Spatial Correlation-based Resource Sharing in Cognitive Radio SWIPT Networks

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Received May 20, 2022; revised July 23, 2022; accepted August 3, 2022; published September 30, 20222

Abstract

Cognitive radio-simultaneous wireless information and power transfer (CR-SWIPT) has attracted much interest since it can improve both the spectrum and energy efficiency of wireless networks. This paper focuses on the resource sharing between a point-to-point primary system (PRS) and a multiuser multi-antenna cellular cognitive radio system (CRS) containing a large number of cognitive users (CUs). The resource sharing optimization problem is formulated by jointly scheduling CUs and adjusting the transmit power at the cognitive base station (CBS). The effect of accessing CUs' spatial channel correlation on the possible transmit power of the CBS is investigated. Accordingly, we provide a low-complexity suboptimal approach termed the semi-correlated semi-orthogonal user selection (SC-SOUS) algorithm to enhance the spectrum efficiency. In the proposed algorithm, CUs that are highly correlated to the information decoding primary receiver (IPR) and mutually near orthogonal are selected for simultaneous transmission to reduce the interference to the IPR and increase the sum rate of the CRS. We further develop a spatial correlation-based resource sharing (SC-RS) strategy to improve energy sharing performance. CUs nearly orthogonal to the energy harvesting primary receiver (EPR) are chosen as candidates for user selection. Therefore, the EPR can harvest more energy from the CBS so that the energy utilization of the network can improve. Besides, zero-forcing precoding and power control are adopted to eliminate interference within the CRS and meet the transmit power constraints. Simulation results and analysis show that, compared with the existing CU selection methods, the proposed low-complex strategy can enhance both the achievable sum rate of the CRS and the energy sharing capability of the network.

Keywords: Cognitive radio, Resource sharing, SWIPT, Spatial correlation, User access control

This work was supported by the National Natural Science Foundation of China under Grant 61701043, the Fundamental Research Funds for the Central Universities of China under Grant 300102248307, and the Natural Science Foundation of ShaanXi Province of China under Grant 211424200112.

http://doi.org/10.3837/tiis.2022.09.019 **ISSN : 1976-7277**

1. Introduction

DUE to the explosive growth of mobile data traffic, massive device connections, and the continuous emergence of new business and application scenarios, scarcity of spectrum and energy resources has become a critical issue in the fifth generation (5G) mobile network. Consequently, new technologies have emerged. On the one hand, cognitive radio (CR) [1–4] and spectrum sharing [5][6] can solve the conflict between the shortage and underutilization of spectrum resources. On the other hand, energy harvesting (EH) from the environment [7] is a feasible solution for prolonging the lifetime of wireless communication devices. Furthermore, as a radio frequency (RF) signal can carry information and energy at the same time, simultaneous wireless information and power transfer (SWIPT) [8–11] technology is utilized to realize energy harvesting and information decoding from the same received RF signal. Cognitive radio-simultaneous wireless information and power transfer (CR-SWIPT) has drawn a lot of research interest since it can improve both spectrum efficiency and energy efficiency of wireless networks [12–18]. Several resource-sharing strategies have been proposed for CR-SWIPT networks. In [12], each primary transmitter's harvesting and guard zones were designed to permit secondary transmitter access. As for multi-antenna cognitive receivers, the antenna switching technique [13] selected a subset of the antennas to decode information and the rest to harvest energy. Energy harvesting was modeled as a maximization problem with multiple constraints and transformed into a convex optimization problem by relaxing the integer variable and introducing an auxiliary variable [14]. The energy-rate trade-off of cognitive massive multi-input multi-output (MIMO) systems with underlay spectrum sharing were expressed in closed-form [15]. Authors in [16] investigated the cooperative spectrum sharing with SWIPT in the cognitive Internet of Things (IoT) network. IoT devices (IoDs) accessed the primary spectrum by serving as orthogonal frequency division multiplexing (OFDM) relays. Specifically, in phase 1, the IoD transmitter (DT) utilized a part of subcarriers to decode information from primary transmitters and another part of subcarriers to harvest energy. In phase 2, DT transmitted the signals of the primary system and itself to the corresponding receivers. A multi-antenna CR-SWIPT system with non-orthogonal multiple access (NOMA) was considered in [17]. In an underlay scenario, the authors minimized system power consumption by jointly designing the transmitting beamformer and the receiving power splitter. Besides, energy efficiency was maximized in CR networks with NOMA by SWIPT [18]. However, the above methods concentrated on the theoretical performance of CR-SWIPT systems. Therefore, some high-complexity algorithms were adopted, such as stochastic-geometry [12], the Lagrangian method [14][16], asymptotic analysis [15], classic semi-definite relaxation and successive convex approximation [17], Dinkelbach method [18], and even one-dimensional search algorithm [14]. The computational complexity of these techniques often leads to tremendous consumption of energy. In this paper, we aim to propose a low-complexity strategy that is more suitable for practical transmission.

Spatial channel correlation-based user access control is an effective way to increase the throughput of multi-user multi-antenna networks. Ref. [19] proposed a semi-orthogonal user selection (SUS) algorithm. The nearly spatially orthogonal users can be grouped for simultaneous transmission to enhance the throughput. The authors have proved that, combined with zero-forcing beamforming (ZFB), this scheduling algorithm can achieve the same asymptotic sum rate of MIMO broadcast channels (BCs) as dirty paper coding (DPC) but with much lower complexity. Similarly, the random unitary beamforming (RUB) algorithm [20] also selected users for access based on the correlation between the spatial channels and random orthonormal beams. It was shown that the throughput of the RUB scheme scales as the same as the capacity of MIMO BCs. Since they can achieve good performance with computational efficiency, the spatial channel correlation-based user selection algorithms were introduced to the cognitive radio networks (CRNs). Ref. [21-23] proposed a semi-orthogonal user selection (SOUS) method. Cognitive users (CUs) whose channels are nearly orthogonal to the primary user's channel were preselected to minimize the interference to the primary user. Then, cognitive users whose channels are near orthogonal were scheduled from the preselected CUs. Besides, the channel similarity-based user selection (CSUS) algorithm [24][25] was also a feasible solution for user access control in practical CRNs. Although it selected CUs according to the channel similarity instead of orthogonality, it was essentially a spatial channel correlation-based user selection scheme. The RUB scheme has also been applied in the multi-antenna CRN for user selection and interference cancellation [26]. While there are ongoing interests in using spatial channel correlation-based user selections, it is still unclear why such schemes can enhance the spectrum efficiency of the multi-user multi-antenna CRNs, especially under mutual interference. Besides, there is a lack of consideration for energy sharing in the above references.

Our work is motivated by a joint investigation of both the opportunistic spectrum access and energy harvesting in CRNs. In this paper, we study how the achievable downlink sum rate of CUs is impacted by the combined effects of spatial channel correlation-based user selection and ZFB. Furthermore, a CU selection algorithm and a resource sharing strategy are developed for CR-SWIPT networks to maximize the sum rate of CUs as well as improve energy sharing between the cognitive radio system (CRS) and the primary system (PRS) under the power and interference constraints. The main contributions of this paper are as follows:

- We formulate the joint spectrum and energy sharing optimization problem for the CR-SWIPT network and disclose the different impacts of spatial channel correlation-based user selection on maximizing the sum rate of the CRS and limiting the interference to the primary receiver, respectively. We provide an insight into the difference between mutual interference among CUs and the interference from CRS to the primary receiver.
- To improve the spectrum efficiency of the CRN, we propose the semi-correlated semi-orthogonal user selection (SC-SOUS) algorithm, which addresses the problem of joint user selection and power control for the multi-user multi-antenna underlay CRN. The algorithm is different from the SOUS algorithm in [21-23] since they have opposite rules in their first selection steps.
- We further provide the spatial correlation-based resource sharing (SC-RS) strategy to enhance resource sharing in the CR-SWIPT network. In addition to discussing spectrum efficiency in the existing spatial channel correlation-based user selection approaches [21-26], our work also considers energy utilization.
- We evaluate and analyze the performance of our proposed approaches. The algorithm SC-SOUS and SC-RS are compared with the user selection schemes in [21-26] from the perspectives of the sum rate and multi-user diversity gain of the CRS, harvested power at the energy harvesting primary receiver (EPR), and the computational complexity. In addition, the influences of the correlation and orthogonality thresholds are also studied on the network's performance.

