Abstract—This paper deals with a multiple-input single-output (MISO) network where the receivers are characterized by both quality-of-service (QoS) and radio-frequency (RF) energy harvesting (EH) constraints. We consider the power splitting RF-EH technique where each receiver divides the received signal into two parts a) the first part for information decoding and b) the second part for battery charging. The minimum required energy that supports both the QoS and the RF-EH constraints at each receiver is formulated by an optimization problem and is discussed for two standard beamforming designs, the zero-forcing (ZF) and the maximum ratio transmission (MRT). The optimal solution for ZF beamforming is derived in closed-form, while optimization algorithms based on second-order cone programming (SOCP) and Linear Programming (LP) are developed for MRT beamforming to solve the problem. Numerical results indicate that MRT significantly outperforms ZF in terms of transmitted power, as the associated cross-interference becomes beneficial from an EH standpoint, while ZF always ensures the existence of a solution for the optimization problem considered.

Index Terms—Radio frequency energy transfer, energy harvesting, power splitting, MISO, second-order cone programming, optimization.

I. INTRODUCTION

Recently, there is a lot of interest for energy harvesting (EH) communication systems that can harvest energy from a variety of natural and man-made sources (solar, wind, mechanical vibration, etc.) for sustainable network operation. EH opens new challenges on energy efficiency and enables the design of new transmission schemes and protocols that efficiently handle the energy harvested [1], [2]. A promising harvesting technology is the radio frequency (RF) energy transfer where the ambient RF radiation is captured by the receiver antennas and converted into a direct current (DC) voltage through appropriate circuits (rectennas) [3]. For some applications where other EH technologies can not be deployed (such as wireless soil sensor networks [4]), RF energy transfer seems to be a suitable solution.

RF-EH is a new research area that attracts the attention of both academia and industry [5]. The long term perspective is to be able to capture the electromagnetic radiation that is available in the surrounding (TV towers, cellular base-stations etc.) and use it in order to power communication systems. Most of the work on RF energy transfer focuses on the circuit and rectenna design as it is a vital requirement in order to make RF-EH feasible [6], [7]. On the other hand, the development of protocols and transmission techniques for wireless networks with RF-EH capabilities seems to be a new research direction and few studies appear in the literature. The fundamental concept of simultaneous wireless transmission of energy and information is discussed in [8] from an information theoretic standpoint. However, due to practical hardware constraints, simultaneous energy and information transmission is not possible with existing technology. In [9] the authors study practical beamforming techniques in a simplified multiple-input multiple-output (MIMO) network that ensure quality-of-service (QoS) and EH constraints for two separated receivers, respectively. In that work, the authors also discuss two practical receiver approaches for simultaneous wireless power and information transfer a) “time switching”, where the receiver switches between decoding information and harvesting energy and b) “power splitting”, where the receiver splits the received signal in two parts for decoding information and harvesting energy, respectively. This work is extended in [10] for scenarios with imperfect channel state information (CSI) at the transmitter and a robust beamforming design is presented. On the other hand, the authors in [11] propose a dynamic switching between decoding information and EH in order to minimize the outage probability of the system; this fundamental switching is employed in [12] for a cooperative relaying scenario with a discrete-level battery at the RF-EH relay node.

In this paper, we focus on the power splitting approach [9] and we study a conventional multiple-input single-output (MISO) network where the receivers are characterized by both QoS and EH constraints. For fixed beamforming weights and known CSI at the sources, we optimize the values for the power split at each receiver as well as the transmitted power for each source with the objective of minimizing the total transmitted energy. Different solution methodologies are proposed for general beamforming schemes, such as the maximum ratio transmission (MRT) [13], [14], while an optimal closed-form solution is derived for zero-forcing (ZF) beamforming. A comparison between them shows that ZF, which is considered as an efficient beamforming design for conventional MISO systems, requires significantly more transmit power compared to MRT beamforming, but always leads to feasible solutions for the considered problem.

This paper is organized as follows: Section II sets up the system model. Section III discusses two main MISO beamforming schemes, the ZF and the MRT. The optimization
algorithms considered for the solution of the optimization problem is presented in Section IV. Simulation results are presented in Section V, and are followed by our conclusions in Section VI.

