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On Simultaneous Wireless Information and Power Transfer for Receive Spatial Modulation

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ABSTRACT In this paper, we study the performance of receive spatial modulation (RSM) with simultaneous wireless information and power transfer (SWIPT) capabilities. RSM is a multi-antenna modulation scheme, where the information bits are encoded into complex constellation symbols and the indices of the receive antennas. We show how RSM can be combined with SWIPT, by allowing the receivers to increase their data rate and, at the same time, to recharge their batteries. An optimization problem is formulated in order to optimize the fraction of transmit power to be used for information decoding and energy harvesting, as well as the covariance matrix of the energy waveform. Efficient numerical algorithms to tackle the associated optimization problems are proposed. Our analysis shows that RSM-SWIPT is a flexible transmission scheme that is capable of achieving different rate-energy demands. RSM-SWIPT, in particular, can be configured to leverage only the energy waveform for transmitting information data and power simultaneously. Compared with conventional SWIPT-enabled multiple-antenna systems, the proposed RSM-SWIPT scheme increases the amount of harvested energy for low values of the rate and avoids the need of using energy cancellation algorithms if information and power are transmitted only through the energy waveform.

INDEX TERMS Receive spatial modulation, simultaneous wireless information and power transfer, optimization.

I. INTRODUCTION

Multiple-input multiple-output (MIMO) wireless systems are capable of providing rate, diversity and array gains, by using transmission techniques such as spatial multiplexing (SMX), receive combining, and transmit beamforming [1]–[3]. As a result, MIMO systems are widely used for wireless information transfer (MIMO-WIT) [4]–[6], wireless power transfer (MIMO-WPT) [7]–[18], and simultaneous wireless information and power transfer (MIMO-SWIPT) [19]–[27].

MIMO-WIT has a long history of development. It transmits multiple data streams from all the available antennas. A more recent alternative for increasing the rate at a low complexity is spatial modulation (SM) [5], [28]–[40], which takes advantage of the whole antenna array at the transmitter, while using a limited number of radio-frequency (RF) chains. In SM, additional information bits are mapped onto a spatial constellation diagram, where each constellation symbol is made of a subset of indices of the antenna elements. This is shown to reduce the circuitry complexity and to enhance the energy efficiency [6]. A modification of SM that simplifies its incorporation in the broadcast channel is receiver spatial modulation (RSM) [41], [42]. In RSM, by using linear precoding, the information bits are transferred to the receiver by applying the concept of spatial modulation at the receive antennas, i.e., by encoding the bits onto the indices of the receive antennas. Recently, RSM has been studied for application to a wide range of different communication scenarios [43]–[49]. Stavridis *et al.* [43] studied RSM in the context of virtual MIMO relaying systems. In [44], RSM is combined with SMX for increasing the bandwidth efficiency. In [45], differential RSM is analyzed. In [46], energy pattern RSM is introduced for information and power transfer. In addition, the benefits of RSM for improving the secrecy of wireless systems are studied in [48] and [49]. Recent research contributions can be found in [50], [51] and [52].

Compared with MIMO-WIT, MIMO-WPT has a shorter history of development. Most research efforts [7]–[9] are concerned with the design of beamforming strategies and channel state information (CSI) feedback mechanisms for improving the charging efficiency. The main aim is to maximize the harvested energy via power allocation and by taking into account the tradeoff between channel estimation and power transfer. An important challenge of WPT is to increase the RF-DC conversion efficiency of the rectifying circuits [10]. Recent works in this field of research have focused their attention on the performance of the rectifiers by considering different types of signals, including multi-sine signals [11], chaotic waveforms [12], and modulated orthogonal frequency division multiple access (OFDM) signals [13]. Recently, it was reported that signals with a high peak-to-average power ratio (PAPR) can improve the efficiency [14].

MIMO-SWIPT is a concept that jointly combines WIT and WPT by sharing a common circuitry. It offers the possibility of delivering controllable and on-demand wireless information and energy concurrently, which enables one to design low-cost wireless systems for self-sustainable operation and without modifying the hardware at the transmitter [19]. However, it is known that optimizing SWIPT-enabled systems is a challenging task [20]. More specifically, the optimal rate is achieved by using SMX with a Gaussian codebook and the water-filling power allocation scheme [21]. In contrast, the maximum harvested power is achieved by using transmit beamforming, where the transmitted signal depends on the strongest eigenmode of the transmit covariance matrix [15]. The optimization of SWIPT systems brings about a new optimization space and tradeoffs.

In the present paper, we study and optimize RSM-SWIPT. The main contributions made by this paper are as follows:

- The first RSM-SWIPT scheme is proposed and analyzed.
- A general model for the energy waveform is introduced.
- The rate bounds of the proposed RSM-SWIPT scheme are computed.
- Efficient algorithms for optimizing RSM-SWIPT are proposed.

Compared with conventional MIMO systems that employ SWIPT based on zero-forcing (ZF) precoding, RSM-SWIPT is shown to have a better flexibility for optimizing the rate-energy region. In particular, RSM-SWIPT provides one with an additional option for information and energy transfer by exploiting only the energy waveform and, hence, by encoding the information bits only onto the indices of the receive antennas. For high energy demands, this results in a system that is capable of providing a non-zero rate while conventional MIMO-SWIPT systems are shown to offer a rate that is close to zero.

The rest of this paper is organized as follows. In Section II, the system model is introduced. In Section III and IV, RSM-SWIPT with receivers that can and cannot remove the energy signal for information decoding are studied, respectively. In Section V, setups with a large RSM codebook are analyzed. In Section VI, numerical illustrations are shown and discussed. Finally, Section VII concludes the paper.

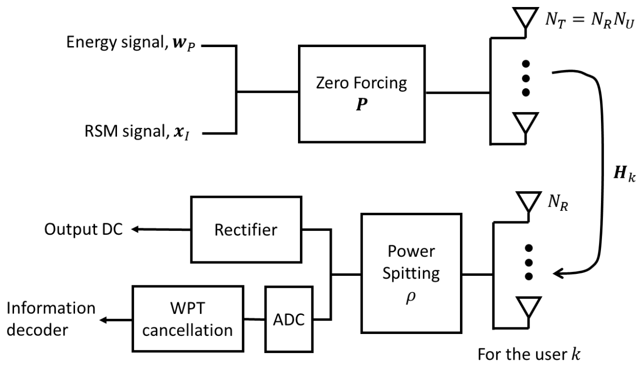

FIGURE 1. The RSM-SWIPT system for user k.

