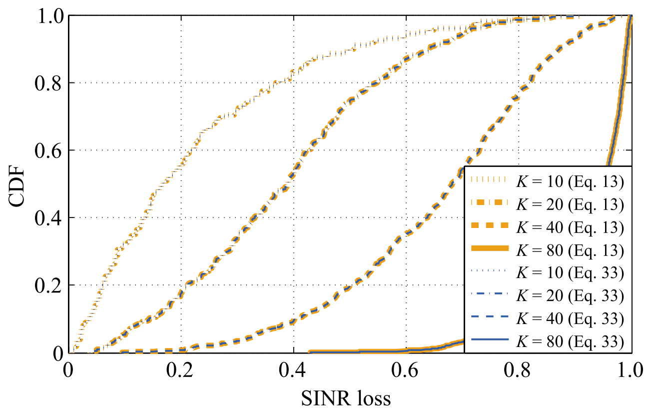

FIGURE 2 SINR loss calculated by different equations ($M = 128$)

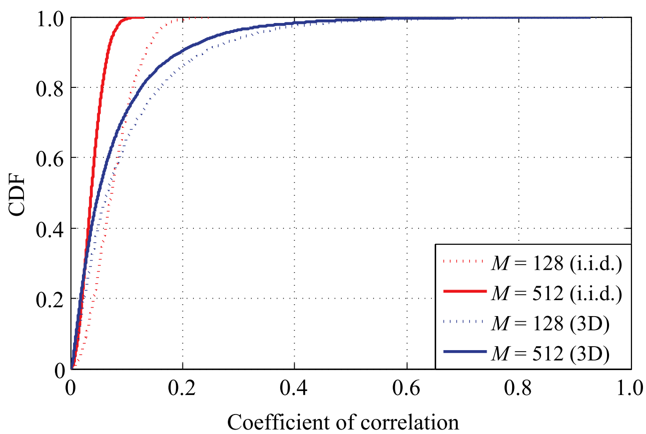

FIGURE 3 Coefficient of correlation between different users

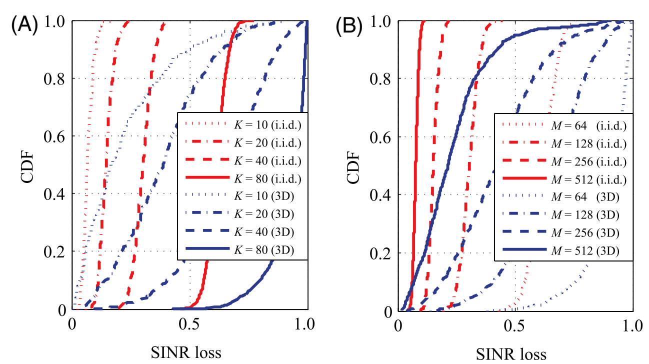

FIGURE 4 SINR loss in different cases: (A) SINR loss with different number of users K ($M = 128$) and (B) SINR loss with different number of antennas M ($K = 40$)

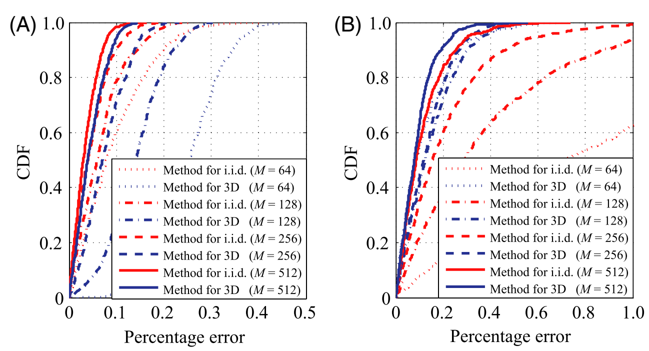

FIGURE 5 Performance of different approximate expressions: (A) i.i.d. model, $K = 40$ and (B) 3D model, $K = 40$

scenario with the 3D channel model. We can see that the proposed method for the 3D channel model performed better in this scenario. In general, the expressions of (38) and (39) were able to denote the relation with low complexity and percentage error.

In Figure 6, we investigated the performance of user selection using different selection methods. K users were selected from 200 users by these methods, and M was set to 128. Three methods reducing the loss caused by SC were compared with the method proposed in Section 5 (SSCV). The first was the random method, which randomly selects users from the user set [12]. The second method we investigated was that which eliminates the maximum correlation value (EMCV), which can be regarded as the semi-orthogonal method. This method iteratively eliminates the two users who have the largest correlation value between them. It ends when the number of users equals the value we set for a group. The third method uses the SCV as the metric instead of SSCV. Because the method using the ACV with a group has the same results as with SCV, we show only the results of SCV here. Note that the ideas of EMCV [9–11], ACV [13–15], and SCV [12,16] are all widely used in studies to reduce the performance loss caused by SC in a group.