II. SYSTEM MODEL

We assume a simple MISO interference channel consisting of $K$ sources and $K$ receivers where each source $S_i$ communicates with its corresponding receiver $D_i$ ($i = 1, \ldots, K$). The sources are equipped with $K$ antennas while the receivers have a single antenna. The system model considered is depicted in Fig. 1. We assume that the source $S_i$ transmits with a power $P_i$ and let $s_i$ be its transmitted data symbol with $E\{\|s_i\|^2\} = 1$. The transmitted data symbol $s_i$ is mapped onto the antenna array elements by the beamforming vector $w_i \in \mathbb{C}^{K \times 1}$ with $\|w_i\|^2 = 1$.

All wireless links exhibit independent fading and Additive White Gaussian Noise (AWGN) with zero mean and variance $\sigma^2$. The fading is assumed to be frequency non-selective Rayleigh block fading. This means that the fading coefficients $h_{i,j} \in \mathbb{C}^{K \times 1}$ (for the $j \rightarrow i$ link) remain constant during one slot, but change independently from one slot to another according to a circularly symmetric complex Gaussian distribution with zero mean and unit variance. The received signal at receiver $D_i$ can be expressed as

$$y_i = \sqrt{P_i}h_{i,i}^T w_i s_i + \sum_{j \neq i} \sqrt{P_j}h_{i,j}^T w_j s_j + n_i,$$

where $n_i$ denotes the AWGN component; therefore the received power at $D_i$ is equal to

$$P_i^r = \sum_{j=1}^{K} |h_{i,j}^T w_j|^2 P_j + \sigma^2.$$

The receivers have RF-EH capabilities and therefore can harvest energy from the received RF signal based on the power split technique [9]. With this approach, each receiver splits its received energy in two parts a) one part is converted to a baseband signal for further signal processing and data detection and b) the other part is driven to the required circuits for conversion to DC voltage and energy storage. Let $\rho_i \in (0, 1)$ denote the energy split parameter for the $i$-th receiver; this means that $100\rho_i\%$ of the received power is used for data detection while the remaining amount is the input to the RF-EH circuitry. More specifically, after reception of the RF signal at the receiver, a power splitter divides the power $P_i^r$ into two parts according to $\rho_i$, so that $\rho_i P_i^r$ is directed towards the decoding unit and $(1 - \rho_i) P_i^r$ towards the EH unit. During the decoding phase, additional circuit AWGN, $v_i$, with zero mean and variance $\sigma_C^2$ is added to the decoded signal [9]. Fig. 2 schematically shows the power splitting technique for the $i$-th receiver.

The signal-to-interference-plus-noise ratio (SINR) metric characterizing the data detection process at the $i$-th receiver is given by:

$$\Gamma_i = \frac{\rho_i P_i |h_{i,i}^T w_i|^2}{\rho_i \left( \sigma^2 + \sum_{j \neq i} P_j |h_{i,j}^T w_j|^2 \right) + \sigma_C^2}.$$

On the other hand, the total electrical power that can be stored is equal to $P_i^S = \zeta(1 - \rho_i) P_i^r$, where $\zeta \in (0, 1)$ denotes the conversion efficiency of the EH unit\(^1\) ($100 \cdot \zeta\%$ of the RF energy received at the EH unit can be stored as electrical energy). We note that in this study, the RF-EH constraints considered refer to the required rectennas’ input without discussing energy storage efficiency issues.

A. Optimization problem

We assume that both receivers are characterized by strict QoS and EH constraints. The QoS constraint requires that the SINR should be higher than the threshold $\gamma_i$; the energy constraint requires that the input to the RF energy circuitry is higher than the energy threshold $\lambda_i$. We focus on the power allocation problem and we introduce the following optimization problem where the system satisfies both QoS and energy constraints while the overall transmitted power is minimized. Based on the previous notation, the optimization problem can be defined as

\(^1\) In [3] a practical cellular energy harvesting system was designed, operating at $\zeta \approx 0.25$ conversion efficiency.
The minima of the beamforming is given by \[14\]

subject to \( \Gamma_i \geq \gamma_i, \forall i \), \( (1 - \rho_i)P_i^r \geq \lambda_i, \forall i \), \( P_i \geq 0, \| w_i \|^2 = 1 \), \( 0 \leq \rho_i \leq 1, \forall i \) \[4\]

III. CONVENTIONAL MISO BEAMFORMING SCHEMES: ZF AND MRT

In this section, we briefly present two standard beamforming designs that are well-known in conventional MISO systems. More specifically, we focus on the ZF and the MRT beamforming schemes (represent two extreme strategies); in the next section, we examine their performance under the considered QoS and EH constraints.