II. SYSTEM MODEL

We consider a multi-user MIMO downlink system model as depicted in Fig. 1. The transmitter emits an energy signal and an information (or RSM signal) with the aid of ZF precoding. At the receiver, the signal is input to a rectifier for energy harvesting and to an information decoder for retrieving the information bits. The following notation is used: N_U is the number of users, N_R is the number of receive antennas, $N_T = N_R N_U$ is the number of transmit antennas, $\mathbf{P} \in \mathbb{C}^{N_T \times N_R N_U}$ is the precoding matrix at the transmitter, ρ is the power splitting ratio at the receiver, and $\mathbf{H} \in \mathbb{C}^{N_R N_U \times N_T}$ is the channel matrix. In addition, $\mathbf{I}$ denotes the identity matrix, $(\cdot)^H$ and $(\cdot)^T$ denote Hermitian transpose and transpose, respectively, $\binom{\cdot}{\cdot}$ denotes the binomial coefficient, $\mathrm{tr}(\cdot)$ denotes the trace operator, $\det(\cdot)$ denotes the determinant of a matrix, $\mathbb{E}\{\cdot\}$ denotes the expectation operator, and $\otimes$ denotes the Kronecker product.

A. INFORMATION DECODER

The signal at the input of the information decoder can be written, for the N_U users, as follows:

$$\mathbf{y} = \sqrt{\rho}\,\mathbf{HP}\left(\mathbf{x_I} + \mathbf{w_P}\right) + \mathbf{n} \tag{1}$$

where $\mathbf{y} \in \mathbb{C}^{N_R N_U \times 1}$ is the received signal, $\mathbf{x}_I \in \mathbb{C}^{N_R N_U \times 1}$ is the information (RSM) signal, $\mathbf{w}_P \in \mathbb{C}^{N_R N_U \times 1}$ is the energy signal, and $\mathbf{n} \in \mathbb{C}^{N_R N_U \times 1}$ is the additive white Gaussian noise (AWGN). By assuming ZF precoding, $\mathbf{P}$ can be formulated as follows:

$$\mathbf{P} = \mathbf{H}^H \left(\mathbf{H}\mathbf{H}^H\right)^{-1} \tag{2}$$

As for the kth user, the received signal simplifies as follows:

$$\mathbf{y}_k = \sqrt{\rho}\left(\mathbf{x}_k + \mathbf{w}_k\right) + \mathbf{n}_k \tag{3}$$

where $\mathbf{x}_k \in \mathbb{C}^{N_R \times 1}$ is the RSM signal, $\mathbf{w}_k \in \mathbb{C}^{N_R \times 1}$ is the energy signal, and $\mathbf{n}_k \sim \mathcal{CN}(0, \sigma^2 \mathbf{I}) \in \mathbb{C}^{N_R \times 1}$ is the AWGN where each entry of the vector has variance σ^2.

B. RSM SIGNAL

Let N_S be the number of information streams to be transmitted, with $N_S \le N_R$. The RSM signal $\mathbf{x}_k$ is a sparse vector, which has $N_S \le N_R$ non-zero elements and $N_R - N_S$ zero elements. It can be formulated as follows:

$$\mathbf{x}_k = \mathbf{B}_k \mathbf{s}_k \tag{4}$$

where $\mathbf{B}_k$ is a $N_R \times N_S$ binary matrix that is referred to as RSM codeword. The number of matrices $\mathbf{B}_k$ is $N_B = \binom{N_R}{N_S}$. Also $\mathbf{s}_k$ is a $N_S \times 1$ vector that collects the N_S streams that are transmitted, where $\mathbf{s}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. For example, if $N_S = 2$ and $N_R = 4$, the matrix $\mathbf{B}_k$ that corresponds to transmitting the two streams from the first and the third antenna is as follows:

$$\mathbf{B}_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}^T$$

C. ENERGY HARVESTER

The rectifier converts the received signal into a direct current (DC) and then energy. The signal at the input of the rectifier can be written as follows:

$$\mathbf{r}_k = \sqrt{1-\rho}\,(\mathbf{x}_k + \mathbf{w}_k) + \mathbf{n}'_k \tag{5}$$

where $\mathbf{n}'_k$ is the associated AWGN vector.

The average harvested energy can be formulated as [10]:

$$\begin{aligned} Q_k &= \alpha_0 + \alpha_2 \mathbb{E}\{\mathrm{tr}\left(\mathbf{r}_k \mathbf{r}_k^H\right)\} \\ &= \alpha_0 + \alpha_2(1-\rho)\left(\mathbb{E}\{\mathrm{tr}\left(\mathbf{x}_k \mathbf{x}_k^H\right)\} + \mathbb{E}\{\mathrm{tr}\left(\mathbf{w}_k \mathbf{w}_k^H\right)\}\right) \\ &\quad + \alpha_2 \mathbb{E}\{\mathrm{tr}\left(\mathbf{n}'_k \mathbf{n}'^H_k\right)\} \\ &= \alpha_2(1-\rho)\mathrm{tr}\left(\frac{1}{N_B}\sum_{i=1}^{N_B} \mathbf{B}_{k,i}\mathbb{E}\{\mathbf{s}_k\mathbf{s}_k^H\}\mathbf{B}_{k,i}^H\right) \\ &\quad + \alpha_2(1-\rho)\mathrm{tr}\left(\mathbf{S}_E\right) + \alpha_0 + \alpha_2\sigma^2 N_R \\ &= \alpha_2(1-\rho)\mathrm{tr}\left(\mathbf{\Sigma}_B + \mathbf{S}_E\right) + \varrho_k \end{aligned} \tag{6}$$

where α_0 and α_2 are constants that depend on the specific rectifier being used, and the definitions $\mathbf{\Sigma}_B = \frac{1}{N_B}\sum_{i=1}^{N_B} \mathbf{B}_{k,i}\mathbf{B}_{k,i}^H$ and $\varrho_k = \alpha_0 + \alpha_2\sigma^2 N_R$ are used. $\mathbf{\Sigma}_B$ is an Hermitian matrix.

D. ENERGY SIGNAL

The energy signal $\mathbf{w}_k$ is assumed to be a zero-mean Gaussian random variable with covariance matrix $\mathbf{S}_E$, i.e., $\mathbf{w}_k \sim \mathcal{CN}(\mathbf{0}, \mathbf{S}_E)$. The covariance matrix $\mathbf{S}_E$ and the power splitting factor ρ are the two parameters to be optimized for jointly maximizing the harvested energy and rate.

