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Simultaneous Wireless Information and Power Transfer Optimization in Multiple-Antenna Broad-Cast Systems

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Abstract
Simultaneous Wireless Information and Power Transfer (SWIPT) systems enable mobile phones to live much longer in the network. In this paper, we formulate an optimization problem to best design a multi-user multi-antenna Broad-Cast (BC) system by simultaneously maximizing the sum of harvested energy and minimizing the sum Mean Square Error (MSE) for symbol detection at each receiver. This design problem is then recast as a multi-objective problem with the Difference of Convex (DC) bilinear structure. The final design problem is solved using the Alternating Convex Search (ACS) method and the Penalty Convex-Concave Program (PCCP) procedure. Simulation results are extensively undergone to assess the performance of the proposed algorithms.

Keywords
Simultaneous Wireless Information and Power Transfer (SWIPT) systems, Difference of Convex (DC) problem, Penalty Convex-Concave Program (PCCP) procedure, Multiple-Input Multiple-Output (MIMO) Systems

Introduction
Due to the emergence and expansion of the Internet of Things (IoT) and wireless sensor networks (WSN) which are mostly battery powered devices, it is needed that in accordance with the submission of information, the power is also transferred to the devices. In this world, SWIPT (Simultaneous Wireless Information and Power Transfer) systems are must-have technologies for the future. In recent years, much attention has been paid to SWIPT and several research papers have been published: [1]-[3].
In a SWIPT-based system, there is an inverse relationship between the amount of harvested energy and the amount of system information capacity [4]. Therefore, a compromise must be made between the harvested energy and the amount of system information capacity. Therefore most research papers optimize one criterion with subject to another one[5]-[9].
Unlike most research papers, there are some papers that both criteria, harvested energy and information rate, are simultaneously optimized. A Multiple-User (MU) Multiple-Input Multiple-Output (MIMO) SWIPT system is studied in [10] with one transmitter having N antennas and two distinct groups of receivers equipped with M antennas. The first group is composed of only Information Decoder (ID) receivers and the other group is made up from sole Energy harvesting (EH) receivers. Therefore none of the receivers can decode information and harvest energy simultaneously.
In this paper, maximizing both the sum of harvested energy and the data rate is targeted. This problem is cast as a Difference of Convex (DC) problem. The authors solve this problem using a Majorization-Minimization (MM) approach. In [11] a heterogeneous energy harvesting network is studied, in which a Power Beacon (PB) (to transfer the

energy) and a Base Station (BS) (to transmit the information) coexist. The authors assumed K EH and one ID single-antenna users. Because both PB and BS are close to each other, there should be trade off between the harvested energy and the data rate. Because transferring energy would interfere with transmitting the information. To reduce this effect, a energy beamforming (BF) scheme is proposed. The authors aim to find the best energy BF vector in a way that, the sum of harvested energy and the data rate are maximized concurrently. To solve DC problem they use the proposed method in [12].

In the current paper, we want to design a MU-MIMO SWIPT system with k receivers each of which has two parts, ID & EH. Every ID part is equipped with a decoder. Corresponding with each receiver, there is a precoder matrix in the transmitter. In the our problem formulation, we want to jointly optimize the precoders and decoders by simultaneously maximizing the sum of all energy harvested in all receivers, and minimizing the sum MSE of the symbol detection in them, with a constraint on the transmit power of the BS. As it can be seen, this problem can be cast as global multi-objective program which is a non-convex problem. To solve this DC problem we use a Penalty Convex-Concave Program (PCCP) procedure [13],[14].

System Model

Let's assume a MU-MIMO SWIPT system with one BS, and k users in a broadcasting configuration, i.e., one transmitter and k receivers. The BS is equipped with n antennas and each of the receivers has m antennas. Vector of $\mathbf{s}_i \in \mathbb{C}^{t_i \times 1}, i = 1, \cdots, k$ is transmitted to the ith receiver by BS, in which, t_i is the number of symbols of the ith receiver. We suppose that the distribution of these symbols are complex normal with zero-mean and variance of one, i.e., $\mathbf{s_i} \sim \mathrm{CN}(\mathbf{0}, \mathbf{I}_{t_i})$. The noise at each receiver is also assumed to have a complex normal distribution, i.e., $\mathbf{n}_i \in \mathbb{C}^{m \times 1} \sim \mathrm{CN}(\mathbf{0}, \sigma_n^2 \mathbf{I}_m)$. At the transmitter side, each vector of symbols is precoded using a matrix $\mathbf{A}_i \in \mathbb{C}^{n \times t_i}$ and would be equalized at the receiver side using a matrix $\mathbf{B}_i \in \mathbb{C}^{t_i \times m}$. At the end, the output vector at each of the receivers is denoted by $\mathbf{z_i} \in \mathbb{C}^{t_i \times 1}$. In addition, the power splitter splits the received power, P_r, into two parts controlled using a parameter, α $(0 \leq \alpha \leq 1)$. αP_r portion of it is sent to the ID module while the rest of it, $(1 - \alpha)P_r$, is sent to the EH module. After conversion, this energy is saved in a battery (BAT) that is used in uplink the mode. We also assume that the conversion efficiency of the EH module is $0 \leq \eta \leq 1$.