A. Zero Forcing

In ZF, the weights are selected such as the co-channel interference is canceled i.e., for the desired user \( i \), the ZF condition becomes \( h_{j,i}^T w_j = 0 \). More specifically, the ZF weight is provided by the solution of the following optimization problem:

\[
\max_{w_i} | h_{i,i}^T w_i |^2 \\
\text{s. t.} \quad H_i^T w_i = 0_{(K-1) \times 1} \\
\| w_i \|^2 = 1
\]

where \( H_i = [h_{1,i}, \ldots, h_{i-1,i}, h_{i+1,i}, \ldots, h_{K,i}]^T \). The solution of the beamforming is given by \([14]\)

\[
w_i^{(ZF)} = \frac{(IK - F) h_{i,i}^*}{\| (IK - F) h_{i,i}^* \|}
\]

where \( F = H_i^H H_i \) and \( H_i^H = H_i^H (H_i H_i^H)^{-1} \) is the Moore-Penrose inverse of \( H_i \).

B. Maximum Ratio Transmission

The MRT beamforming maximizes the signal-to-noise ratio (SNR) at each receiver \( \| h_{i,i}^T w_i \|^2 / \sigma^2 \) and it requires only the knowledge of the direct links \( h_{i,i} \); due to this limited CSI knowledge, it is of low complexity and is suitable for practical applications with strict computational/time constraints. The MRT beamforming is expressed as \([13]\)

\[
w_i^{(MRT)} = \frac{h_{i,i}^*}{\| h_{i,i}^* \|}
\]

IV. PROBLEM SOLUTION FOR FIXED BEAMFORMING

In this section we propose solutions to the considered problem for the two beamforming schemes described in Section III. In ZF beamforming, the optimization problem attains a special form that allows an optimal closed-form solution. In MRT beamforming, the problem remains general, so that the proposed solution methods apply to any arbitrary beamforming schemes \( w_j^r \).

A. Problem solution for ZF beamforming

Letting \( G_{i,j} = | h_{i,j}^T w_j | \) denote the link gain between \( S_i \) and \( D_j \), the SINR and the total received power at the \( i \)-th receiver are simplified because \( G_{ij} = 0 \), for \( i \neq j \). Hence the original optimization problem simplifies into the following formulation:

\[
ZF : \min_{P, P_i} \sum_{i=1}^K P_i \quad \text{subject to} \quad \frac{\rho_i G_{i,i} P_i}{\rho_i \sigma^2 + \sigma_C^2} \geq \gamma_i, \forall i \quad (7a) \\
(1 - \rho_i)(G_{i,i} P_i + \sigma^2) \geq \lambda_i, \forall i \quad (7c) \\
P_i \geq 0, \quad 0 \leq \rho_i \leq 1, \forall i \quad (7d)
\]

**Theorem 1.** Let \( \alpha = (\gamma_i + 1) \sigma^2 \) and \( \beta = \gamma_i \sigma_C^2 \). A feasible solution to optimization problem \( ZF \) always exists, while its optimal solution can be expressed in closed-form as:

\[
P_i^* = \frac{1}{G_{ii}} \left( \frac{\alpha + \beta + \lambda_i + \sqrt{(\alpha + \beta + \lambda_i)^2 - 4 \lambda_i \alpha}}{2} \right) - \sigma^2,
\]

\[
\rho_i^* = \frac{\beta G_{ii} P_i^*}{G_{ii} P_i^* + \sigma^2 - \alpha} = 1 - \frac{\lambda_i}{G_{ii} P_i^* + \sigma^2}.
\]

**Proof:** In optimization problem \( ZF \), the ith set of constraints \((7b)-(7d)\) are decoupled as the variables \( P_i, \rho_i \) do not appear in other constraints; also, the variables in the objective function are in separable form. Hence, problem \( ZF \) can be decomposed into the \( K \) independent problems \( SZF_i \), so that the optimal solution of \( ZF \) is equal to the sum of the optimal solutions of these independent problems.

\[
SFZ_i : \min_{P_i, \rho_i} P_i \\
\frac{\rho_i G_{i,i} P_i}{\rho_i \sigma^2 + \sigma_C^2} \geq \gamma_i, \quad (8) \\
(1 - \rho_i)(G_{i,i} P_i + \sigma^2) \geq \lambda_i, \quad (9) \\
P_i \geq 0, \quad 0 \leq \rho_i \leq 1.
\]

Note that in the considered problem, \( \rho_i \in (0, 1) \), otherwise the problem constraints are not satisfied for \( \gamma_i, \lambda_i > 0 \).