E. TRANSMIT POWER

The transmit power can be written as follows:

$$\begin{aligned} P &= \mathbb{E}\left\{\mathrm{tr}\left(\mathbf{P}\left(\mathbf{x}_I + \mathbf{w}_P\right)\left(\mathbf{x}_I + \mathbf{w}_P\right)^H \mathbf{P}^H\right)\right\} \\ &= \mathbb{E}\left\{\mathrm{tr}\left(\mathbf{P}\mathbf{x}_I\mathbf{x}_I^H\mathbf{P}^H\right)\right\} + \mathbb{E}\left\{\mathrm{tr}\left(\mathbf{P}\mathbf{w}_P\mathbf{w}_P^H\mathbf{P}^H\right)\right\} \\ &= \mathrm{tr}\left(\mathbf{P}\mathbb{E}\left\{\mathbf{x}_I\mathbf{x}_I^H\right\}\mathbf{P}^H\right) + \mathrm{tr}\left(\mathbf{P}\mathbb{E}\left\{\mathbf{w}_P\mathbf{w}_P^H\right\}\mathbf{P}^H\right) \\ &= \mathrm{tr}\left(\mathbf{P}\left(\mathbf{I}\otimes\mathbf{\Sigma}_B\right)\mathbf{P}^H\right) + \mathrm{tr}\left(\mathbf{P}\left(\mathbf{I}\otimes\mathbf{S}_E\right)\mathbf{P}^H\right) \\ &= \mathrm{tr}\left(\mathbf{P}\left(\mathbf{I}\otimes\left(\mathbf{\Sigma}_B + \mathbf{S}_E\right)\right)\mathbf{P}^H\right) \end{aligned} \tag{7}$$

In the sequel, the optimization problems are formulated by assuming a power constraint on P.

III. IDEAL CANCELLATION OF THE ENERGY SIGNAL

Since the energy signal $\mathbf{w}_k$ is deterministic and does not contain any information, it could be completely removed at the information receivers if they are appropriately designed and are sufficiently powerful. In this section, as an optimistic benchmark (best case), we assume that the information receivers are capable of removing the energy signal.

A. CAPACITY BOUND

By assuming an ideal cancellation of the energy signal, the received signal in (3) can be re-written as follows:

$$\mathbf{y}_k = \sqrt{\rho}\mathbf{x}_k + \mathbf{n}_k = \sqrt{\rho}\left(\mathbf{B}_k\mathbf{s}_k\right) + \mathbf{n}_k \tag{8}$$

The channel capacity is obtained by maximizing the mutual information $\mathbb{I}(\mathbf{x}_k;\mathbf{y}_k)$ and can be obtained as follows:

$$\begin{aligned} \mathbb{I}(\mathbf{x}_k;\mathbf{y}_k) &= \mathbb{H}(\mathbf{y}_k) - \mathbb{H}(\mathbf{y}_k|\mathbf{x}_k) \\ &= \mathbb{H}(\mathbf{y}_k) - \mathbb{H}(\mathbf{n}_k) \\ &\le \mathbb{H}(\mathbf{y}_k, \mathbf{B}_k) - \mathbb{H}(\mathbf{n}_k) \\ &= \mathbb{H}(\mathbf{y}_k|\mathbf{B}_k) + \mathbb{H}(\mathbf{B}_k) - \mathbb{H}(\mathbf{n}_k) \triangleq R_k \end{aligned} \tag{9}$$

where $\mathbb{H}(\cdot)$ denotes the entropy function, and the inequality is obtained by taking into account that $\mathbb{H}(\mathbf{y}_k, \mathbf{B}_k) \ge \mathbb{H}(\mathbf{y}_k)$ [53, Lemma 2.3.2] and by using the chain rule of the joint entropy, i.e., $\mathbb{H}(\mathbf{y}_k, \mathbf{B}_k) = \mathbb{H}(\mathbf{y}_k|\mathbf{B}_k) + \mathbb{H}(\mathbf{B}_k)$ in [53, Lemma 5.3.1].

If $\mathbf{x}$ is a vector of circularly-symmetric and zero-mean complex random variables with covariance matrix $\mathbf{\Sigma}$, its entropy is equal to $\mathbb{H}(\mathbf{x}) = \log\det(\pi e \mathbf{\Sigma})$ [54]. Therefore, we obtain the following expressions of the entropies:

$$\begin{aligned} \mathbb{H}(\mathbf{y}_k|\mathbf{B}_k) &= \frac{1}{N_B}\sum_{i=1}^{N_B}\mathbb{H}(\mathbf{y}_k|\mathbf{B}_{k.i}) \\ &= \frac{1}{N_B}\sum_{i=1}^{N_B}\log\det\left(\pi e \mathbf{\Phi}_{k,i}\right) \\ \mathbb{H}(\mathbf{B}_k) &= -\log(\frac{1}{N_B}) = \log(N_B) \\ \mathbb{H}(\mathbf{n}_k) &= \log\det\left(\pi e \sigma^2 \mathbf{I}\right) \end{aligned}$$

where $\mathbf{\Phi}_{k,i} = \rho\mathbf{B}_{k,i}\mathbf{B}_{k,i}^H + \sigma^2\mathbf{I}$.

Thus, the channel capacity can be formulated as:

$$\begin{aligned} \mathbb{C}^{\mathrm{IC}_{RSM}} &\le \max_{\rho} R_k \\ &= \max_{\rho}\frac{1}{N_B}\sum_{i=1}^{N_B}\log\det\left(\mathbf{\Phi}_{k,i}\right) + \xi_k \end{aligned} \tag{10}$$

where $\xi_k = \log(N_B) - \log\det(\pi e \sigma^2 \mathbf{I})$ is a constant.

In this case, ρ is the only parameter of $\mathbf{\Phi}_{k,i}$ that needs to be optimized.

B. PROBLEM FORMULATION

Our objective is to maximize the sum rate subject to a given energy harvesting requirement, Q_0, and a transmit power constraint, P_0. More specifically, the optimization problem can be formulated as follows:

$$\begin{aligned} \mathrm{P1}:\ &\max_{\rho,\mathbf{S}_E}\ \sum_{k=1}^{N_U} R_k \\ &\text{s.t. } Q_k \ge Q_0, \quad \text{for } k = 1,\ldots,N_U \\ &\qquad P \le P_0, \quad \mathbf{S}_E \succeq 0,\ 0 \le \rho \le 1 \end{aligned}$$

P1 is a non-convex optimization problem due to the coupled parameters $\mathbf{S}_E$ and ρ in the harvested energy constraint [55]. Nevertheless, it can be reformulated as a convex problem. To this end, let us define the new variable $\mathbf{X}_E =$

$\rho \mathbf{S}_E$. Replacing $\mathbf{S}_E$ by $\mathbf{X}_E$ in P1, with the aid of some algebraic manipulations we obtain the equivalent optimization problem as follows:

$$\max_{\rho, \mathbf{X}_E} \sum_{k=1}^{N_U} R_k \tag{11a}$$

$$\text{s.t. } \alpha_2 \text{tr}\left(\rho \boldsymbol{\Sigma}_B + \mathbf{X}_E\right) + \frac{\rho}{1-\rho}(\varrho_k - Q_0) \geq 0, \quad k = 1, \ldots, N_U \tag{11b}$$

$$\text{tr}\left(\mathbf{P}\left(\mathbf{I} \otimes (\rho \boldsymbol{\Sigma}_B + \mathbf{X}_E)\right) \mathbf{P}^H\right) \leq \rho P_0 \tag{11c}$$

$$\mathbf{X}_E \succeq 0, \quad 0 \leq \rho \leq 1 \tag{11d}$$

The constraints (11c) and (11d) are affine and thus pose no challenge. Instead, the properties of constraint (11b) are more involved to analyze because the function $\frac{\rho}{1-\rho}(\varrho_k - Q_0)$ can be concave or convex depending on the range of ρ and on the sign of $\varrho_k - Q_0$. To proceed further, we exploit the following remark.