Notations: Vectors and matrices are denoted by lower- and upper-case letters in boldface, respectively. The operators $(\cdot)^T$, $(\cdot)^\dagger$, $\mathrm{Tr}(\cdot)$, $\|\cdot\|$, $\mathrm{cond}(\cdot)$, and $(\cdot)^{-1}$ indicate the transpose, conjugate transpose, trace, Frobenius norm, condition number, and inverse of a matrix, respectively. The symbol diag($\mathbf{x}$) constructs a diagonal matrix with entries specified by $\mathbf{x}$, and

$\mathbf{I}_M$ represents an identity matrix of dimension M by M. $\lfloor \cdot \rfloor$ stands for the floor operation. Finally, C_n^k means the number of combinations of n items taken k at a time.

The paper is organized as follows. The system model and the problem formulation are introduced in Section 2. In Section 3, the effect of spatial channel correlation on the performance of the CR-SWIPT network is investigated. Based on the analysis, a user selection method and a resource sharing strategy are proposed in Section 4. Performance analysis and simulation results are presented in Sections 5 and 6, respectively. Finally, Section 7 concludes the paper and presents future work guidelines.

2. System Model

2.1 CR-SWIPT Network

We consider a multi-user CRN with underlay spectrum sharing [27], comprising a point-to-point PRS and a cellular CRS. There are three single-antenna primary terminals, including a primary transmitter (PT), an information-decoding primary receiver (IPR), and an EPR [18][28]. The cognitive base station (CBS) has M antennas sufficiently distant from each other in a nonline-of-sight rich scattering environment [19] to guarantee the independence between spatial sub-channels [29]. The total number of CUs is K, where $K \gg M$. Each CU has only one antenna. Thus CBS can simultaneously transmit information to CUs in the same spectrum band as PT using MIMO spatial multiplexing [21]. The CR-SWIPT network is depicted in **Fig. 1**.

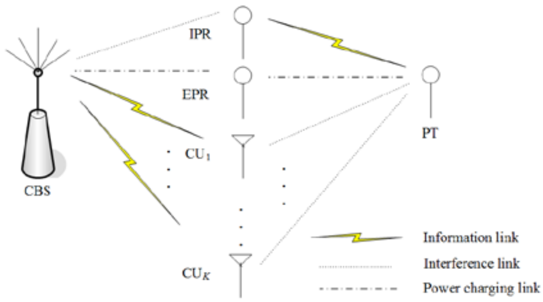

Fig. 1. CR-SWIPT network.

We use a simple channel model where the channel gain from a transmit antenna to a user is described by a zero-mean circularly symmetric complex Gaussian (ZMCSCG) random variable [19]. $\mathbf{h}_{c,k}$ and $\mathbf{h}_{p,l}$ are channel vectors from the CBS to the kth CU and the lth primary receiver (the 1st is the IPR, and the 2nd is the EPR), respectively, whose entries are complex Gaussian random variables with zero-mean and unit variance [23-25]. Meanwhile, $g_{c,k}$ is the channel gain from PT to the kth CU. Since $K \gg M$, it is too complicated for the receivers to decode the information when all the K CUs are active simultaneously. To decrease decoding complexity and acquire multi-user diversity gain, the CBS can choose M CUs to access every time and separate their information by zero-forcing beamforming (ZFB) [19][21-26][30]. The set of selected CUs is $\mathcal{A}$, and $\mathcal{A}$'s cardinality is $|\mathcal{A}| = M$. s_k is the signal intended to the kth CU from CBS, where $|s_k|^2 = 1$, while x_p is the transmitted signal from PT to the IPR. Due to the sharing of the same frequency band, the received signal at the IPR is interfered by the signals transmitted from CBS. Similarly, the received signals at the CUs are interfered by the signal transmitted from the PT. Therefore, the received complex baseband signal at CU$_k$ is

$$y_k = \mathbf{h}_{c,k}\mathbf{x} + g_{c,k}x_p + n_k, \tag{1}$$

where $\mathbf{x} = \mathbf{WPs}$. If $A = \{k_1, k_2, ..., k_M\}$, $\mathbf{P} = \mathrm{diag}\left(\sqrt{P_{k_1}}, \sqrt{P_{k_2}}, ..., \sqrt{P_{k_M}}\right)$ accounts for power loading, and $\mathbf{s} = \begin{bmatrix} s_{k_1} & s_{k_2} & \ldots & s_{k_M} \end{bmatrix}^T$. We suppose that $\mathbf{H} = \begin{bmatrix} \mathbf{h}_{c,k_1}^T & \mathbf{h}_{c,k_2}^T & \ldots & \mathbf{h}_{c,k_M}^T \end{bmatrix}^T$ is the combined channel matrix of all the accessing CUs. According to ZFB, the precoding matrix is $\mathbf{W} = \mathbf{H}^\dagger\left(\mathbf{HH}^\dagger\right)^{-1}$ [19][21-26][30]. n_k is the additive white Gaussian noise at CU$_k$. $\mathbf{h}_{c,k}$ and $\mathbf{h}_{p,l}$ are attainable by CBS through sensing [31].

2.2 Mathematical Model of CU Access Control Problem

In the CR-SWIPT network, CRS accesses the spectrum of PRS by underlay spectrum sharing with the interference constraint of the IPR. Aiming to improve the sum rate of CUs and the energy from CBS to the EPR, we formulate the CU selection and power control [32] problem as **P1**.

P1:

$$\max_{\mathbf{P},A} \sum_{m=1,k_m\in A}^{M} \log_2\left(1 + SINR_{k_m}\right), \tag{2}$$

$$\max_{\mathbf{P},A} \zeta \sum_{m=1,k_m\in A}^{M} P_{k_m}\left(\mathbf{h}_{p,2}\mathbf{WW}^\dagger\mathbf{h}_{p,2}^\dagger\right), \tag{3}$$

$$\text{s.t.} \sum_{m=1,k_m\in A}^{M} P_{k_m}\mathrm{Tr}\left(\mathbf{WW}^\dagger\right) \le P_t, \tag{4}$$

$$\sum_{m=1,k_m\in A}^{M} P_{k_m}\left(\mathbf{h}_{p,1}\mathbf{WW}^\dagger\mathbf{h}_{p,1}^\dagger\right) \le \gamma_0, \tag{5}$$

$$P_{k_m} \ge 0, \quad 1 \le m \le M, \tag{6}$$

where $\zeta \in [0,1]$ is the energy conversion efficiency [16][33-36]. P_t is the maximum transmit power of CBS. The signal-to-noise-ratio of the k_m th CU is defined as

$$SINR_{k_m} = \frac{\left|\mathbf{h}_{c,k_m}\mathbf{w}_m\right|^2 P_{k_m}}{I_{k_m} + \sigma_{k_m}^2}, \tag{7}$$

where $\mathbf{w}_m$ is the mth column of $\mathbf{W}$. I_{k_m} is the interference from the PT to CU$_{k_m}$. γ_0 is the interference constraint of the IPR. $\sigma_{k_m}^2$ is the noise power at CU$_{k_m}$. It is too hard to obtain an optimal access set A^* and a suitable transmit power matrix $\mathbf{P}^*$ through the exhaustive method for its complexity, especially when K is large. Consequently, in this paper, we analyze the relationship between spatial channel correlation of CUs and **P1** and design low complex CU access control methods for practical systems.

3. The Effect of Spatial Channel Correlation on the Performance of CR-SWIPT Network

In order to focus on the CUs' access control problem, we set $P_{k_1} = P_{k_2} = ... = P_{k_M} = P$ for simplicity, where P should satisfy (4) - (6). It can be easily extended to the general case by a water-filling power allocation. Here we analyze the access control problem of CUs based on their spatial channel correlation.

Firstly, Since CBS adopts ZFB, the unified equivalent channel matrix of accessing CUs has become to

$$\mathbf{H}_{eq} = \mathbf{HW} = \mathbf{HH}^{\dagger}\left(\mathbf{HH}^{\dagger}\right)^{-1} = \mathbf{I}_M, \tag{8}$$

where $\mathbf{I}_M$ represents an identity matrix of dimension M by M.