It should also be noted that the channel matrices of $\mathbf{H}_i \in \mathbb{C}^{m \times n}$, between the BS and the ith user, are assumed to be completely known. The transmitted vector of symbols at the BS is denoted as $\mathbf{x} \in^{n \times 1}$. It can be written as $\mathbf{x} = \sum_{i=1}^{k} \mathbf{A}_i \mathbf{s_i}$.

The received signals of each reciever in the ID module can be written as:

$$\mathbf{y}_{i,ID} = \sqrt{\alpha}\,(\mathbf{H}_i \mathbf{x} + \mathbf{n}_i) = \sqrt{\alpha}\left(\mathbf{H}_i \sum_{j=1}^{k} \mathbf{A}_j \mathbf{s}_j + \mathbf{n_i}\right)$$
$$= \sqrt{\alpha}\,\mathbf{H}_i \mathbf{A}_i \mathbf{s}_i + \sqrt{\alpha}\,\sum_{j=1 \neq i}^{\mathbf{k}} \mathbf{H}_i \mathbf{A}_j \mathbf{s}_j + \sqrt{\alpha}\mathbf{n}_i \qquad (1)$$

while the received signal of EH module would be

$$\mathbf{y}_{i,EH} = \sqrt{1-\alpha}\left(\sum_{j=1}^{k} \mathbf{H}_i \mathbf{A}_j \mathbf{s}_j + \mathbf{n}_i\right). \qquad (2)$$

At each receiver, the ID module would decode its received signal using $\mathbf{B}_i$ matrices and thus the output signal of each ID module would be

$$\mathbf{z}_i = \mathbf{B}_i\mathbf{y}_{i,ID} = \sqrt{\alpha}\,\mathbf{B}_i\mathbf{H}_i\mathbf{A}_i\mathbf{s}_i + \sqrt{\alpha}\,\sum_{j=1\neq i}^{k}\mathbf{B}_i\mathbf{H}_i\mathbf{A}_j\mathbf{s}_j + \sqrt{\alpha}\mathbf{B}_i\mathbf{n}_i \qquad (3)$$

The Proposed Algorithm with Perfect CSI
In this paper, we want to find the best $\mathbf{A_i}$ and $\mathbf{B}_i, i = 1,\cdots,k$ matrices, such that the sum of harvested energy in their EH module is maximized while the sum MSE over all receivers is simultaneously minimized. It means that we want to solve both P1 and P2 problems at the same time:

$$(\mathrm{P1}) \quad \min_{\{\mathbf{A_i},\mathbf{B_i}\}_{i=1}^{k}} \sum_{i=1}^{k}\mathrm{MSE}_i \qquad\qquad (\mathrm{P2}) \quad \max_{\{\mathbf{A_i}\}_{i=1}^{k}} \sum_{i=1}^{k} Q_i$$

$$\mathrm{s.t.} \quad \mathrm{TxP} \le \mathrm{P} \qquad\qquad \mathrm{s.t.} \quad \mathrm{TxP} \le \mathrm{P} \qquad (4)$$

where

$$Q_i = \eta\,\mathbb{E}[\|\,\mathbf{y}_{i,EH}\,\|^2] = \eta(1-\alpha)\left[\sum_{j=1}^{k}\|\,\mathbf{H}_i\mathbf{A}_j\,\|_F^2 + m\sigma_n^2\right]$$

is the harvested energy[1] in each node

$$\mathrm{TxP} = \mathbb{E}[\|\,\mathbf{x}\,\|^2] = \sum_{i=1}^{k}\|\,\mathrm{vec}(\mathbf{A}_i)\,\|^2$$