Remark 1: Without loss of generality, it is possible to assume $\varrho_k - Q_0 \leq 0$ in (11b). If $\varrho_k - Q_0 > 0$, in fact, the constraint in (11b) would be always fulfilled for any resource allocation setup that fulfils the other constraints. This is because $\alpha_2 \text{tr}\left(\rho \boldsymbol{\Sigma}_B + \mathbf{X}_E\right)$ is non-negative for any positive semidefinite $\mathbf{X}_E$, $\boldsymbol{\Sigma}_B$, and $\rho \geq 0$, $\alpha_2 \geq 0$. Moreover, $\frac{\rho}{1-\rho} \geq 0$ holds if $0 \leq \rho \leq 1$. Therefore, if $\varrho_k - Q_0 > 0$, the constraint (11b) becomes redundant and can be removed from the optimization problem. In summary, the case study of interest is when $\varrho_k - Q_0 \leq 0$.

Based on *Remark 1*, we evince that the constraint function in (11b) is concave if $\frac{\rho}{1-\rho}$ is convex. It is easy to check that the function $\frac{\rho}{1-\rho}$ is indeed convex in the feasible set of (11), i.e., for $0 \leq \rho \leq 1$. This can be verified by computing the second-order derivative of $\frac{\rho}{1-\rho}$ and checking that it is always non-negative for $0 \leq \rho \leq 1$. In conclusion, (11) is a convex maximization problem and, thus, it can be optimally and efficiently solved by using standard convex optimization algorithms.

IV. NO CANCELLATION OF THE ENERGY SIGNAL

In this section, we consider a pessimistic benchmark (worst case) and assume that the energy signal cannot be removed at the receiver. In particular, the energy signal is processed by the information receiver without any pre-processing.

A. CAPACITY BOUND

Without interference cancellation, the energy signal $\mathbf{w}_k$ is treated as noise. The received signal in (3) can be re-written as follows:

$$\mathbf{y}_k = \sqrt{\rho}\left(\mathbf{B}_k \mathbf{s}_k\right) + \mathbf{n}'_k \tag{12}$$

where $\mathbf{n}'_k = \sqrt{\rho}\mathbf{w}_k + \mathbf{n}_k$ and $\mathbf{n}'_k \sim \mathcal{CN}(\mathbf{0}, \rho \mathbf{S}_E + \sigma^2 \mathbf{I})$.

Similar to the case study with ideal cancellation of the energy signal, the mutual information can be formulated as:

$$\begin{aligned} \mathbb{I}(\mathbf{x}_k; \mathbf{y}_k) &= \mathbb{H}(\mathbf{y}_k) - \mathbb{H}(\mathbf{n}'_k) \\ &\leq \mathbb{H}(\mathbf{y}_k, \mathbf{B}_k) - \mathbb{H}(\mathbf{n}'_k) \\ &= \mathbb{H}(\mathbf{y}_k | \mathbf{B}_k) + \mathbb{H}(\mathbf{B}_k) - \mathbb{H}(\mathbf{n}'_k) \triangleq R'_k \end{aligned} \tag{13}$$

where the entropy functions are the following:

$$\mathbb{H}(\mathbf{y}_k | \mathbf{B}_k) = \frac{1}{N_B} \sum_{i=1}^{N_B} \log\det\left(\pi e \boldsymbol{\Phi}'_{k,i}\right)$$

$$\mathbb{H}(\mathbf{B}_k) = -\log(\frac{1}{N_B}) = \log(N_B)$$

$$\mathbb{H}(\mathbf{n}'_k) = \log\det\left(\pi e\left(\rho \mathbf{S}_E + \sigma^2 \mathbf{I}\right)\right)$$

with $\boldsymbol{\Phi}'_{k,i} = \rho \mathbf{B}_{k,i} \mathbf{B}_{k,i}^H + \rho \mathbf{S}_E + \sigma^2 \mathbf{I}$.

Therefore, the capacity can be formulated as follows:

$$\begin{aligned} \mathbb{C}^{\text{NC}_{\text{RSM}}} &\leq \max_{\rho, \mathbf{S}_E} R'_k \\ &= \max_{\rho, \mathbf{S}_E} \frac{1}{N_B} \sum_{i=1}^{N_B} \log\det\left(\boldsymbol{\Phi}'_{k,i}\right) \\ &\quad - \log\det\left(\rho \mathbf{S}_E + \sigma^2 \mathbf{I}\right) + \xi'_k \end{aligned} \tag{14}$$

where $\xi'_k = \log(N_B)$ is a constant.

In this case, ρ and $\mathbf{S}_E$ are the optimization parameters.

B. PROBLEM FORMULATION

The optimization problem can be formulated as follows:

$$\begin{aligned} \text{P2}: \max_{\rho, \mathbf{S}_E} \ & \sum_{k=1}^{N_U} R'_k \\ \text{s.t. } & Q_k \geq Q_0, \quad \text{for } k = 1, \ldots, N_U \\ & P \leq P_0, \quad \mathbf{S}_E \succeq 0, \ 0 \leq \rho \leq 1 \end{aligned}$$

Unlike P1, the optimization problem P2 poses the additional challenge that the objective function is not jointly concave in ρ and $\mathbf{S}_E$. This is because $\mathbf{S}_E$ and ρ appear in the difference of logarithmic functions, and the difference of two concave functions is, in general, neither concave nor convex. This necessitates more advanced algorithms to tackle P2. In the next section, we show that the minorization-maximization (MM) algorithm is a convenient method to use.

C. MINORIZATION-MAXIMIZATION ALGORITHM

In order to tackle P2, we first re-formulate it as done for P1, i.e., by introducing the new variable $\mathbf{X}_E = \rho \mathbf{S}_E$. By neglecting irrelevant constants and by introducing, for ease of notation, the definition, $\widetilde{\mathbf{B}}_{k,i} = \mathbf{B}_{k,i}\mathbf{B}_{k,i}^H$, P2 can be re-formulated as follows:

$$\begin{aligned} \max_{\rho, \mathbf{X}_E} \ & \sum_{k=1}^{N_U} \frac{1}{N_B} \sum_{i=1}^{N_B} \log\det\left(\rho \widetilde{\mathbf{B}}_{k,i} + \mathbf{X}_E + \sigma^2 \mathbf{I}\right) \\ & - \log\det\left(\mathbf{X}_E + \sigma^2 \mathbf{I}\right) \end{aligned} \tag{15a}$$

$$\text{s.t. } \alpha_2 \text{tr}\left(\rho \boldsymbol{\Sigma}_B + \mathbf{X}_E\right) + \frac{\rho}{1-\rho}(\varrho_k - Q_0) \geq 0, \quad k = 1, \ldots, N_U \tag{15b}$$

$$\text{tr}\left(\mathbf{P}\left(\mathbf{I} \otimes (\rho \boldsymbol{\Sigma}_B + \mathbf{X}_E)\right) \mathbf{P}^H\right) \leq \rho P_0 \tag{15c}$$

$$\mathbf{X}_E \succeq 0, \quad 0 \leq \rho \leq 1 \tag{15d}$$

The MM algorithm, also known as sequential optimization or inner approximation method [56]–[58], is an iterative algorithm that solves, at each iteration, an auxiliary problem whose objective function is a lower-bound of (15a). Moreover, such a lower bound and its gradient must be equal, respectively, to the true function in (15a) and to the gradient of the true function in (15a) at a given point $\mathbf{X}_E^{(0)}$, which is updated at the end of each iteration of the algorithm.