Assuming that:

\[
x_i = G_{i,i} P_i + \sigma^2 \geq \sigma^2, \quad (10) \\
\alpha = (\gamma_i + 1) \sigma^2, \quad (11) \\
\beta = \gamma_i \sigma_C^2, \quad (12)
\]
constraints (8) and (9) can be written as:

\[
\rho_i \geq \frac{\beta}{x_i - \alpha} < 1, \quad (13)
\]

\[
\rho_i \leq 1 - \frac{\lambda_i}{x_i} > 0. \quad (14)
\]

This implies that \(x_i > \alpha + \beta \) and \(x_i > \lambda_i\), otherwise \(\rho_i \notin (0, 1)\); in other words \(x_i\) must be greater than \(\max(\lambda_i, \alpha + \beta)\). Problem \(\mathbb{SZF}\) requires at least one of the constraints to be binding, otherwise the value of \(P_i\) can further be reduced. Hence, at least one of the following two equalities must be true at the optimal solution.

\[
\rho_i = \frac{\beta}{x_i - \alpha}, \quad (15)
\]

\[
\rho_i = 1 - \frac{\lambda_i}{x_i}. \quad (16)
\]

Let us assume that (15) is true. Substituting this equation into (14) and rearranging the terms yields:

\[
x_i^2 - (\alpha + \beta + \lambda_i)x_i + \alpha \lambda_i \geq 0. \quad (17)
\]

Interestingly, we obtain (17) even if we follow the same procedure for the other binding constraint. This implies that binding any of the two equations will yield the same solution. Because \(x_i\) is a monotonically increasing function of \(P_i\), the optimal solution to problem \(\mathbb{SZF}\) is the smallest value of \(x_i\) which satisfies (17) and \(x_i > \max(\lambda_i, \alpha + \beta)\). It can be easily verified that the discriminant \(\Delta\) of the quadratic expression in (17) is always positive, which implies that there are two distinct solutions \(x_1\) and \(x_2\), and that the feasible region of (17) is \(x \leq x_1\) and \(x \geq x_2\), where:

\[
x_1 = \frac{1}{2} \left( \alpha + \beta + \lambda_i - \sqrt{(\alpha + \beta + \lambda_i)^2 - 4\alpha \lambda_i} \right), \quad (18)
\]

\[
x_2 = \frac{1}{2} \left( \alpha + \beta + \lambda_i + \sqrt{(\alpha + \beta + \lambda_i)^2 - 4\alpha \lambda_i} \right). \quad (19)
\]

It can be easily shown that \(x_1 < \max(\lambda_i, \alpha + \beta)\), because \(\Delta > 0\), and \(\alpha + \beta + \lambda_i \leq 2 \max(\lambda_i, \alpha + \beta)\). Next we show that \(\max(\lambda_i, \alpha + \beta) < x_2\).

If we assume that \(\lambda_i \geq \alpha + \beta\) we need to show that:

\[
\alpha + \beta + \lambda_i + \sqrt{(\alpha + \beta + \lambda_i)^2 - 4\alpha \lambda_i} > 2 \lambda_i \Rightarrow \\
(\alpha + \beta + \lambda_i)^2 - 4\alpha \lambda_i > (\alpha + \beta + \lambda_i)^2 \Rightarrow \\
\alpha^2 + \beta^2 + \lambda_i^2 + 2\alpha \beta + 2 \beta \lambda_i - 2 \alpha \lambda_i > \alpha^2 + \beta^2 + \lambda_i^2 + 2 \alpha \beta - 2 \beta \lambda_i - 2 \alpha \lambda_i \Rightarrow \\
4\beta \lambda_i > 0,
\]

where the latter inequality is true because \(\beta, \lambda_i > 0\). In a similar manner we can easily show that \(\max(\lambda_i, \alpha + \beta) < x_2\) when \(\lambda_i \leq \alpha + \beta\). Hence, we have shown that \(x_1 < \max(\lambda_i, \alpha + \beta) < x_2\), which implies that the optimal solution is \(x_1^* = x_2\). In addition, it can be derived that \(\rho_i^* = \frac{\beta}{x_i - \alpha} = 1 - \frac{\lambda_i}{x_i}\) which implies that both constraints (13) and (14) are binding at the solution. Having derived \(x_i^*\) and \(\rho_i^*\), the optimal power value is \(P_i^* = \frac{1}{\rho_i^*} (x_i^* - \sigma^2)\) which completes the proof.