According to (2) - (4), (6), and (7), it is necessary to minimize $\mathrm{Tr}\left(\mathbf{WW}^{\dagger}\right)$ by CU selection to enlarge P as much as possible. Because $\mathbf{W} = \mathbf{H}^{\dagger}\left(\mathbf{HH}^{\dagger}\right)^{-1}$, $\mathrm{Tr}\left(\mathbf{WW}^{\dagger}\right) = \left\|\mathbf{W}\right\|^2 = \left\|\mathbf{H}^{-1}\right\|^2$ Besides, $\left\|\mathbf{H}^{-1}\right\|^2$ and $\left\|\mathbf{H}\right\|^2$ satisfy the following equation [37]:

$$\left\|\mathbf{H}\right\|^2 \left\|\mathbf{W}\right\|^2 = \left\|\mathbf{H}\right\|^2 \left\|\mathbf{H}^{-1}\right\|^2 = \mathrm{cond}\left(\mathbf{H}\right). \tag{9}$$

Accordingly, we need to increase $\left\|\mathbf{H}\right\|^2$ and decrease $\mathrm{cond}\left(\mathbf{H}\right)$ as much as possible by selecting CUs; that is to say, we should choose suitable $\mathbf{h}_{c,k}$ s to comprise $\mathbf{H}$ with a relatively large $\left\|\mathbf{H}\right\|^2$ and a small $\mathrm{cond}\left(\mathbf{H}\right)$.

Proposition 1: Selecting M orthogonal CUs with relatively large channel gains to access can minimize $\mathrm{Tr}\left(\mathbf{WW}^{\dagger}\right)$.

Proof: For one thing, since $\left\|\mathbf{H}\right\|^2 = \sum_{m=1}^{M}\left\|\mathbf{h}_{c,k_m}\right\|^2$, larger $\left\|\mathbf{h}_{c,k_m}\right\|^2$ can lead to larger $\left\|\mathbf{H}\right\|^2$; for another, the orthogonality of $\mathbf{h}_{c,k_m}$ can minimize $\mathrm{cond}\left(\mathbf{H}\right)$ [37]. According to both the two aspects above as well as (9), it is evident that the selection of M orthogonal CUs with relatively large $\left\|\mathbf{h}_{c,k}\right\|^2$ can minimize $\mathrm{Tr}\left(\mathbf{WW}^{\dagger}\right) = \left\|\mathbf{W}\right\|^2 = \mathrm{cond}\left(\mathbf{H}\right) / \left\|\mathbf{H}\right\|^2$.

In physical systems, there may not exist M CUs which are totally orthogonal to each other. Therefore, we set orthogonality threshold δ_c and choose "semi-orthogonal" CUs whose channel vectors satisfy (10) to access:

$$\Delta\left(\mathbf{h}_{c,i}, \mathbf{h}_{c,j}\right) = \frac{\left|\mathbf{h}_{c,i}\mathbf{h}_{c,j}^{\dagger}\right|}{\left\|\mathbf{h}_{c,i}\right\|\left\|\mathbf{h}_{c,j}\right\|} \le \delta_c. \tag{10}$$

Secondly, concerning (2), (3), and (5) - (7), we should design a CU access control scheme to minimize $\mathbf{h}_{p,1}\mathbf{WW}^{\dagger}\mathbf{h}_{p,1}^{\dagger}$ so as to increase P under interference constraint (5).

Proposition 2: Selecting M orthogonal CUs with relatively large channel gains and whose channel vectors are as high correlated to $\mathbf{h}_{p,1}$ as possible to access can minimize $\mathbf{h}_{p,1}\mathbf{WW}^{\dagger}\mathbf{h}_{p,1}^{\dagger}$.

Proof: Here, we analyze $\mathbf{h}_{p,1}\mathbf{WW}^{\dagger}\mathbf{h}_{p,1}^{\dagger}$ with the singular values and vectors of $\mathbf{H}$. We suppose that the singular values of $\mathbf{H}$ are $\left\{\lambda_1, ..., \lambda_M\right\}$. In order to construct M parallel spatial sub-channels after ZFB, we should choose M orthogonal CUs to access simultaneously to ensure that $\mathbf{H}$ is full rank, which is also coincident with **Proposition 1**. Consequently, we can assume that $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_M > 0$. Moreover, the right singular vector corresponding to λ_i is $\mathbf{u}_i$, $1 \leq i \leq M$. As a result, $\left(\lambda_i^2, \mathbf{u}_i\right)$ is an Eigen pair of the Hermitian matrix $\mathbf{H}^\dagger\mathbf{H}$. Since $\mathbf{W}\mathbf{W}^\dagger = \left(\mathbf{H}^\dagger\mathbf{H}\right)^{-1}$, $\left(\frac{1}{\lambda_i^2}, \mathbf{u}_i\right)$ is an Eigen pair of the Hermitian matrix $\mathbf{W}\mathbf{W}^\dagger$ [37]. According to the spectral decomposition [37], we have

$$\mathbf{H}^\dagger\mathbf{H} = \sum_{i=1}^{M} \lambda_i^2 \mathbf{u}_i \mathbf{u}_i^\dagger, \tag{11}$$

$$\mathbf{W}\mathbf{W}^\dagger = \sum_{i=1}^{M} \frac{1}{\lambda_i^2} \mathbf{u}_i \mathbf{u}_i^\dagger. \tag{12}$$

Based on the function expansion of the quadratic form [37], we can obtain

$$\mathbf{h}_{p,1}\mathbf{H}^\dagger\mathbf{H}\mathbf{h}_{p,1}^\dagger = \sum_{i=1}^{M} \lambda_i^2 \left|\mathbf{h}_{p,1}\mathbf{u}_i\right|^2, \tag{13}$$

$$\mathbf{h}_{p,1}\mathbf{W}\mathbf{W}^\dagger\mathbf{h}_{p,1}^\dagger = \sum_{i=1}^{M} \frac{1}{\lambda_i^2} \left|\mathbf{h}_{p,1}\mathbf{u}_i\right|^2. \tag{14}$$

From (14), it is obvious that $\mathbf{h}_{p,1}\mathbf{W}\mathbf{W}^\dagger\mathbf{h}_{p,1}^\dagger$ can be represented by a summation which contains M terms, each of which includes two parts: $\frac{1}{\lambda_i^2}$ and $\left|\mathbf{h}_{p,1}\mathbf{u}_i\right|^2$. Since $\left\{\mathbf{u}_i, 1 \leq i \leq M\right\}$ is a set of orthonormal bases of the M dimensional complex space [37], $\sum_{i=1}^{M}\left|\mathbf{h}_{p,1}\mathbf{u}_i\right|^2 = \left\|\mathbf{h}_{p,1}\right\|^2$. From (14), we find that $\mathbf{h}_{p,1}\mathbf{W}\mathbf{W}^\dagger\mathbf{h}_{p,1}^\dagger$ can be minimized from two aspects:

1) Maximize all of the singular values of $\mathbf{H}$ so as to minimize each $\frac{1}{\lambda_i^2}$;

2) Maximize the term $\left|\mathbf{h}_{p,1}\mathbf{u}_1\right|^2$, which is multiplied by $\frac{1}{\lambda_1^2}$ — the minimum Eigen value of $\mathbf{W}\mathbf{W}^\dagger$ — so as to minimize the sum of all the multiplications.

Firstly, in order to minimize all the singular values of $\mathbf{H}$, on the one hand, since $\sum_{i=1}^{M}\lambda_i^2 = \left\|\mathbf{H}\right\|^2 = \sum_{m=1}^{M}\left\|\mathbf{h}_{c,k_m}\right\|^2$ [37], we need to choose $\mathbf{h}_{c,k}$ s with large Frobenius norms as the row vectors of $\mathbf{H}$; on the other hand, orthogonal CUs should be selected to minimize the condition number of $\mathbf{H}$, which is $\mathrm{cond}\left(\mathbf{H}\right) = \lambda_1 / \lambda_M$, so as to guarantee that all the singular values of $\mathbf{H}$ are large and all the Eigen values of $\mathbf{W}\mathbf{W}^\dagger$ are small.