For the case at hand, more precisely, we resort to the following inequality, which holds for any $\mathbf{X}_E^{(0)}$:

$$\log\det\left(\mathbf{X}_E+\sigma^2\mathbf{I}\right) \leq \log\det\left(\mathbf{X}_E^{(0)}+\sigma^2\mathbf{I}\right) + \mathrm{tr}\left((\mathbf{X}_E-\mathbf{X}_E^{(0)})(\mathbf{X}_E^{(0)}+\sigma^2\mathbf{I})^{-1}\right) \tag{16}$$

which is obtained by recalling that any concave function is upper-bounded by its first-order Taylor expansion around any given point.

As a result, the following concave lower-bound for (15a) is obtained:

$$R'_k \geq \frac{1}{N_B}\sum_{i=1}^{N_B}\log\det\left(\rho\widetilde{\mathbf{B}}_{k,i}+\mathbf{X}_E+\sigma^2\mathbf{I}\right) \tag{17}$$

$$- \mathrm{tr}\left(\mathbf{X}_E(\mathbf{X}_E^{(0)}+\sigma^2\mathbf{I})^{-1}\right)+\bar{\xi}$$

$$\triangleq \bar{R}'_k\left(\mathbf{X}_E|\mathbf{X}_E^{(0)}\right) \tag{18}$$

where $\bar{\xi} = \log\det(\mathbf{X}_E^{(0)}+\sigma^2\mathbf{I})+\log(N_B)-\mathrm{tr}(\mathbf{X}_E^{(0)}(\mathbf{X}_E^{(0)}+\sigma^2\mathbf{I})^{-1})$ is a constant term with respect to the optimization variables.

Then, a sub-problem that fulfills the assumptions of the MM method can be formulated as follows:

$$\text{P3}: \max_{\rho,\mathbf{X}_E} \sum_{k=1}^{N_U}\bar{R}'_k\left(\mathbf{X}_E|\mathbf{X}_E^{(0)}\right) \tag{19a}$$

$$\text{s.t. } \alpha_2\mathrm{tr}\left(\rho\mathbf{\Sigma}_B+\mathbf{X}_E\right)+\frac{\rho}{1-\rho}(\varrho_k-Q_0)\geq 0, \quad k=1,\ldots,N_U \tag{19b}$$

$$\mathrm{tr}\left(\mathbf{P}\left(\mathbf{I}\otimes(\rho\mathbf{\Sigma}_B+\mathbf{X}_E)\right)\mathbf{P}^H\right)\leq\rho P_0 \tag{19c}$$

$$\mathbf{X}_E\succeq 0, \quad 0\leq\rho\leq 1 \tag{19d}$$

Since (19a) is jointly concave in $(\rho,\mathbf{X}_E)$, and the feasible set can be shown to be concave with the aid of similar arguments as those used in Section III, we conclude that P3 is a convex problem and, thus, it can be globally and efficiently solved by convex optimization methods. The resulting MM algorithm for solving P2 is formulated in Table 1.

TABLE 1. MM algorithm to solve P2

Algorithm I – MM algorithm to solve P2
Input: P_0, Q_0
Output: ρ, $\mathbf{S}_E$
1: Initialize $\mathbf{X}_E^{(0)}$
2: Repeat
3: Solve the convex problem in P3 and obtain $(\rho,\mathbf{X}_E)$
5: Set $\mathbf{X}_E^{(0)}=\mathbf{X}_E$
6: Until convergence is reached
7: $\mathbf{S}_E=\frac{1}{\rho}\mathbf{X}_E$

From the properties of the MM method, it can be shown that Algorithm I in Table 1 monotonically increases the value of the true objective function of P2 after each iteration. This implies the convergence of Algorithm I to the objective value. Since the objective function of P2 is continuous and the feasible set is compact, then the objective function of P2 is bounded over the feasible set by virtue of the Weierstrass extreme value theorem. Moreover, denoting the point generated by Algorithm I after iteration n by $(\rho_n,\mathbf{X}_{E,n})$, it can be shown, from [58], that any limit point of the sequence $\{(\rho_n,\mathbf{X}_{E,n})\}_n$ fulfills the Karush-Kuhn-Tucker (KKT) conditions of (15).

V. LARGE RSM CODEBOOK

If the number of sparse RSM matrices is large, a better rate can be obtained. However, the optimization complexity increases. In this section, we discuss how to reduce the associated computational complexity under the assumption that the receiver is capable of removing the energy signal. If the energy signal cannot be removed, only approximated solutions can be found, which, for brevity, are not discussed in the present paper.

The capacity in (10) needs the computation of:

$$U=\frac{1}{N_B}\sum_{i=1}^{N_B}\log\det\left(\rho\mathbf{B}_{k,i}\mathbf{B}_{k,i}^H+\sigma^2\mathbf{I}\right) \tag{20}$$

For a large size of the available codebook, e.g., $N_B = \binom{16}{8} = 12870$, the log-det function needs to be computed 12870 times for every instance of the optimization problem. A possible approach to reduce the complexity is to use the Jensen's inequality as follows:

$$U \leq \log\det\left(\frac{1}{N_B}\sum_{i=1}^{N_B}\rho\bar{\boldsymbol{B}}_i+\sigma^2\mathbf{I}\right)$$

$$=\log\det\left(\rho\left(\frac{N_S}{N_R}\mathbf{I}\right)+\sigma^2\mathbf{I}\right)\triangleq U_J \tag{21}$$

where $\bar{\boldsymbol{B}}_i=\mathbf{B}_{k,i}\mathbf{B}_{k,i}^H$.