### B. Problem solution for MRT beamforming

When the MRT beamforming scheme is used we have that \(G_{ij} \neq 0, \forall i, j\). After rearranging the terms in formulation (4) we obtain:

\[
\mathcal{O} : \min_{P, \rho} \sum_{i=1}^{K} P_i \quad (20a)
\]

\[
\text{s.t.} (1 + \gamma_i)G_{i,j}P_i \geq \frac{1}{\rho_i} \gamma_i \sigma_C^2 + \gamma_i P_i^r, \forall i \quad (20b)
\]

\[
(1 - \rho_i)P_i^r \geq \lambda_i, \forall i \quad (20c)
\]

\[
\sum_{j=1}^{K} G_{i,j} P_j + \sigma^2 = P_i^r, \forall i \quad (20d)
\]

\[
P_i \geq 0, \quad P_i^r \geq 0, \quad 0 \leq \rho_i \leq 1, \forall i \quad (20e)
\]

Optimization problem \(\mathcal{O}\) is convex because it is comprised of a linear objective function and convex constraints. Constraint (20b) is convex because the term \(\frac{1}{\rho_i} \gamma_i \sigma_C^2\) is convex for \(\rho_i > 0\) and the other terms are linear, (20c) is a restricted hyperbolic constraint and (20d) is linear. Next we show how the problem can be cast into a Second-Order Cone Programming (SOCP) formulation, which can be optimally and reliably solved using off-the-shelf algorithms.

**SOCP Solution:** SOCP problems are convex optimization problems in which a linear function is minimized subject to linear and second-order cone constraints [15]. SOCP has been successfully applied in several applications because not only can it solve a large family of problems (including Linear Programming(LP) and Quadratically Constrained Quadratic Programming(QCQP) problems), but also because there are several fast and robust SOCP solvers (mostly based on interior-point methods) [16]. SOCP problems can be written in standard form as:

\[
\min_{\mathbf{x}} \quad \mathbf{e}^T \mathbf{x} \quad (21a)
\]

\[
\text{s.t.} \quad \mathbf{A} \mathbf{x} = \mathbf{b}, \quad (21b)
\]

\[
\|\mathbf{C} \mathbf{x} - \mathbf{d}\| \leq \mathbf{e}_i^T \mathbf{x} + f_i, i = 1, ..., N_C. \quad (21c)
\]

where (21b) denote linear constraints and (21c) second-order cone (SOC) constraints. Among the constraints that can be modeled using SOCs are the restricted hyperbolic constraints which have the form: \(x^T \mathbf{C} \mathbf{x} \leq y z\), where \(x, y, z \in \mathbb{R}^{N \times 1}\), \(y, z \geq 0\). Such a constraint is equivalent to a rotated SOC constraint of the form:

\[
\left\| \begin{pmatrix} 2x \\ y - z \end{pmatrix} \right\| \leq y + z
\]

For example, constraint (20c) is equivalent to the following SOC:

\[
\left\| \frac{2\sqrt{\lambda_i}}{(1 - \rho_i) - P_i^r} \right\| \leq (1 - \rho_i) + P_i^r
\]

In order to cast problem \(\mathcal{O}\) into SOCP form we need to convert (20b) into a restricted hyperbolic constraint. Let us define
TABLE I

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Optimality</th>
<th>Infeasibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K$ (dB)</td>
<td>$\gamma$ (dBm)</td>
<td>$P_i$ (dBm)</td>
</tr>
<tr>
<td>------------</td>
<td>------------</td>
<td>---------------</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>-20</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>-10</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>-20</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>-10</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>-20</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>-10</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>-20</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>-10</td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>-20</td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>-10</td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>-20</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>-10</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>-20</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>-10</td>
</tr>
</tbody>
</table>

TABLE I

OPTIMALITY AND INFEASIBILITY RESULTS FOR DIFFERENT PARAMETER CONFIGURATIONS.