is the transmit power of the BS and it is limited by P, and

$$\mathrm{MSE}_i = \mathbb{E}[\|\,\mathbf{z}_i - \mathbf{s}_i\,\|^2] = \|\,\sqrt{\alpha}\mathbf{B}_i\mathbf{H}_i\mathbf{A}_i - \mathbf{I}_{t_i}\,\|_F^2 + \alpha\sigma_n^2\,\|\,\mathbf{B}_i\,\|_F^2 + \alpha\sum_{j=1\neq i}^{k}\|\,\mathbf{B}_i\mathbf{H}_i\mathbf{A}_j\,\|_F^2$$

is the MSE of the ith link. Using the following notations, we can reformulate P1 and P2 problems. If

$$\mathbf{A} = [\mathbf{A_1},\dots,\mathbf{A_k}]\,,\mathbf{B} = [\mathbf{B_1},\dots,\mathbf{B_k}]$$

$$g_0(\mathbf{A},\mathbf{B}) = \sum_{i=1}^{k}\mathrm{MSE}_i \text{ , and } h_0(\mathbf{A}) = \sum_{i=1}^{k} Q_i$$

are assumed, then P1 and P2 can be written as P3 and P4 respectively.

$$(\mathrm{P3}) \quad \min_{\mathbf{A},\mathbf{B}} g_0(\mathbf{A},\mathbf{B}) \qquad\qquad (\mathrm{P4}) \quad \max_{\mathbf{A}} h_0(\mathbf{A})$$

$$\mathrm{s.t.} \quad \mathrm{TxP} \le \mathrm{P} \qquad\qquad \mathrm{s.t.} \quad \mathrm{TxP} \le \mathrm{P} \qquad (5)$$

where

$$h_0(\mathbf{A}) = \eta(1-\alpha)\sum_{i=1}^{k}\sum_{j=1}^{k}\|\,(\mathbf{I}_{t_i}^T\otimes\mathbf{H}_i)\,\mathrm{vec}(\mathbf{A}_j)\,\|^2 + \eta(1-\alpha)mk\sigma_n^2 \qquad (6a)$$

$$g_0(\mathbf{A},\mathbf{B}) = \alpha\sum_{i=1}^{k}\sum_{j=1\neq i}^{k}\|\,(\mathbf{I}_{t_i}^T\otimes\mathbf{B_i}\mathbf{H}_i)\,\mathrm{vec}(\mathbf{A}_j)\,\|^2 + \sum_{i=1}^{k}\|\,\sqrt{\alpha}\big(\mathbf{I}_{t_i}^T\otimes\mathbf{B_i}\mathbf{H}_i\big)\mathrm{vec}(\mathbf{A}_i) - \mathrm{vec}\big(\mathbf{I}_{t_i}\big)\,\|^2$$

$$+\,\alpha\sigma_n^2\sum_{i=1}^{k}\|\,\mathrm{vec}(\mathbf{B}_i)\,\|^2 \qquad (6b)$$

In this optimization problem. The function, $g_0(\mathbf{A},\mathbf{B})$ is a bi-convex function, i.e., it is not simultaneously convex with respect to both arguments, but if one parameter, for example, $\mathbf{A}$, is fixed, the function would be a convex one with respect to the second parameter.

2- For convenience, in the sequel of the paper the two terms “energy” and “power” may be used interchangeably by assuming the symbol period to be equal to one.

Problem P3 is studied in [15], and the authors use Alternating Convex Search (ACS) [16] to solve it. To solve both P3 and P4 problems simultaneously, which is a multi-objective non-convex problem, we use vector optimization for finding pareto optimal (or optimal) points [17]. Therefore P3 and P4 can be written as P5 which is a convex-concave problem:

$$\text{(P5)} \quad \min_{\mathbf{A},\mathbf{B}} f_0(\mathbf{A},\mathbf{B}) = g_0(\mathbf{A},\mathbf{B}) - h_0(\mathbf{A})$$
$$\text{s.t.} \quad \text{TxP} \leq \text{P} \qquad (7)$$

To solve P5, considering **B** is fixed, then we resort P5 by using ACS algorithm, therefore, we can write P5 into P6 and P7 form. To solve for **A,** we use a PCCP based algorithm to find a suboptimal solution.