Figure 6A and 6B show the SINR loss in the i.i.d. and 3D models, respectively. In Figure 6, we can see that SSCV performed best. However, in the i.i.d. model, the SINR loss of SSCV was close to that of SCV. This is because the correlation values were all very small in the i.i.d. model, and thus the results of user selection in these two methods were close to each other. With respect to the 3D model, SSCV was much better than the others. This is because the range of correlation values between different users increased, and thus more users may have had large correlation values in the 3D model. Therefore, a better result can be obtained when we use SSCV.

In Figure 7, we further investigated these four algorithms with different number of users K. Figures 7A and 7B show the average SINR loss in the i.i.d. and 3D models, respectively. From these figures, we can see that the proposed method SSCV performed best. In other words, the problem in Equation was well solved by SSCV. Notice that with the increase number of users K, the ratio of SSCV to other results decreased in Figure 7. This is because the number of optional users in the user set ($\mathrm{card}(\dot{\mathbf{U}}) = 200$) was not large compared with K. If more users exist in the user set, a more obvious result will be obtained.

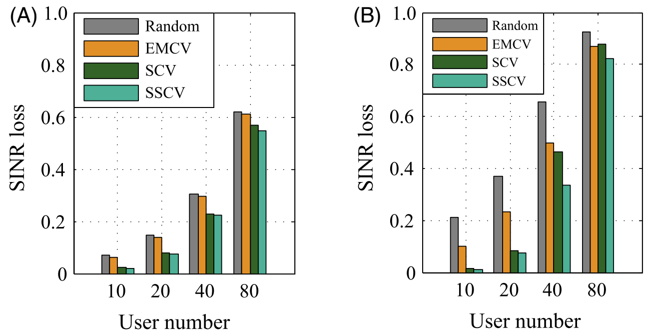

FIGURE 7 Average SINR loss with different user selection algorithms: (A) i.i.d. model, $M = 128$ and (B) 3D model, $M = 128$

In Figure 8, we analyzed the user performance in terms of the user rate. Figures 8A and 8B show the rate performance of users with $K = 40$ and $K = 80$. Method (real) and Method (ort.) in this figure indicate that the SINRs were calculated by (8) and (12) , respectively, and the performance of Method (ort.) could be regarded as the upper bound. From Figure 8, we see that the performance difference between SSCV (real) and SSCV (ort.) was smaller than that of the random method, which means that SSCV achieved a lower SINR loss. This can also be seen from Figures 6 and 7. In addition, note that SSCV achieved higher user throughput. This is because SSCV reduced the effect of other user channels efficiently. In other words, the same user scheduled by SSCV will obtain higher throughput than by the other methods.

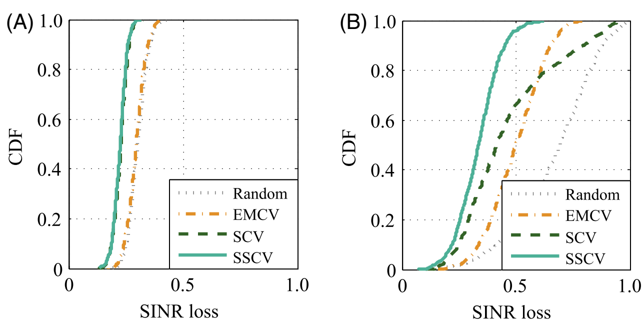

FIGURE 6 SINR loss with different user selection algorithms: (A) i.i.d. model, $K = 40$, $M = 128$ and (B) 3D model, $K = 40$, $M = 128$

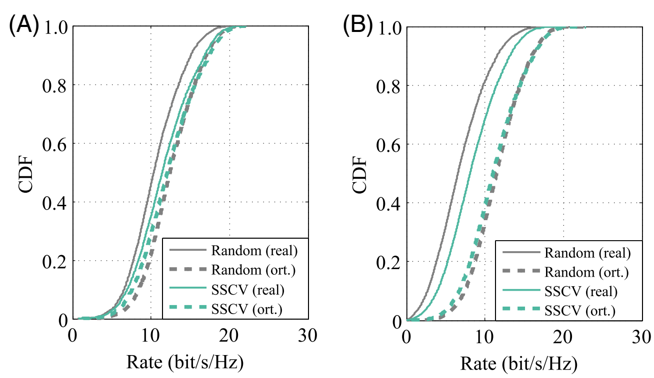

FIGURE 8 Performance of user rate: (A) 3D model, $M = 128$, $K = 40$ and (B) 3D model, $M = 128$, $K = 80$

7 | CONCLUSION

Reducing the loss caused by SC is important for user selection in MU-MISO systems. Because few studies on the accurate analysis of this loss have been conducted, we defined SINR loss in this study and derived a formula to show the accurate relation between SINR loss and CoC. Furthermore, two approximate expressions were proposed to denote the relation in massive MU-MISO systems. A user selection method based on the approximate relation was then proposed that minimized the average SINR loss of users. Compared with the other methods reducing the loss caused by SC, the proposed method is more reasonable and effective.

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