We propose to use the sparse structure of the RSM codeword to get an optimal solution that avoids using the Jensen's inequality. Since only N_S entries are non-zero in each matrix, we have:

$$U=\frac{1}{N_B}\sum_{i=1}^{N_B}\log\det\left(\mathbf{\Sigma}_{k,i}\right)$$

$$=\frac{1}{N_B}\sum_{i=1}^{N_B}\log\left(\left(\rho+\sigma^2\right)^{N_S}\left(\sigma^2\right)^{(N_R-N_S)}\right)$$

$$=N_S\log(\rho+\sigma^2)+(N_R-N_S)\log(\sigma^2)\triangleq U_P \tag{22}$$

where $\mathbf{\Sigma}_{k,i}$ is a diagonal matrix whose diagonal elements are the eigenvalues of the matrix in the log-det function of (20):

$$\mathbf{\Sigma}_{k,i}=\mathrm{diag}(\rho+\sigma^2,\cdots,\rho+\sigma^2,\sigma^2,\cdots,\sigma^2) \tag{23}$$

This result follows from the fact that $\mathbf{B}_{k,i}\mathbf{B}_{k,i}^H$ is a binary diagonal matrix, whose trace is equal to N_S, that has N_S eigenvalues equal to $\rho+\sigma^2$ and N_R-N_S eigenvalues equal to σ^2. As a result, an exact closed-form expression can be obtained without the need of using the Jensen's inequality.

VI. NUMERICAL RESULTS

In this section, we analyze the performance of the proposed optimization methods and show the so-called rate-energy regions. They correspond to setting the energy harvesting

TABLE 2. Simulation parameters

Simulation Parameters	Values
Transmit power constraint	$P_0 = 100\ \mu$W (-10 dBm)
Average AWGN power	$\sigma^2 = 100$ nW (-40 dBm)
Number of users	$N_U = 3$
Number of transmit antennas	$N_T = 12$
Number of receive antennas	$N_R = 4$
Rectifier constants [10]	$\alpha_0 = 0$, $\alpha_2 = 2.89$

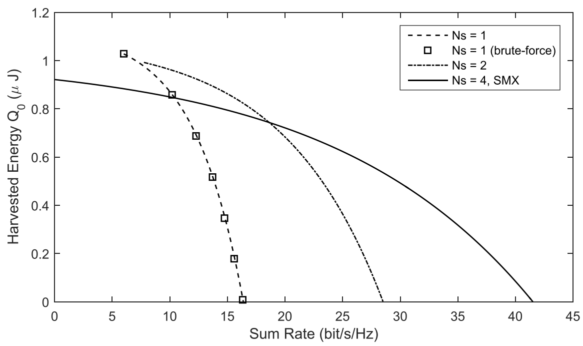

FIGURE 2. Rate-energy region for ideal-cancellation receivers ($N_S = 1, 2, 4$).

requirement Q_0 to a given value and then to optimizing the power splitting ratio and the covariance matrix of the energy signal by solving P1 and P2. Given the solution of the optimization problem, the optimal rate is obtained and then depicted as a function of Q_0.

In Fig. 2, the rate-energy region as a function of N_S and under the assumption of ideal cancellation receivers is illustrated. In particular, the setup $N_S = N_R = 4$ corresponds to the conventional MIMO-SWIPT case. Also, we compare the solution obtained by solving P1 with the proposed algorithm and a brute-force search. We observe a good match. The numerical results highlight that the optimal value of N_S to use, i.e., the number of information streams, depends on Q_0. Only if Q_0 is small, the optimal setup corresponds to the conventional MIMO-SWIPT case. If the energy requirements are high, on the other hand, it is more convenient to reduce the number of information streams and to encode more bits onto the receive antennas. This result originates from the fact that more power is allocated to each stream if N_S decreases.

In Fig. 3, we show results similar to those reported in Fig. 2. The difference is that receivers with non-ideal cancellation capabilities are assumed. As expected, a worse rate-energy region is obtained. In the figure, we highlight the points that correspond to the setups $\rho = 1$, i.e., all the received power is input to the information decoder, and $\rho = 0$, i.e., all the received power is input to the energy receiver. It is interesting to note, with respect to the setup shown in Fig. 2, that the rate does not approach zero for $N_S < N_R$. In fact, an asymptote that is approximately equal to $N_U \log(N_B)$ is reached, which can be obtained from (14) by setting $\rho = 0$. This is because the RSM-SWIPT scheme is capable of transmitting information and power without the need of an information

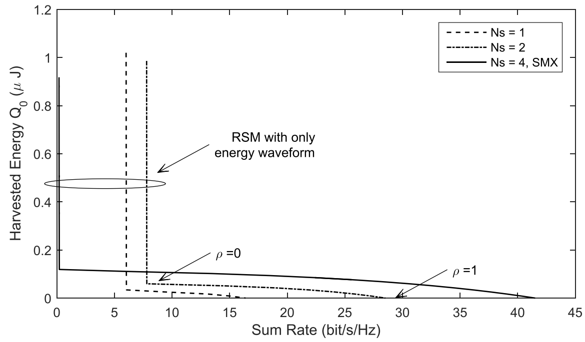

FIGURE 3. Rate-energy region for non-ideal cancellation receivers ($N_S = 1, 2, 4$).

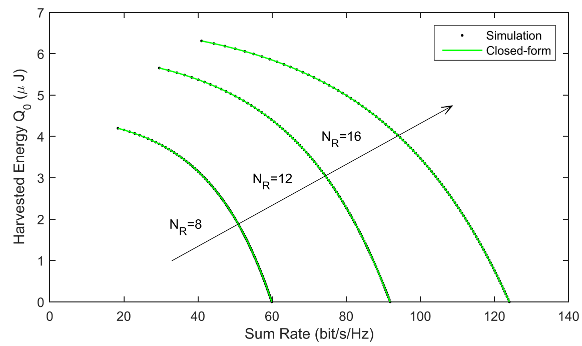

FIGURE 4. Rate-energy region for ideal-cancellation receivers ($N_S = N_R/2$).

signal: the information bits can be encoded only onto the receive antennas, which results in a very efficient system design from the point of view of the power transfer. This is the main benefit of RSM-SWIPT compared with conventional MIMO-SWIPT. It is worth emphasizing that, based on (1), there is no signal at the input of the information decoder if $\rho = 0$. This ambiguity originates from the fact that (14) is an upper-bound. If $\rho = 0$, in practice, an information receiver is not needed and the information bits encoded onto the indices of the receive antennas can be retrieved directly from the power received at the receive antennas.

In Fig. 4, we study the rate-energy regions with ideal-cancellation receivers by assuming a large number of RSM matrices. In particular, we assume $N_S = N_R/2$ and $N_R = 8, 12, 16$. The figure confirms that the proposed closed-form for computing the objective function is accurate and, in addition, it can reduce the computational complexity by a factor equal to $N_B = \frac{N_R!}{N_S!(N_R-N_S)!}$ when computing the expectation with respect to the number of codewords in (20). As expected, the rate-energy region increases with the number of receive antennas.