$z_i = (1 + \gamma_i)G_i \nu_i \gamma_i P_i^r$; it must be true that $z_i \geq 0$ since $\frac{1}{\rho_i} \gamma_i \sigma_C^2 \geq 0$ otherwise (20b) will be infeasible. Substituting $z_i$ into (20b) yields that $\rho_i z_i \geq \gamma_i \sigma_C^2$, which is a convex restricted hyperbolic constraint. Hence, problem $\mathcal{P}$ can be cast to the following convex problem which is equivalent to an SOCP formulation:

$$\text{SOCP : } \min_{P, \rho} \sum_{i=1}^{K} P_i \quad (22a)$$

s.t. $z_i \rho_i \geq \gamma_i \sigma_C^2, \forall i$ \quad (22b)

$z_i + \gamma_i P_i^r = (1 + \gamma_i)G_i \nu_i P_i, \forall i$ \quad (22c)

$(1 - \rho_i)P_i^r \geq \lambda_i, \forall i$ \quad (22d)

$$\sum_{j=1}^{K} G_{i,j} P_j + \sigma^2 = P_i^r, \forall i \quad (22e)$$

$P_i \geq 0, P_i^r \geq 0, \quad z_i \geq 0, \quad 0 \leq \rho_i \leq 1, \forall i \quad (22f)$

V. NUMERICAL RESULTS

We evaluate the performance of the developed algorithms by solving several randomly generated problems for different parameter configurations. All problem instances follow the system model in Section II with $\sigma^2 = \sigma_C^2 = -10$ dBm and strengthened direct channel links by a multiplicative constant $\delta$ (a simple method to ensure that the direct links are much stronger than the interference links [17]), i.e., $B_{hi} \leftarrow \delta B_{hi}$. To avoid parameter configurations that only generate infeasible instances, we ensure feasibility of all generated problems against random beamforming vectors. For simplicity, the detection and energy harvesting thresholds are assumed to be equal for all users ($\gamma_i = \gamma$ and $\lambda_i = \lambda, \forall i$). Mathematical modeling and solution of the SOCP formulation (22) was done using the Gurobi optimization solver [18].

Table I shows the optimality and infeasibility results obtained from 10 instances for different parameter configurations when $\delta = 5$. In the table, algorithm $\mathcal{SOCP}$, uses MRT beamforming, $LP_{\rho}$ corresponds to the solution of the linear program obtained when the energy split parameters are fixed and equal to $\rho_i = 0.5, \forall i$, while $ZF$ indicates the closed-form solution obtained with zero-forcing beamforming. Note that all optimality results are illustrated relative to the optimal MRT solution obtained using algorithm $\mathcal{SOCP}$. Column 4 indicates that the total average power that needs to be transmitted when ZF beamforming is used is significantly larger that the power needed with MRT beamforming. Despite the fact that for high SINR thresholds ($\gamma = 20$ dB) the performance of ZF is relatively good, as the SINR threshold decreases or the EH threshold increases, ZF performance degrades by one or
even two orders of magnitude compared to MRT. Column 5 indicates the importance of optimal selection of the energy split parameters; when they are fixed ($\rho = 0.5$) the total average transmitted power is up to 50% more compared to the SOCP solution where $\rho$ are optimally selected.

Columns 6-8 show the number of infeasible instances (out of 10) obtained from the different solution approaches for each configuration. Two important observations can be made: (a) solution approaches SOCP and CP yield the same number of infeasible problems in all cases considered, and (b) ZF beamforming always provides feasible solutions, while MRT beamforming may lead to infeasibility. This happens because ZF eliminates the interference from non-direct links, so that by using more energy to achieve the desired level of EH the SINR constraints are also improved.

Apart from the performance of the developed algorithms for the solution of problem $O$, the effect of the $\gamma_i$ and $\lambda_i$ parameters has also been investigated. Figures 3, 4 illustrate the average normalized transmit power required for different values of $\gamma_i$ and $\lambda_i$ using 50 problem instances for different parameter combinations. As expected, smaller detection and energy harvesting thresholds result in lower transmit power requirements. Interestingly, larger values of $K$ result in lower requirements for transmit power; the main reason for this behavior is that as $K$ increases, the cross-interference which is beneficial for the EH constraints also increases and results in significant energy savings.

VI. CONCLUSION

This paper has dealt with the RF-EH power splitting technique for a MISO interference channel with QoS and EH constraints. The minimum required energy has been formulated via an optimization problem for constant beamforming weights at the sources. Solution algorithms have been investigated for two standard MISO beamforming designs, the ZF and the MRT. For ZF, a closed-form always feasible solution has been derived, while for MRT a convex SOCP program has been obtained and solved to optimality. We have shown that MRT outperforms ZF in terms of energy consumption, while ZF always ensures feasibility. An interesting extension of this work is to relax the constraint of fixed beamforming and solve the general optimization problem.

REFERENCES