Secondly, since $\sum_{i=1}^{M}\left|\mathbf{h}_{p,1}\mathbf{u}_i\right|^2 = \left\|\mathbf{h}_{p,1}\right\|^2$ and each term on the left side is non-negative, we try to construct $\mathbf{H}$ by selecting $\mathbf{h}_{c,k}$ s to maximize $\left|\mathbf{h}_{p,1}\mathbf{u}_1\right|^2$. Considering $\left\|\mathbf{u}_1\right\| = 1$, we have

$$\left|\mathbf{h}_{p,1}\mathbf{u}_1\right| = \left\|\mathbf{h}_{p,1}\right\|\Delta(\mathbf{h}_{p,1}, \mathbf{u}_1), \tag{15}$$

where

$$\Delta(\mathbf{h}_{p,1},\mathbf{u}_1)=\frac{\left|\mathbf{h}_{p,1}\mathbf{u}_1\right|}{\left\|\mathbf{h}_{p,1}\right\|\left\|\mathbf{u}_1\right\|}=\frac{\left|\mathbf{h}_{p,1}\mathbf{u}_1\right|}{\left\|\mathbf{h}_{p,1}\right\|} \tag{16}$$

is defined as the correlation coefficient of $\mathbf{h}_{p,1}$ and $\mathbf{u}_1$, which reveals the spatial similarity of the two vectors. Therefore, we are aiming at constructing $\mathbf{H}$ with the right singular vector $\mathbf{u}_1$ resembles $\overline{\mathbf{h}}_{p,1}=\frac{\mathbf{h}_{p,1}}{\left\|\mathbf{h}_{p,1}\right\|}$ as much as possible. Since $\mathbf{u}_1$ is the eigenvector of $\mathbf{H}^{\dagger}\mathbf{H}$ corresponding to its largest eigenvalue, based on the characteristic of the Rayleigh quotient, if $\left\|\mathbf{x}\right\|^2=1$, only when $\mathbf{x}=\mathbf{u}_1$, the quadratic form $\mathbf{x}\mathbf{H}^{\dagger}\mathbf{H}\mathbf{x}^{\dagger}$ can be maximized. Accordingly, we should construct $\mathbf{H}$ to make

$$\overline{\mathbf{h}}_{p,1}=\arg\max_{\mathbf{x},\left\|\mathbf{x}\right\|^2=1}\mathbf{x}\mathbf{H}^{\dagger}\mathbf{H}\mathbf{x}^{\dagger}. \tag{17}$$

Since

$$\overline{\mathbf{h}}_{p,1}\mathbf{H}^{\dagger}\mathbf{H}\overline{\mathbf{h}}_{p,1}^{\dagger}=\overline{\mathbf{h}}_{p,1}\begin{bmatrix}\mathbf{h}_{c,k_1}\\ \cdots\\ \mathbf{h}_{c,k_M}\end{bmatrix}^{\dagger}\begin{bmatrix}\mathbf{h}_{c,k_1}\\ \cdots\\ \mathbf{h}_{c,k_M}\end{bmatrix}\overline{\mathbf{h}}_{p,1}^{\dagger}=\sum_{m=1}^{M}\overline{\mathbf{h}}_{p,1}\mathbf{h}_{c,k_m}^{\dagger}\mathbf{h}_{c,k_m}\overline{\mathbf{h}}_{p,1}^{\dagger}=\sum_{m=1}^{M}\left|\eta_m\right|^2, \tag{18}$$

where $\left|\eta_m\right|=\left|\mathbf{h}_{c,k_m}\overline{\mathbf{h}}_{p,1}^{\dagger}\right|$, the maximization of $\overline{\mathbf{h}}_{p,1}\mathbf{H}^{\dagger}\mathbf{H}\overline{\mathbf{h}}_{p,1}^{\dagger}$ and $\left|\eta_m\right|,\left(1\le m\le M\right)$ are equivalent. The correlation coefficient of $\overline{\mathbf{h}}_{p,1}$ and $\mathbf{h}_{c,k_m}$ is

$$\Delta(\mathbf{h}_{c,k_m},\overline{\mathbf{h}}_{p,1})=\frac{\left|\mathbf{h}_{c,k_m}\overline{\mathbf{h}}_{p,1}^{\dagger}\right|}{\left\|\mathbf{h}_{c,k_m}\right\|}. \tag{19}$$

If the coefficient is bigger, $\overline{\mathbf{h}}_{p,1}$ can lead to a bigger $\overline{\mathbf{h}}_{p,1}\mathbf{H}^{\dagger}\mathbf{H}\overline{\mathbf{h}}_{p,1}^{\dagger}$, which implies a greater similarity between $\overline{\mathbf{h}}_{p,1}$ and $\mathbf{u}_1$.

As stated above, we can minimize $\mathbf{h}_{p,1}\mathbf{W}\mathbf{W}^{\dagger}\mathbf{h}_{p,1}^{\dagger}$ by choosing M orthogonal $\mathbf{h}_{c,k}$ s with relatively large Frobenius norms and highly correlated with $\mathbf{h}_{p,1}$ as row vectors of $\mathbf{H}$.

Here are some explanations for **Proposition 2**. After ZFB, the energy distribution of transmitted signals from CBS is decided by $\mathbf{W}$, hence the physical meaning of $\min_{\mathbf{W}}\mathbf{h}_{p,1}\mathbf{W}\mathbf{W}^{\dagger}\mathbf{h}_{p,1}^{\dagger}$ is to minimize the energy projected on the interference channel $\mathbf{h}_{p,1}$ so as to minimize the interference from CBS to the IPR. Equivalently, when γ_0 is given, $\min_{\mathbf{W}}\mathbf{h}_{p,1}\mathbf{W}\mathbf{W}^{\dagger}\mathbf{h}_{p,1}^{\dagger}$ means to maximize P under the constraint (5). Furthermore, due to $\mathbf{W}=\mathbf{H}^{\dagger}\left(\mathbf{H}\mathbf{H}^{\dagger}\right)^{-1}$, the energy distribution of $\mathbf{W}$ is the inversion of that of $\mathbf{H}$. Accordingly, the less correlative between columns of $\mathbf{W}$ and $\mathbf{h}_{p,1}$, the more correlative between rows of $\mathbf{H}$ and $\mathbf{h}_{p,1}$. Therefore, we should choose $\mathbf{h}_{c,k}$ s which are high correlated with $\mathbf{h}_{p,1}$ as the rows of $\mathbf{H}$ so as to minimize $\mathbf{h}_{p,1}\mathbf{W}\mathbf{W}^{\dagger}\mathbf{h}_{p,1}^{\dagger}$.

In physical systems, there may not exist M $\mathbf{h}_{c,k}$ s which are totally correlated to $\mathbf{h}_{p,1}$. Hence, we set correlation threshold δ_i and choose “semi-correlated” CUs whose channel vectors satisfy (20) to access:

$$\Delta(\mathbf{h}_{c,k},\mathbf{h}_{p,1})=\frac{\left|\mathbf{h}_{c,k}\mathbf{h}_{p,1}{}^{\dagger}\right|}{\left\|\mathbf{h}_{c,k}\right\|\left\|\mathbf{h}_{p,1}\right\|}\geq\delta_i. \tag{20}$$

In this paper, we propose a semi-correlated semi-orthogonal user selection (SC-SOUS) method by jointly considering the above two steps. The SC-SOUS method can enhance the transmit power of CBS under the interference and power constraints so as to increase the sum rate of CRS and the energy to EPR. However, in these two steps, we have not paid attention to the term $\mathbf{h}_{p,2}\mathbf{W}\mathbf{W}^{\dagger}\mathbf{h}_{p,2}{}^{\dagger}$ in (3). Therefore, we can improve the energy sharing efficiency further.