$$\text{(P6)} \quad \min_{\mathbf{A}} f(\mathbf{A}) = g_0(\mathbf{A}) - h_0(\mathbf{A}) \qquad \text{(P7)} \quad \min_{\mathbf{B}} g_0(\mathbf{B})$$
$$\text{s.t.} \quad \text{TxP} \leq \text{P} \qquad (8)$$

To solve P6, we need to rewrite it using real-valued parameters. If

$$\mathbf{a_i} = [\Re\{\text{vec}(\mathbf{A_i})\}^T, \Im\{\text{vec}(\mathbf{A_i})\}^T] \in \mathbb{R}^{2nt_i \times 1},$$

$$\mathbf{C_i} = \mathbf{I_{t_i}^T} \otimes \mathbf{B_i}\mathbf{H}_i \in \mathbb{C}^{t_i^2 \times nt_i}, \quad \mathbf{D_i} = \mathbf{I}_{t_i}^T \otimes \mathbf{H}_i \in \mathbb{C}^{mt_i \times nt_i}, \quad \mathbf{G_i} = \Xi[\mathbf{C_i}], \quad \mathbf{W_i} = \Xi[\mathbf{D_i}]$$

Where

$$\Xi[\mathbf{X}] = [\Xi_1, \Xi_2]$$

in which

$$\Xi_1 = [\Re\{\mathbf{X}\}^T, \Im\{\mathbf{X}\}^T]^T, \Xi_2 = [-\Im\{\mathbf{X}\}^T, \Re\{\mathbf{X}\}^T]^T.$$

therefore, we can convert

$$f(\mathbf{A}) = g_0(\mathbf{A}) - h_0(\mathbf{A})$$

to a real-valued function $f(\mathbf{a})$ as follows :

$$f(\mathbf{a}) = \sum_{i=1}^{k} \| \sqrt{\alpha}\, \mathbf{G_i}\mathbf{a_i} - \mathbf{e_i} \|^2 + \alpha \sum_{i=1}^{k} \sum_{j=1 \neq i}^{k} \| \mathbf{G_i}\mathbf{a}_j \|^2 - \eta(1-\alpha) \sum_{i=1}^{k} \sum_{j=1}^{k} \| \mathbf{W_i}\mathbf{a}_j \|^2 - \eta(1-\alpha) mk\, \sigma_n^2 \quad (9)$$

where

$$\mathbf{e_i} = \left[\text{vec}\left(\mathbf{I}_{t_i}\right)^T, \ \mathbf{0}_{t_i^2 \times 1}^T\right]^T$$

and

$$\mathbf{a} = [\mathbf{a_1}, \cdots, \mathbf{a_k}].$$

Afterthese manipulations, P6 can be written as P8:

$$\text{(P8)} \quad \min_{\mathbf{a}} f(\mathbf{a}) = g_0(\mathbf{a}) - h_0(\mathbf{a})$$
$$\text{s.t.} \quad P_{Tx} = \sum_{i=1}^{k} \| \mathbf{a_i} \|^2 \leq P \qquad (10)$$

To solve P8, we use Algorithm 1.

Algorithm 1 PCCP based Algorithm to solve (P8)

1: Set $L \leftarrow 0$, and generate $\mathbf{a^0} = [\mathbf{a_1^0}, \cdots, \mathbf{a_k^0}]$ randomly
2: Repeat
3: Convexification: use the following equation to find a first-order approximate of $h_0(\mathbf{a})$ at a typical point like $\mathbf{a^L}$.

$$\hat{h}_0(\mathbf{a}) = h_0(\mathbf{a^L}) + \nabla h_0(\mathbf{a^L})^T(\mathbf{a} - \mathbf{a^L}) = h_0(\mathbf{a^L}) + 2\eta(1-\alpha)\sum_{i=1}^{k}\sum_{j=1}^{k}(\mathbf{a}_j^L)^T \mathbf{W_i^T W_i}(\mathbf{a}_j - \mathbf{a}_j^L) \quad (11)$$

4: Solve the following problem

$$\min_{\mathbf{a}}\{f(\mathbf{a}) = g_0(\mathbf{a}) - \hat{h}_0(\mathbf{a}) \mid P_{Tx} \le P\} \quad (12)$$

5: $\mathbf{a^{L+1}} \leftarrow \mathbf{a}$
6: $L \leftarrow L + 1$
7: Until some conditions are met, like $L = L_{max}$, i.e., maximum iterations number or a small increment is seen for the objective function, i.e.,

$$\left| f(\mathbf{a^L}) - f(\mathbf{a^{L+1}}) \right| \le \beta$$

Proof of the convergence Algorithm 1 is in [18]. Therefore final algorithm for solving P5 is Algorithm 2.