VII. CONCLUSION

In this paper, we have proposed, studied and optimized the performance of a new RSM scheme that transmits information and power simultaneously. We have introduced computationally efficient algorithms for performance optimization and numerically validated their effectiveness. We have shown that RSM-SWIPT provides the flexibility of obtaining a good rate-energy trade-off, by appropriately optimizing the number of information streams as a function of the energy harvesting requirement. Thus, it constitutes a more flexible option compared with conventional MIMO-SWIPT schemes where the number of information streams is equal to the number of receive antennas regardless of the energy harvesting requirements.

REFERENCES

[1] G. J. Foschini and M. J. Gans, "On limits of wireless communications in a fading environment when using multiple antennas," *Wireless Pers. Commun.*, vol. 6, no. 3, pp. 311–335, Mar. 1998.

[2] D. N. C. Tse, P. Viswanath, and L. Zheng, "Diversity-multiplexing tradeoff in multiple-access channels," *IEEE Trans. Inf. Theory*, vol. 50, no. 9, pp. 1859–1874, Sep. 2004.

[3] A. J. Paulraj, D. A. Gore, R. U. Nabar, and H. Bolcskei, "An overview of MIMO communications—A key to gigabit wireless," *Proc. IEEE*, vol. 92, no. 2, pp. 198–218, 2004.

[4] J. Xu and L. Qiu, "Energy efficiency optimization for MIMO broadcast channels," *IEEE Trans. Wireless Commun.*, vol. 12, no. 2, pp. 690–701, Feb. 2013.

[5] M. Di Renzo, H. Haas, and P. M. Grant, "Spatial modulation for multiple-antenna wireless systems: A survey," *IEEE Commun. Mag.*, vol. 49, no. 12, pp. 182–191, Dec. 2011.

[6] A. Stavridis, S. Sinanovic, M. Di Renzo, and H. Haas, "Energy evaluation of spatial modulation at a multi-antenna base station," in *Proc. IEEE Veh. Technol. Conf.*, Sep. 2013, pp. 1–5.

[7] G. Yang, C. K. Ho, and Y. L. Guan, "Dynamic resource allocation for multiple-antenna wireless power transfer," *IEEE Trans. Signal Process.*, vol. 62, no. 14, pp. 3565–3577, Jul. 2014.

[8] Y. Zeng and R. Zhang, "Optimized training design for wireless energy transfer," *IEEE Trans. Commun.*, vol. 63, no. 2, pp. 536–550, Feb. 2015.

[9] Y. Zeng and R. Zhang, "Optimized training for net energy maximization in multi-antenna wireless energy transfer over frequency-selective channel," *IEEE Trans. Commun.*, vol. 63, no. 6, pp. 2360–2373, Jun. 2015.

[10] A. Boaventura, D. Belo, R. Fernandes, A. Collado, A. Georgiadis, and N. B. Carvalho, "Boosting the efficiency: Unconventional waveform design for efficient wireless power transfer," *IEEE Microw. Mag.*, vol. 16, no. 3, pp. 87–96, Apr. 2015.

[11] A. J. S. Boaventura, A. Collado, A. Georgiadis, and N. B. Carvalho, "Spatial power combining of multi-sine signals for wireless power transmission applications," *IEEE Trans. Microw. Theory Techn.*, vol. 62, no. 4, pp. 1022–1030, Apr. 2014.

[12] A. Collado and A. Georgiadis, "Improving wireless power transmission efficiency using chaotic waveforms," in *IEEE Int. Microw. Symp. Dig.*, Jun. 2012, pp. 1–3.

[13] A. Collado and A. Georgiadis, "Optimal waveforms for efficient wireless power transmission," *IEEE Microw. Wireless Compon. Lett.*, vol. 24, no. 5, pp. 354–356, May 2014.

[14] A. Boaventura, A. Collado, N. B. Carvalho, and A. Georgiadis, "Optimum behavior: Wireless power transmission system design through behavioral models and efficient synthesis techniques," *IEEE Microw. Mag.*, vol. 14, no. 2, pp. 26–35, Mar. 2013.

[15] R. Zhang and C. K. Ho, "MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 1989–2001, May 2013.

[16] B. Clerckx, E. Bayguzina, D. Yates, and P. D. Mitcheson, "Waveform optimization for wireless power transfer with nonlinear energy harvester modeling," in *Proc. IEEE Int. Symp. Wireless Commun. Syst.*, Aug. 2015, pp. 276–280.

[17] B. Clerckx. (2016). "Waveform and transceiver design for simultaneous wireless information and power transfer." [Online]. Available: https://arxiv.org/abs/1607.05602

[18] Y. Huang and B. Clerckx. (Sep. 2016). "Large-scale multi-antenna multi-sine wireless power transfer." [Online]. Available: https://arxiv.org/abs/1609.02440

[19] X. Lu, P. Wang, D. Niyato, D. I. Kim, and Z. Han, "Wireless networks with RF energy harvesting: A contemporary survey," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 2, pp. 757–789, 2nd Quart., 2015.

[20] P. Grover and A. Sahai, "Shannon meets tesla: Wireless information and power transfer," in *Proc. IEEE Int. Symp. Inf. Theory*, Jun. 2010, pp. 2363–2367.

[21] İ. E. Telatar, "Capacity of multi-antenna Gaussian channels," *Eur. Trans. Telecommun.*, vol. 10, no. 6, pp. 585–595, 1999.

[22] X. Lu, P. Wang, D. Niyato, D. I. Kim, and Z. Han, "Wireless charging technologies: Fundamentals, standards, and network applications," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1413–1452, 2nd Quart., 2015.

[23] X. Zhou, R. Zhang, and C. K. Ho, "Wireless information and power transfer: Architecture design and rate-energy tradeoff," *IEEE Trans. Commun.*, vol. 61, no. 11, pp. 4754–4767, Nov. 2013.

[24] S. Sanayei and A. Nosratinia, "Antenna selection in MIMO systems," *IEEE Commun. Mag.*, vol. 42, no. 10, pp. 68–73, Oct. 2004.

[25] A. F. Molisch and M. Z. Win, "MIMO systems with antenna selection," *IEEE Commun. Mag.*, vol. 5, no. 1, pp. 46–56, Mar. 2004.

[26] S. Zhao, Q. Li, Q. Zhang, and J. Qin, "Antenna selection for simultaneous wireless information and power transfer in MIMO systems," *IEEE Commun. Lett.*, vol. 18, no. 5, pp. 789–792, May 2014.

[27] B. Koo and D. Park, "Interference alignment and wireless energy transfer via antenna selection," *IEEE Commun. Lett.*, vol. 18, no. 4, pp. 548–551, Apr. 2014.

[28] M. Di Renzo, H. Haas, A. Ghrayeb, S. Sugiura, and L. Hanzo, "Spatial modulation for generalized MIMO: Challenges, opportunities, and implementation," *Proc. IEEE*, vol. 102, no. 1, pp. 56–103, Jan. 2014.

[29] P. Yang, M. Di Renzo, Y. Xiao, S. Li, and L. Hanzo, "Design guidelines for spatial modulation," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 6–26, 1st Quart., 2015.