Here we analyze how to amplify the energy from CBS to the EPR further. According to the above analysis, the transmit power P has been determined by **Proposition 1** and **2**. Thus now we try to increase $\mathbf{h}_{p,2}\mathbf{W}\mathbf{W}^{\dagger}\mathbf{h}_{p,2}{}^{\dagger}$ in (3). Similar to **Proposition 2**, based on the properties of the Hermitian matrix eigenvalues, Rayleigh quotient, spectral decomposition, and quadratic form, it can be concluded that selecting CUs whose channel vectors are orthogonal to $\mathbf{h}_{p,2}$ to access is beneficial for maximizing $\mathbf{h}_{p,2}\mathbf{W}\mathbf{W}^{\dagger}\mathbf{h}_{p,2}{}^{\dagger}$. Similarly, it is difficult to find M $\mathbf{h}_{c,k}$ s which are totally orthogonal to $\mathbf{h}_{p,2}$. Hence, we set orthogonality threshold δ_e and choose the "semi-orthogonal" CUs which satisfy (21) to access:

$$\Delta(\mathbf{h}_{c,k},\mathbf{h}_{p,2})=\frac{\left|\mathbf{h}_{c,k}\mathbf{h}_{p,2}{}^{\dagger}\right|}{\left\|\mathbf{h}_{c,k}\right\|\left\|\mathbf{h}_{p,2}\right\|}\leq\delta_e. \tag{21}$$

Maximization of the harvested power at EPR is discussed further in this step, leading to improved capability of energy sharing. As a result, we bring together all the three steps above and propose the spatial correlation-based resource sharing (SC-RS) strategy in Section 4.

4. Spatial Correlation-Based Resource Sharing

According to the analysis in Section 3, firstly, we propose the SC-SOUS method in **Table 1**.

Table 1. Specific steps of the proposed SC-SOUS method

1) δ_i -correlated (semi-correlated) CU selection
   a) $\mathcal{A}=\phi$;
   b) The candidates of CUs satisfying δ_i -correlated condition are denoted by
   $$T_1=\left\{k\left|\Delta\left(\mathbf{h}_{p,1},\mathbf{h}_{c,k}\right)\geq\delta_i,k=1,\ldots,K\right.\right\}; \tag{22}$$
   c) The first selected CU is determined by $\mathcal{A}\left(1\right)=\arg\max_{k\in T_1}\left\|\mathbf{h}_{c,k}\right\|$.
   $T_1\leftarrow T_1-\mathcal{A}$.
2) δ_c -orthogonal (semi-orthogonal) CU selection
   a) $i=1$;
   b) While $i<M$
      i. $i=i+1$
      ii. The candidates of CUs satisfying δ_c -orthogonal condition are denoted by

$$T_i = \left\{ k \middle| \Delta\left(\mathbf{h}_{c,\mathcal{A}(i-1)}, \mathbf{h}_{c,k}\right) \le \delta_c, \forall k \in T_{i-1} \right\}; \tag{23}$$

iii. The i th selected CU is determined by

$$\mathcal{A}(i) = \arg\max_{k \in T_i} \left\| \mathbf{h}_{c,k} \right\|. \tag{24}$$

end While

The main difference between the proposed SC-SOUS method and the semi-orthogonal user selection (SOUS) method [21-23] is in step 1. In this paper, we have developed **Proposition 1** and **2** as well as the user selection criteria (10) and (20) through the analysis of (2) **-** (6) in the optimization problem. The conclusion in (20) is opposite to that in [21-23]. In the SOUS method [21-23], the semi-orthogonal selection was adopted in both steps 1) and 2). However, interference between accessing CUs is canceled by ZFB, so the purpose of user selection inside the CRS is to maximize the power from the CBS to CUs; on the contrary, between CUs and the IPR, user selection is aiming at minimizing the power from CBS to the IPR. According to the opposite goals in these two steps, we should give opposite criteria for user selections. As a result, in this paper, our SC-SOUS method has applied the opposite “semi-correlated” and “semi-orthogonal” standards in the two steps, respectively, which is suitable for the requirements of user selections.

Secondly, the SC-RS strategy is shown in the following. We still compare the SC-RS strategy with the SOUS method [21-23]. δ_i-correlated user selection is adopted in step 2) of the proposed approach instead of δ_p-orthogonal user selection in the SOUS method [21-23]. Moreover, δ_e-orthogonal CU selection is also applied to improve energy utilization.

Table 2. Specific steps of the proposed SC-RS strategy

1) δ_e-orthogonal CU selection
   a) $\mathcal{A} = \phi$;
   b) The candidate set S is denoted by

$$S = \left\{ k \middle| \Delta\left(\mathbf{h}_{p,2}, \mathbf{h}_{c,k}\right) \le \delta_e, k = 1, \dots, K \right\}; \tag{25}$$

2) δ_i-correlated (semi-correlated) CU selection
   a) The candidate set Q_1 is denoted by

$$Q_1 = \left\{ k \middle| \Delta\left(\mathbf{h}_{p,1}, \mathbf{h}_{c,k}\right) \ge \delta_i, \forall k \in S \right\}; \tag{26}$$

   b) The first selected CU is determined by $\mathcal{A}(1) = \arg\max_{k \in Q_1} \left\| \mathbf{h}_{c,k} \right\|$.

   $Q_1 \leftarrow Q_1 - \mathcal{A}$.

3) δ_c-orthogonal (semi-orthogonal) CU selection
   a) $i = 1$;
   b) While $i < M$
      i. $i = i + 1$
      ii. The candidates of CUs satisfying δ_c-orthogonal condition are denoted by

$$Q_i = \left\{ k \middle| \Delta\left(\mathbf{h}_{c,\mathcal{A}(i-1)}, \mathbf{h}_{c,k}\right) \le \delta_c, \forall k \in Q_{i-1} \right\}; \tag{27}$$

      iii. The i th selected CU is determined by

$$\mathcal{A}(i) = \arg\max_{k \in Q_i} \left\| \mathbf{h}_{c,k} \right\|. \tag{28}$$

end While

4) Combine the channel vectors $\mathbf{h}_{c,k}, k \in A$ to make the matrix $\mathbf{H}$, and acquire $\mathbf{W} = \mathbf{H}^{\dagger}\left(\mathbf{H}\mathbf{H}^{\dagger}\right)^{-1}$ as the ZFB precoding matrix for the CBS in order to eliminate the interference between CUs;
5) Maximize P under the constraints (4) and (5).

5. Performance Analysis

5.1 Multi-User Diversity Gain

This subsection calculates the multi-user diversity gain in the SC-SOUS algorithm and SC-RS strategy. Multi-user diversity gain is related to the size of the set from which CU$_k$ is chosen [19][23]. Firstly, considering the two steps in the SC-SOUS algorithm, we estimate the cardinality $|T_i|$ by calculating the probability that CU$_k$ can be chosen in each step. In the following, we will analyze the multi-user gain for both stages of the user selection.

(1). δ_i-correlated CU selection

In the δ_i-correlated CU selection, the CU candidates are chosen based on the δ_i-correlation. For CU$_k$, the probability of this user being selected by the δ_i-correlated CU selection algorithm is [See Appendix].

$$\Pr\{k \in T_1\} = \left(1-\delta_i^2\right)^{M-1}. \tag{29}$$

Applying the law of large numbers, at large K, the cardinality $|T_1|$ can be approximated as

$$|T_1| \approx \left\lfloor K \Pr\{k \in T_1\} \right\rfloor = \left\lfloor K\left(1-\delta_i^2\right)^{M-1} \right\rfloor. \tag{30}$$

(2). δ_c-orthogonal CU selection

In this step, CU$_k$ is chosen based on the δ_c-orthogonality defined in (10). For CU$_k$, the probability of this user being selected by the δ_c-orthogonal CU selection is [19][23]

$$\Pr\{k \in T_i\} = I_{\delta_c^2}\left(i, M-i\right), \tag{31}$$

where $I_x(a,b)$ denotes the regularized incomplete beta function. For a large number of CUs, $|T_i|$ can be approximated as

$$|T_i| \approx \left\lfloor |T_1| \Pr\{k \in T_i\} \right\rfloor \approx \left\lfloor K\left(1-\delta_i^2\right)^{M-1} I_{\delta_c^2}\left(i, M-i\right) \right\rfloor, \quad i = 2,\ldots,M. \tag{32}$$

Secondly, we analyze the multi-user diversity gain in the SC-RS strategy. Since the SC-RS strategy has the additional δ_e-orthogonal CU selection, the cardinality of S can be approximated as [23]

$$|S| \approx \left\lfloor K \Pr\{k \in S\} \right\rfloor = \left\lfloor K\left(1-\left(1-\delta_e^2\right)^{M-1}\right) \right\rfloor. \tag{33}$$

Consequently, the size of Q_1 in the δ_i-correlated CU selection step can be approximated as

$$|Q_1| \approx \left\lfloor |S| \Pr\{k \in Q_1\} \right\rfloor \approx \left\lfloor K\left(1-\left(1-\delta_e^2\right)^{M-1}\right)\left(1-\delta_i^2\right)^{M-1} \right\rfloor. \tag{34}$$

And then, the size of Q_i in the δ_c-orthogonal CU selection step can be approximated as

$$\left|Q_i\right| \approx \left\lfloor \left|Q_1\right| \Pr\left\{k \in Q_i\right\} \right\rfloor \approx \left\lfloor K\left(1-\left(1-\delta_e^2\right)^{M-1}\right)\left(1-\delta_i^2\right)^{M-1} I_{\delta_c^2}\left(i, M-i\right) \right\rfloor, \tag{35}$$

where $i = 2,...,M$.