Algorithm 2 Algorithm to solve (P5)

1: Generate **B** randomly and put it in $f(\mathbf{A})$
2: Repeat
3: Solve (P8) using Algorithm 1 to find **a**
4: Convert **a** to **A** put it in $g_0(\mathbf{B})$
5: Solve (P7), then put **B** in $f(\mathbf{A})$
6: Until $f_0(\mathbf{A}, \mathbf{B})$ changes is converged

Simulation Results

We assess the performance of our system in three different scenarios. We assume $\forall i, t_i = t$. To continue the simulation process, we choose the following value for the parameter: $\beta \le 10^{-4}$. This value is chosen so that Algorithm 1 have enough time to converge with a proper performance [14]. We have done 200 rounds of Monte-Carlo simulations and all the given graphs have been averaged over these runs.

Let's set $n = 4, m = 3, k = 2, t = 1, P = 1$, $\eta = 1$ and $\alpha = 0.3$. In this scenario the PCCP approach is compared with two other algorithms, MM [10] and the Block Diagonalization (BD) [19]. In [19] writters used BD procedure to maximaize system throughput by finding optimal precoders when power of interference signal become zero per users. Hence we can calculate the sum of harvested energy by finding optimal precoders and then compare it to PCCP. In [10], as we point it before, authors maximized sum rate and sum harvested energy over two distinct groups of users (ID and EH users) concurently with the MM procedure, therefore we can evaluate the common trend, "the sum of harvested energy", in contrast with PCCP. As you see in Figure.1, the harvested energy by the BD approach is much less than the other two approches because the number of degrees of freedom of BD procedure is less than the MM & PCCP [10]. The sum function energy has two parts, i.e., signal and noise part. As you can see in Figure. ١, PCCP & MM are nearly equal up to about SNR = 5dB because in low SNR (high noise power) regimes the noise part overcome the signal part and the noise part are the same for MM & PCCP. With increasing SNR the signal part will be overcome the noise part. If we can find better beamformers, the amount of the signal part of the sum energy function is boosted. This graph showes us the users of the PCCP procedure absorb about 30% more power than the users of the MM procedure.

Let's set $n = 4, k = 3,\ t = 2, P = 1, \eta = 0.7$ and $\alpha = 0.3$. As you know massive MIMO systems are sperading in wireless communication networks then in this scenario we want to show the effect of adding one more receiving antennas. Because of limitations on computer resources we can't simulate with more antennas. In Figure.2, solid lines is the sum of harvested energy trend and dash lines is the sum MSE of symbol detection trend. At high SNR regime, the sum of harvested energy is somehow independent of SNR. It is because the dominant term of energy comes from the signal part and the contribution of noise is low. It is also obvious from this Figure that by reducing the SNR, or apparently, by increasing the noise level, the noise signal can also contribute to the harvested energy and this increases the amount of absorbed energy. As it is expected, if $m = 3$ receive antennas are exploited , a better MSE can be experienced. when the SNR at the transmitter side is very poor or very high, there is no large gain of using one more antennas. In the middle of these two bounds, we can see the effect of adding one more receiving antennas. The sum of harvested energy at mid-to-high SNR and at low SNR regimes, and for the sum MSE at mid-SNR regimes on average, 21% and 23% and 5% the performance improvement is gained, respectively.

Let's set $n = 3, m = 2,\ k = 3,\ t = 2, P = 1$ and $\eta = 0.7$. The influence of variation of the power splitter ratio α, can be seen obviously in Figure. ٣. A larger portion of the received energy is transferred to the ID module by increasing α . Therefore, the harvested energy (solid lines) in the EH module will decrease and the sum MSE (dash lines) would be better. There is no big difference between the sum MSE of the system at high SNR regimes, i.e., low noise powers, because there is enough energy in the ID module to find the information symbols despite of the value of α, This difference get more clear with large noise powers. By decreasing α, the harvested energy would improve around 50% and vice versa , increasing α causes that the sum MSE would improve around 5%.