[30] P. Yang *et al.*, "Single-carrier SM-MIMO: A promising design for broadband large-scale antenna systems," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 3, pp. 1687–1716, 3rd Quart., 2016.

[31] M. Di Renzo, H. Haas, A. Ghrayeb, S. Sugiura, and L. Hanzo, *Spatial Modulation for Multiple–Antenna Communication*. Hoboken, NJ, USA: Wiley, 2016.

[32] E. Basar, M. Wen, R. Mesleh, M. Di Renzo, Y. Xiao, and H. Haas, "Index modulation techniques for next-generation wireless networks," *IEEE Access*, vol. 5, pp. 16693–16746, 2017.

[33] M. Di Renzo and H. Haas, "Bit error probability of SM-MIMO over generalized fading channels," *IEEE Trans. Veh. Technol.*, vol. 61, no. 6, pp. 1124–1144, Mar. 2012.

[34] N. Serafimovski, "Practical implementation of spatial modulation," *IEEE Trans. Veh. Technol.*, vol. 62, no. 9, pp. 4511–4523, Nov. 2013.

[35] A. Younis, S. Sinanovic, M. Di Renzo, R. Mesleh, and H. Haas, "Generalised sphere decoding for spatial modulation," *IEEE Trans. Commun.*, vol. 61, no. 7, pp. 2805–2815, Jul. 2013.

[36] M. D. Renzo and H. Haas, "On transmit diversity for spatial modulation MIMO: Impact of spatial constellation diagram and shaping filters at the transmitter," *IEEE Trans. Veh. Technol.*, vol. 62, no. 6, pp. 2507–2531, Jul. 2013.

[37] K. Ntontin, M. Di Renzo, A. I. Perez-Neira, and C. Verikoukis, "A low-complexity method for antenna selection in spatial modulation systems," *IEEE Commun. Lett.*, vol. 17, no. 12, pp. 2312–2315, Dec. 2013.

[38] M. Le, V. Ngo, H. Mai, X. Tran, and M. Di Renzo, "A low-complexity method for antenna selection in spatial modulation systems," *IEEE Trans. Commun.*, vol. 62, no. 1, pp. 85–99, Dec. 2014.

[39] M. Di Renzo and H. Haas, "Transmit-diversity for spatial modulation (SM): Towards the design of high-rate spatially-modulated space-time block codes," in *Proc. IEEE Int. Conf. Commun.*, Jun. 2011, pp. 1–6.

[40] T. Fath, H. Haas, M. Di Renzo, and R. Meslesh, "Spatial modulation applied to optical wireless communications in indoor LOS environments," in *Proc. IEEE Global Commun. Conf.*, Dec. 2011, pp. 1–5.

[41] R. Zhang, L.-L. Yang, and L. Hanzo, "Generalised pre-coding aided spatial modulation," *IEEE Trans. Wireless Commun.*, vol. 12, no. 11, pp. 5434–5443, Nov. 2013.

[42] R. Zhang, L.-L. Yang, and L. Hanzo, "Error probability and capacity analysis of generalised pre-coding aided spatial modulation," *IEEE Trans. Wireless Commun.*, vol. 14, no. 1, pp. 364–375, Jan. 2015.

[43] A. Stavridis, D. Basnayaka, S. Sinanovic, M. Di Renzo, and H. Haas, "A virtual MIMO dual-hop architecture based on hybrid spatial modulation," *IEEE Trans. Commun.*, vol. 62, no. 9, pp. 3161–3179, Sep. 2014.

[44] C. Masouros and L. Hanzo, "Dual-layered MIMO transmission for increased bandwidth efficiency," *IEEE Trans. Veh. Technol.*, vol. 65, no. 5, pp. 3139–3149, May 2016.

[45] J. Zheng, "Fast receive antenna subset selection for pre-coding aided spatial modulation," *IEEE Wireless Commun. Lett.*, vol. 4, no. 3, pp. 317–320, Jun. 2015.

[46] M. Zhang, M. Wen, X. Cheng, and L.-L. Yang, "Pre-coding aided differential spatial modulation," in *Proc. IEEE Global Commun. Conf.*, Dec. 2015, pp. 1–6.

[47] R. Zhang, L.-L. Yang, and L. Hanzo, "Energy pattern aided simultaneous wireless information and power transfer," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 8, pp. 1492–1504, Aug. 2015.

[48] F. Wu, L.-L. Yang, W. Wang, and Z. Kong, "Secret precoding-aided spatial modulation," *IEEE Commun. Lett.*, vol. 19, no. 9, pp. 1544–1547, Sep. 2015.

[49] F. Wu, R. Zhang, L.-L. Yang, and W. Wang, "Transmitter precoding-aided spatial modulation for secrecy communications," *IEEE Trans. Veh. Technol.*, vol. 65, no. 1, pp. 467–471, Jan. 2016.

[50] A. Stavridis, M. Di Renzo, P. M. Grant, and H. Haas, "On the asymptotic performance of receive space modulation in the shadowing broadcast channel," *IEEE Commun. Lett.*, vol. 20, no. 10, pp. 2103–2106, Oct. 2016.

[51] A. Stavridis, M. Di Renzo, and H. Haas, "Performance analysis of multi-stream receive spatial modulation in the MIMO broadcast channel," *IEEE Trans. Wireless Commun.*, vol. 15, no. 3, pp. 1808–1820, Mar. 2016.

[52] P. Yang, Y. L. Guan, Y. Xiao, M. Di Renzo, S. Li, and L. Hanzo, "Transmit precoded spatial modulation: Maximizing the minimum Euclidean distance versus minimizing the bit error ratio," *IEEE Trans. Wireless Commun.*, vol. 15, no. 3, pp. 2054–2068, Mar. 2016.

[53] R. M. Gray, *Entropy and Information Theory*. New York, NY, USA: Springer, 2011.

[54] T. L. Narasimhan and A. Chockalingam, "On the capacity and performance of generalized spatial modulation," *IEEE Commun. Lett.*, vol. 20, no. 2, pp. 252–255, Feb. 2016.

[55] Q. Shi, L. Liu, W. Xu, and R. Zhang, "Joint transmit beamforming and receive power splitting for MISO SWIPT systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 6, pp. 3269–3280, Jun. 2014.

[56] B. R. Marks and G. P. Wright, "A general inner approximation algorithm for non-convex mathematical programs," *Oper. Res.*, vol. 26, no. 4, pp. 681–683, 1978.

[57] A. Beck, A. Ben-Tal, and L. Tetruashvili, "A sequential parametric convex approximation method with applications to nonconvex truss topology design problems," *J. Global Optim.*, vol. 47, no. 1, pp. 29–51, 2010.

[58] M. Razaviyayn, M. Hong, and Z.-Q. Luo, "A unified convergence analysis of block successive minimization methods for nonsmooth optimization," *SIAM J. Optim.*, vol. 23, no. 2, pp. 1126–1153, 2013.

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