5.2 Computational Complexity

Here we analyze the computational complexities of the proposed SC-SOUS algorithm and SC-RS strategy and compare them with the SOUS algorithm. Meanwhile, we apply the exhaustive search as the baseline.

Firstly, the SC-SOUS algorithm consists of two steps, which are "δ_i-correlated CU selection" and "δ_c-orthogonal CU selection."

(1). In the "δ_i-correlated CU selection" step, the operations in (20) should be carried out for each $\mathbf{h}_{c,k}$ and $\mathbf{h}_{p,1}$. So there are K times inner products and $2K$ times vector Frobenius norm calculations. We suppose μ as a constant proportionality corresponding to one inner product and two vector Frobenius norm calculations. Consequently, the complexity of the "δ_i-correlated CU selection" step is $K\mu$.

(2). In the "δ_c-orthogonal CU selection" step, we denote the number of selected CUs in the i th-selection by J_i. Then the computational complexity of this step is

$$\mu \sum_{i=1}^{M-1} J_i. \tag{36}$$

Therefore, the complexity of the SC-SOUS algorithm is

$$\mu\left(K + \sum_{i=1}^{M-1} J_i\right). \tag{37}$$

Now we analyze μ in terms of adding or multiplying two real numbers. Since $\mathbf{h}_{c,k}$ and $\mathbf{h}_{p,1}$ are all $1\times M$ vectors, the inner product needs $4M$ multiplications and $2M$ additions. Besides, the Frobenius norm calculation of a $1\times M$ vector needs $2M$ multiplications and M additions. Accordingly, $\mu = 12M$.

Given all that and $K \gg M$, the complexity order of the SC-SOUS algorithm is $O\left(KM^2\right)$.

We combine the SC-SOUS with ZFB to accomplish user selection and interference cancellation. ZFB is realized by matrix inversion whose complexity is $O(M^3)$. Since $K \gg M$, the complexity of SC-SOUS+ZFB is still $O\left(KM^2\right)$.

Secondly, we consider the SC-RS strategy. This strategy has only one more step than SC-SOUS+ZFB, which is the "δ_e-orthogonal" CU selection. Based on the complexity analysis of the "δ_i-orthogonal" CU selection step in the SC-SOUS algorithm, we know that the complexity of the "δ_e-orthogonal" CU selection is also $K\mu$. Consequently, the complexity of the SC-RS strategy is still $O\left(KM^2\right)$.

The computational complexities of the proposed SC-SOUS algorithm combined with ZFB, SC-RS strategy, the SOUS algorithm together with ZFB [23], and the exhaustive-search (ES) CU selection combined with ZFB are summarized in **Table 3**. The two algorithms proposed in this paper have the same complexity order with the SOUS+ZFB in [23]. An exhaustive search, therefore, involves formidable complexity. For example, if $K = 300$ and $M = 8$, we have $C_K^M M^3 = 7.5830\times10^{17} \gg KM^2 = 1.92\times10^4$.

Table 3. The complexity of four resource sharing methods

	SC-SOUS + ZFB	SC-RS	SOUS + ZFB [23]	ES + ZFB
User selection	$O(KM^2)$	$O(KM^2)$	$O(KM^2)$	$O(C_K^M)$
ZFB	$O(M^3)$	$O(M^3)$	$O(M^3)$	$O(M^3)$
In all	$O(KM^2)$	$O(KM^2)$	$O(KM^2)$	$O(C_K^M M^3)$

6. Simulation Results and Discussions

In the simulation, it is supposed that $K = 300$ [23] and $M = 8$. P_t changes from 1w to 100w. Noise power $\sigma_k^2 = 1\text{w}$ [26][38]. The transmit power of PT is $P_p = 1\text{w}$. The interference constraint of the IPR is $\gamma_0 = 0.1P_t$ [39], and the energy conversion efficiency of the EPR is $\zeta = 0.6$ [33]. Firstly, we set $\delta_i = \delta_p = 0.45$, $\delta_c = \delta_e = 0.4$ (where δ_p and δ_c are the thresholds of the two selections in the SOUS algorithm [21-23], respectively). The Monte Carlo simulation results of the sum rate of CRS and the harvested power at EPR from the CBS are shown in **Fig. 2** and **Fig. 3**.

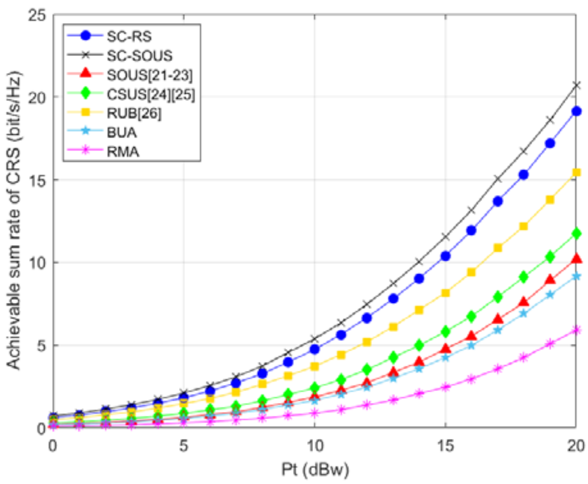

Fig. 2. Achievable sum rate of CRS

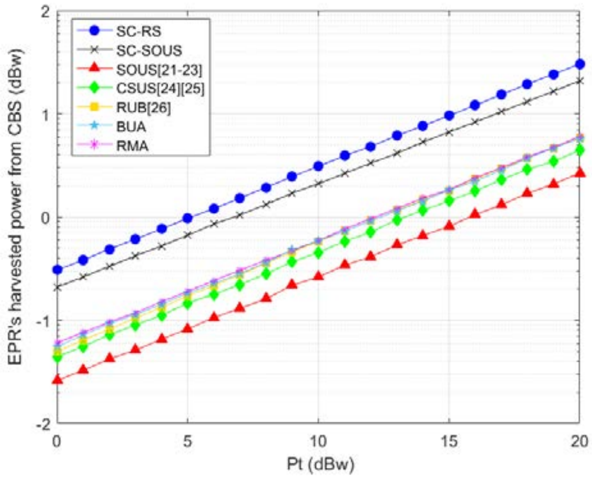

Fig. 3. EPR's harvested power from CBS

The achievable sum rates of CRS acquired by seven different methods are shown in **Fig. 2**. The proposed SC-SOUS method can provide a larger sum rate and higher spectrum sharing efficiency than the other methods. This method is based on a theoretical analysis of spatial channel correlation, which has two conclusions about the transmit power at CBS. First, the CBS can increase transmit power when the selected CUs are semi-correlated with the IPR (it is opposite to [21-23]). Second, semi-orthogonality between the selected CUs can also increase the transmit power of CBS and the achievable sum rate of CRS (it is the same with [21-23], but there was no proof in the above references). The SC-SOUS method has made a distinction between two selection steps. The first CU selection step is designed to minimize the power received by the IPR from CBS; conversely, since ZFB removes the interference between CUs, the second CU selection step aims to increase the power from CBS to selected CUs after ZFB. The opposite objectives lead to different selection criteria, both of which can improve the performance of the CR network.

The proposed SC-RS strategy gives further consideration of energy sharing efficiency. The tradeoff is made between the CUs' sum rate and the EPR's harvested energy, so there is a slight sum-rate loss compared with the SC-SOUS method. However, the sum rate is still higher than the other methods. In the SOUS [21-23] and CSUS [24][25] methods, the first user selection step is designed as "semi-orthogonal selection" instead of "semi-correlated selection," which goes against the maximization of P under the constraint of (5). As a result, both the power gain and CUs' sum rate decrease. But ZFB precoding in these methods and the RUB [26] method, as well as the "best user" selection in the best user access (BUA) method, is beneficial for the performance, so all their sum rates are higher than that in the Random Access (RMA) method.