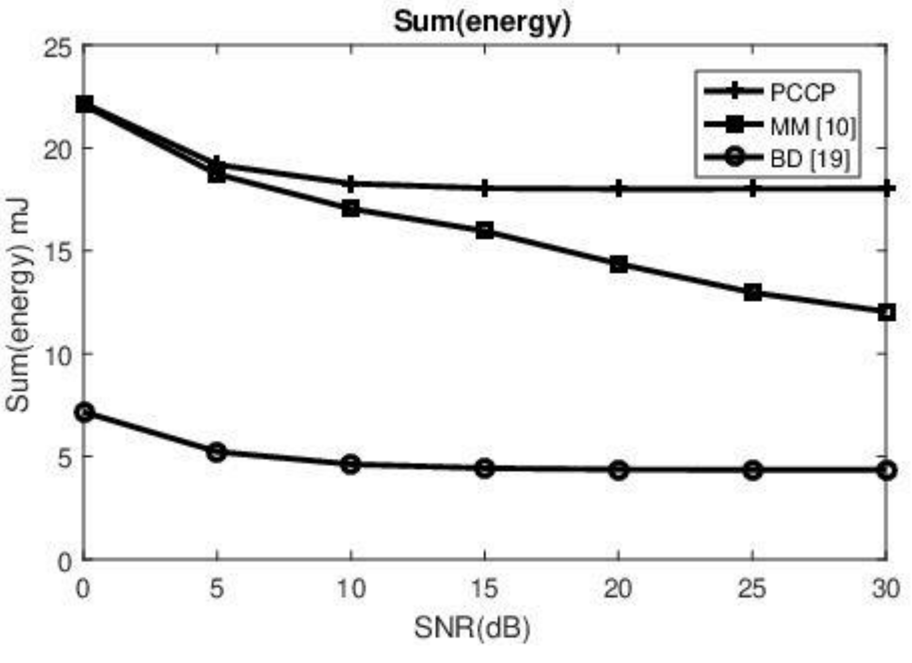

Figure 1. Comparison of sum harvested energy with 3 different methods, PCCP, MM, BD