The curves in **Fig. 3** show the EPR's harvested power from CBS obtained by seven different methods. The proposed SC-RS strategy can provide higher power harvesting efficiency for the EPR than the other methods, which means it has the highest energy sharing capability. Besides the increase in P caused by the "δ_i-correlated" and "δ_c-orthogonal" selection steps, the SC-RS strategy further improves $\mathbf{h}_{p,2}\mathbf{W}\mathbf{W}^{\dagger}\mathbf{h}_{p,2}^{\dagger}$ by the "δ_e-orthogonal" CU selection to enhance the energy harvesting efficiency of the EPR. Although there is no "δ_e-orthogonal" selection step in the proposed SC-SOUS method, the EPR's harvested power increases with the other two selection steps. The "δ_p-orthogonal" selection step in SOUS [21-23] and CSUS [24][25] methods reduces the transmit power of CBS, so the EPR's harvested power is smaller than that in the other methods.

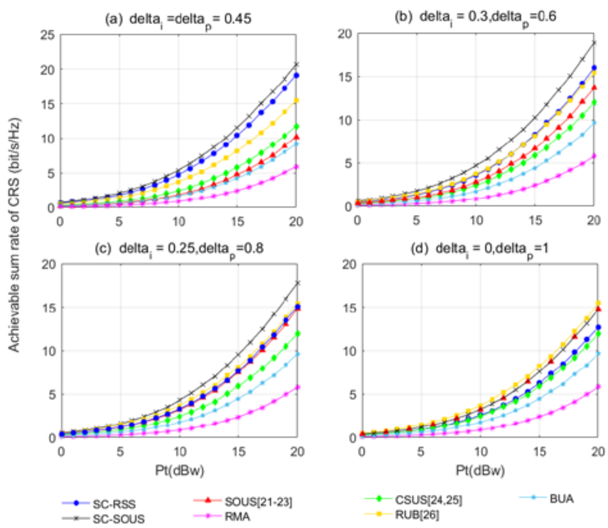

Fig. 4. Achievable sum rate of CRS with different δ_i

In **Fig. 4**, we demonstrate the achievable sum rate of the CRS with different values of δ_i. We set $\delta_e = \delta_c = 0.4$, while $\delta_i = 0.45$, 0.3, 0.25, and 0 in the SC-RS strategy and the SC-SOUS method. When δ_i decreases, the "δ_i-correlated" selection becomes less and less effective. As a result, the CR system's sum-rate decreases in these two methods. When $\delta_i = 0$, the "δ_i-correlated" user selection becomes invalid, the sum rates in the SC-RS strategy and SC-SOUS method are even lower than that in the RUB [26] method. The above results reflect the effection of "δ_i-correlated" selection in improving the sum rate of CRS. Correspondingly, we set $\delta_p = 0.45$, 0.6, 0.8, and 1 in SOUS [21-23] method, which can also make its "δ_p-orthogonal" selection less and less effective and become invalid when $\delta_p = 1$. The simulation results show that the CR system's sum rate increases along with δ_p, and the highest sum rate is acquired when $\delta_p = 1$. It is evident that the "δ_p-orthogonal" selection backfires. Besides, when $\delta_i = 0$ and $\delta_p = 1$, both "δ_i-correlated" selection in the SC-SOUS method and "δ_p-orthogonal" selection in the SOUS [21-23] method are invalid, so these two methods can achieve the same sum rate. This result is consistent with our analysis.

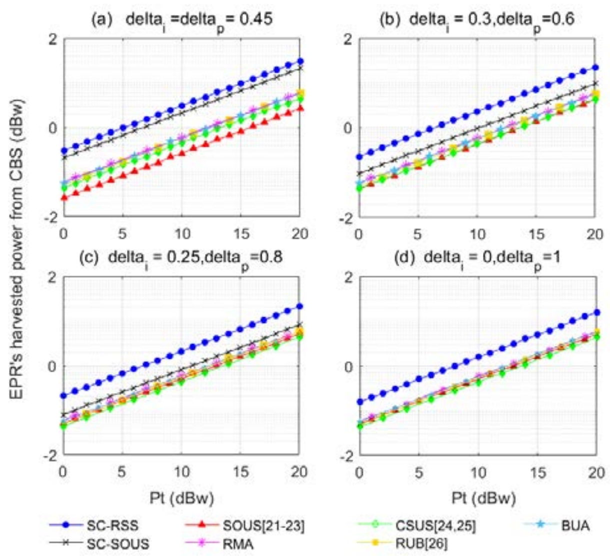

Fig. 5. EPR's harvested power from CRS with different δ_i

Fig. 5 exhibits the EPR's power charged from the CBS. We also set $\delta_e = \delta_c = 0.4$, δ_i = 0.45, 0.3, 0.25, 0, and δ_p = 0.45, 0.6, 0.8, 1, respectively. The power obtained by the SC-RS strategy decreases along with δ_i. However, it is always higher than that in the other methods. The main reason is that when δ_i decreases, the "δ_i-correlated" selection becomes more and more ineffective, which reduces P; nevertheless, the "δ_e-orthogonal" CU selection can enhance the power harvesting. On the contrary, when δ_p increases, the "δ_p-orthogonal" selection in the SOUS [21-23] method becomes more and more ineffective, which means the selected CUs' spatial channel vectors are more and more correlative to the IPR's spatial channel vector $\mathbf{h}_{p,1}$. As shown in Fig. 5, the power acquired by the EPR increases, which confirms the conclusion of **Proposition 2.**

Fig. 6 provides the charging power from the CBS to the EPR when $\delta_i = 0.45$ and $\delta_c = 0.4$, as well as δ_e = 0.4, 0.6, 0.8, and 1. It is shown that in the proposed SC-RS strategy, when δ_e increases, the power for EPR decreases but is still higher than that in all the other methods. Since the proposed strategy can choose CUs whose channel vector $\mathbf{h}_{c,k}$ satisfying the "δ_e-orthogonal" condition with $\mathbf{h}_{p,2}$ to access, it can improve the energy sharing performance. The growing of δ_e can reduce the orthogonality between selected $\mathbf{h}_{c,k}$ and $\mathbf{h}_{p,2}$, which reduces the harvested power. When $\delta_e = 1$, the orthogonality disappears, so the harvested power of the EPR from CBS is the same in both the SC-RS strategy and the SC-SOUS method, whose power gains are acquired from the increase of P by the "δ_i-correlated" and "δ_c-orthogonal" selections.

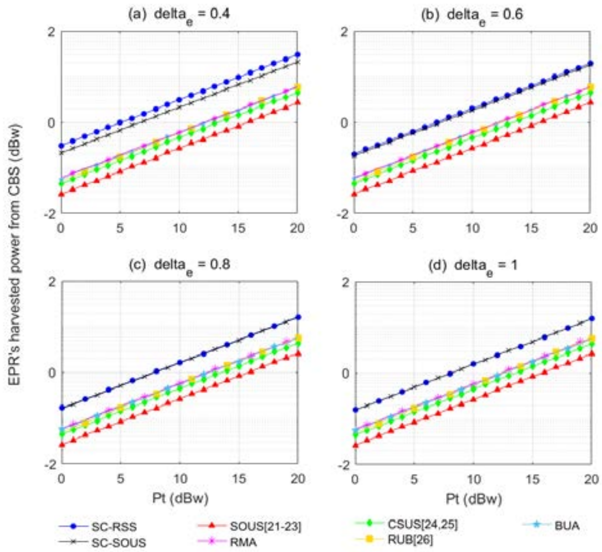

Fig. 6. EPR's harvested power from CBS with different δ_e

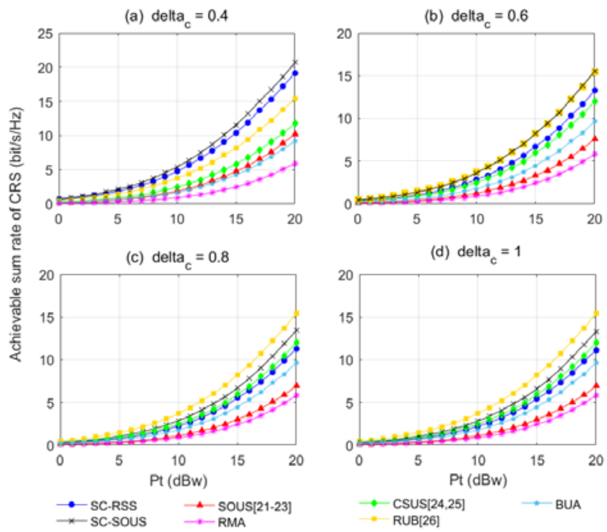

Fig. 7. Achievable sum rate of CRS with different δ_c

From **Fig. 7**, it can be seen that the achievable sum rate of the CRS varies along with δ_c, whereas $\delta_i = 0.45$ and $\delta_e = 0.4$ remain the same. As δ_c increases, the orthogonality between chosen CUs decreases, leading to the reduction of P due to the constraints (4) and (5). Therefore, the sum rates acquired by the SC-RS strategy, the SC-SOUS and SOUS [21-23] methods become lower and lower. The orthogonality between selected CUs disappears when $\delta_c = 1$. However, the "δ_i-correlated" selection step can bring larger sum rates for the proposed methods than the SOUS [21-23] method. The above results reveal the effection of the "δ_c-orthogonal" selection.

Fig. 8 shows the charging power for the EPR from CBS in different cases. We keep $\delta_i = 0.45$ and $\delta_e = 0.4$, and set δ_c = 0.4, 0.6, 0.8 and 1 in four subfigures, respectively. The illustration shows that along with the increase of δ_c, the harvested power in the SC-SOUS method and SC-RS strategy decreases. Nevertheless, the unique "δ_e-orthogonal" CU selection of the SC-RS strategy can make it superior to the other methods.

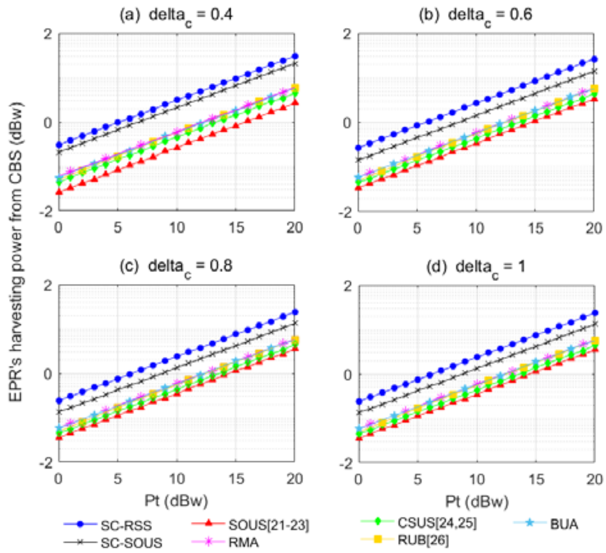

Fig. 8. EPR's harvested power from CRS with different δ_c

7. Conclusions

In this paper, we have investigated the spatial channel correlation-based resource sharing for multi-user multi-antenna CR-SWIPT networks. The optimization of the CU access control and power allocation is implemented to maximize the resource sharing efficiency according to the theoretical analysis of the relationship between accessing CUs' spatial channel vectors and the transmitted power of the CBS. We developed the low-complexity SC-SOUS method and SC-RS strategy, including "semi-correlated" and "semi-orthogonal" user selections, to improve the achievable sum rate of the CRS and the harvested power at the EPR. Simulation results with different parameter values have confirmed our analysis and shown that the proposed methods can notably enhance the spectrum and energy sharing capability in CR-SWIPT networks. The proposed low-complex methods are suitable for realistic scenarios and systems, especially when the total number of CUs is large. In future work, we can extend our methods to the cognitive radio networks with multiple groups of primary users, where each group operates on its licensed frequency band. The CRS can choose the favorite band to access. The primary users on the selected frequency band have an appropriate spatial channel correlation with the CUs. Moreover, we can consider the different decay situations in various frequency bands and achieve a good tradeoff between increasing the power of useful signals and reducing the interference through spectrum decisions. Besides, we also intend to investigate the scenario in that CUs have multiple antennas by supposing each antenna as an independent virtual user.

Appendix

We assume that $\bar{\mathbf{h}}_{p,1} = \mathbf{h}_{p,1} / \| \mathbf{h}_{p,1} \|$, and decompose $\mathbf{h}_{c,k}$ into $\bar{\mathbf{h}}_{p,1}$ and its orthogonal components $\bar{\mathbf{h}}_{p,1}^{\perp}$ as $\mathbf{h}_{c,k} = \mathbf{h}_{c,k}^{\|} \bar{\mathbf{h}}_{p,1} + \mathbf{h}_{c,k}^{\perp} \bar{\mathbf{h}}_{p,1}^{\perp}$, where $\| \mathbf{h}_{c,k}^{\|} \|^2 \sim \Gamma(1,1)$, $\| \mathbf{h}_{c,k}^{\perp} \|^2 \sim \Gamma(M-1,1)$ [23]. Here $\mathbf{x} \sim \Gamma(\rho, \lambda)$ means that $\mathbf{x}$ is distributed according to the gamma distribution with parameters (ρ, λ). Besides, $| \mathbf{h}_{c,k}^{\|} |^2$ and $\| \mathbf{h}_{c,k}^{\perp} \|^2$ are independent, and $\| \mathbf{h}_{c,k} \|^2 = | \mathbf{h}_{c,k}^{\|} |^2 + \| \mathbf{h}_{c,k}^{\perp} \|^2$. Since $\mathbf{h}_{c,k}^{\|} = \mathbf{h}_{c,k} \bar{\mathbf{h}}_{p,1}^{\dagger}$ and $\mathbf{h}_{c,k}^{\perp} = \mathbf{h}_{c,k} (\bar{\mathbf{h}}_{p,1}^{\perp})^{\dagger}$, according to (19), we have

$$\Delta(\mathbf{h}_{c,k}, \mathbf{h}_{p,1})^2 = \frac{| \mathbf{h}_{c,k} \mathbf{h}_{p,1}^{\dagger} |^2}{\| \mathbf{h}_{c,k} \|^2 \| \mathbf{h}_{p,1}^{\dagger} \|^2} = \frac{| \mathbf{h}_{c,k}^{\|} |^2}{| \mathbf{h}_{c,k}^{\|} |^2 + \| \mathbf{h}_{c,k}^{\perp} \|^2}. \tag{38}$$

Based on the property of gamma distribution, we can obtain

$$\Delta(\mathbf{h}_{c,k}, \mathbf{h}_{p,1})^2 = \frac{| \mathbf{h}_{c,k} \mathbf{h}_{p,1}^{\dagger} |^2}{\| \mathbf{h}_{c,k} \|^2 \| \mathbf{h}_{p,1}^{\dagger} \|^2} \sim \beta(1, M-1), \tag{39}$$

where $\beta(a,b)$ denotes the beta distribution. Since the CDF of $\beta(a,b)$ is the regularized incomplete beta function $I_x(a,b)$, we can get

$$\Pr\{k \in T_1\} = \Pr\left\{ \frac{| \mathbf{h}_{c,k} \mathbf{h}_{p,1}^{\dagger} |^2}{\| \mathbf{h}_{c,k} \|^2 \| \mathbf{h}_{p,1}^{\dagger} \|^2} \ge \delta_i^2 \right\} = 1 - I_{\delta_i^2}(1, M-1). \tag{40}$$

From the definition of the regularized incomplete beta function, we can have

$$I_{\delta_i^2}(1, M-1) = \frac{B(\delta_i^2, 1, M-1)}{B(1, M-1)}, \tag{41}$$

where $B(x,a,b)$ and $B(a,b)$ are the incomplete beta function and the beta function, respectively. Specifically, we have

$$B(x,a,b) = \int_0^x t^{a-1} (1-t)^{b-1} \, dt, \tag{42}$$

$$B(a,b) = \int_0^1 t^{a-1} (1-t)^{b-1} \, dt, \tag{43}$$

Therefore, we can obtain

$$\Pr\{k \in T_1\} = (1 - \delta_i^2)^{M-1}. \tag{44}$$

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