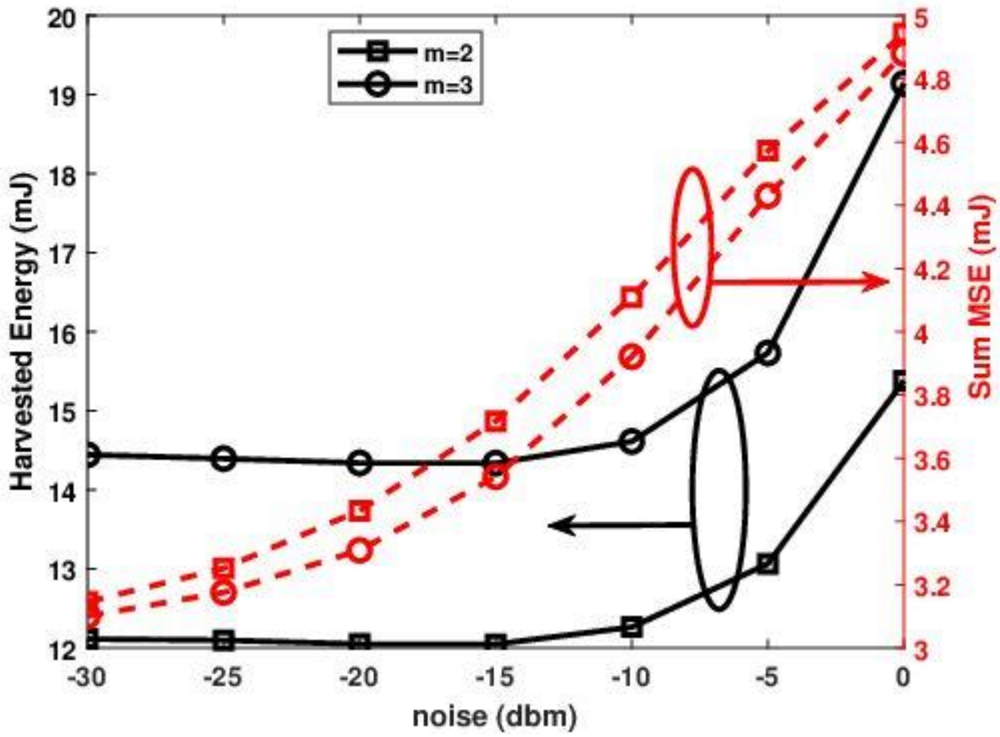

Figure 2. Sum MSE & sum energy by changing m

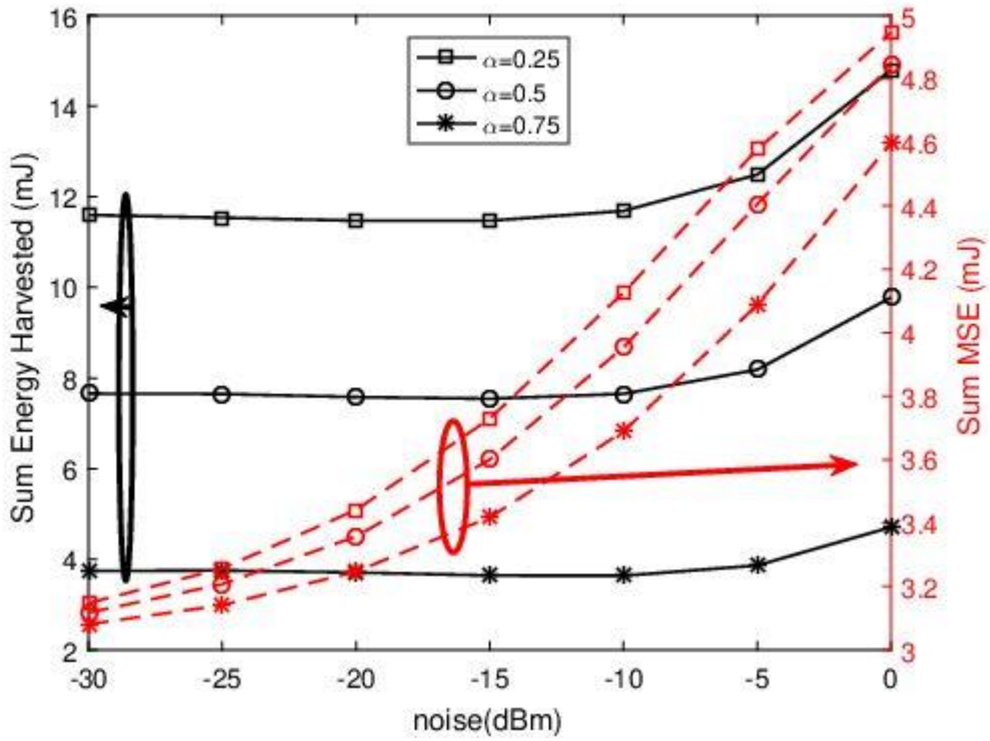

Figure 3. Sum MSE & sum energy by changing power splitter ratio α

Conclusions

In this paper, a MU-MIMO SWIPT system in a BC configuration is examined . We do not restrict the number of users. Each receiver has power splitter and all of them are able to receive both power and information simultaneously. We concurrently maximize the sum of harvested energy in EH modules and minimize the sum MSE of symbol detection of all links with constraint on BS power. We can recast this problem into a DC problem, with function which is bi-convex. We use a PCCP algorithm with a combination of an ACS algorithm to solve the problem. The simulation results confirm the efficiency of the proposed algorithm.

List of Symbols

The following notations and assumptions are used throughout the paper.

1. $(\cdot)^{\mathrm{T}}$, Transpose of a matrix or a vector
2. $(\cdot)^{\mathrm{H}}$, Hermitian of a matrix or a vector
3. $\|\cdot\|_{\mathrm{F}}^{2}$, Squared Frobenius norm of a matrix
4. $\mathrm{vec}(\cdot)$, Vectorized matrix
5. $\mathbf{A} \otimes \mathbf{B}$, Kronecker product of matrices
6. $\mathrm{CN}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, The distribution of a circularly symmetric complex Gaussian (CSCG) random vector with mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$
7. $\mathbb{C}^{\mathrm{x} \times \mathrm{y}}$, The space of $\mathrm{x} \times \mathrm{y}$ complex-valued matrices
8. $\mathbb{R}^{\mathrm{x} \times \mathrm{y}}$, The space of $\mathrm{x} \times \mathrm{y}$ real-valued matrices
9. $\mathbb{E}[.]$, Mathematical expectation of random variables
10. $\mathbf{I}_{\mathrm{k}}$, Identity matrix of size k
11. $\Re\{\cdot\}$ and $\Im\{\cdot\}$, are used, respectively to denote the real and imaginary parts of a complex number.
12. $\nabla \mathrm{h}$, Gradient of h

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