On the Robust design for IoT-based Wireless Information and Power Transmission network

Vien Nguyen-Duy-Nhat*, Mai T. P. Le

Abstract—This work investigates the robust beamforming for a multi-antenna internet of things (IoT) system using wireless information and power transmission (WIPT), given that imperfect channel state information (CSI) assumption is accounted.In particular, we investigate the problem of maximizing the worst-case energy harvested, taking into account the quality of service (QoS) constraint of user rate. The proposed problem is naturally a nonconvex problem, which is hard to tackle directly. On one hand, we rely on a classical method, that is semidefinite programming problem (SDP), to handle this by transforming the original nonconvex optimization problem with infinite number of constraints to a relaxed convex one. On the other hand, we propose another algorithm using Symbiotic Organisms Search (SOS) approach that can effciently solve the formulated problem. In the end, numerical results are provided to verify the effectiveness of the SDP-based algorithm in comparison with that of the SOS-based algorithm.

Index Terms—Symbiotic Organisms Search (SOS); imperfect Channel State Information (CSI); Wireless Information and Power Transmission (WIPT); IoT (Internet of Things); beamforming.

1. Introduction

RECENTLY, the Internet of Things (IoT) has emerged as a smart environment, wherein IoT devices are enabled to communicate with each other and with people seamlessly via Internet [1]. However, powering such a massive number of those IoT devices becomes a critical issue for the current network while satisfying the quality of service (QoS) constraint. This hence leads to the need of solving the longevity and energy efficiency problem of IoT devices [2].

As a matter of fact, there have been several approaches to improve the system energy efficiency, but their availability depends on the environmental variables, ambient parameters, or other time-varying and highly random external factors. Among those, energy harvesting (EH), for instance, is seen as prominent candidates to provide battery longevity, particularly for IoT-based network [3]. Nevertheless, a practical challenge of using EH lies in the fact that it depends on the availability of the energy source. An alternative solution proposed recently is Wireless Information and Power Transmission (WIPT), which is demonstrated to be one of the most potential solutions due to its simplicity, easy implementation, and compability with various EH approaches [4], [5], [6]. In constrast to classical battery-powered systems, WIPT does not require the manual battery charging or replacement, thus improves the system performance and reduces operational expenses.

Owing to the benefits of WIPT, it is of much interest to investigate the system performance of a WIPT-based IoT network [7]. In particular, this work studies the maximized energy harvested problem under the maximum transmit power constraints while satisfying the QoS rate. To solve the formulated problem, we first propose an algorithm based on the classical SDP approach. Then another algorithm, based on bio nature, is developed to further improve the system performance. Finally, we utilize extensive simulations to investigate the effectiveness and feasibility of the two proposed algorithms in terms of average minimum harvested energy and outage percentage.

The structure of the paper is further presented as follows. In Section II, we introduce the downlink WIPT IoT network with the CSI and energy harvesting models. Section III presents the formulated problem aiming to maximize the total harvested power under the QoS and transmit power constraints. In Section IV and V, proposed algorithms are proposed for the formulated problem relying on the SDP and SOS methods, respectively. A constrained SOS-based algorithm is further addressed in Section VI. Numerical results are provided and discussed in Section VII, while conclusion are given in Section VIII.

Notations: Upper-case boldface letters and lower-case boldface letters are used for matrices and for vectors, respectively. $\mathbf{X}^H$ and $\mathrm{Tr}\left(\mathbf{X}\right)$ denote the Hermitian transpose and trace of the matrix $\mathbf{X}$, respectively. $\mathbf{I}_M$ exhibits an $M \times M$ identity matrix while $\mathbb{C}^{N\times M}$ stands for the space of $N \times M$ complex matrices. We denote the complex random vector variable with $\mathbf{z}$ following a Gaussian distribution with mean μ and variance σ^2 as $\mathbf{z} \sim \mathcal{CN}(\mu,\, \sigma^2)$. $\mathrm{rand}(a, b)$ is a random number between

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the interval $[a, b]$.

2. System model

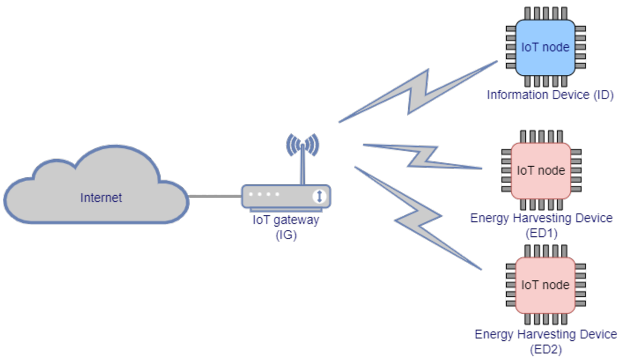

Fig. 1: A simple model of IoT WIPT system.

We first consider a downlink WIPT network as depicted in Fig. 1. The system consists of a IoT gatewate (IG), acting as a transmitter, and IoT nodes with one information devices (ID) and and n_{ED} energy harvesting devices (ED). The IG is equipped with n_T antennas, while the the ID device is with single-antenna, and each ED is equipped with $n_R \geq 1$ antennas for harvesting energy. For a IoT WIPT system, both ID and EDs devices operate in the same service coverage range. This makes malicious EDs receivers become potential eavesdroppers, which should be accounted while considering the secure feature of a network. Without of generality, $n_T > n_R$ is assumed for further beamforming design investigation. At the receivers, the signals received at ID and ED $j \in \{1, \ldots, n_{ED}\}$ per time slot can be expressed as

$$y_{ID} = \mathbf{h}^{\mathrm{H}}\mathbf{w}x + n_{ID}, \tag{1}$$
$$y_{ED_j} = \mathbf{G}_j^{\mathrm{H}}\mathbf{w}x + n_{ED_j}, \tag{2}$$

respectively, where $x \in \mathbb{C}$ is the transmitted data symbol for the information device with $\mathbb{E}\{|x|^2\} = 1$; $\mathbf{w} \in \mathbb{C}^{n_T \times 1}$ is precoding vector; $n_{ID} \sim \mathcal{CN}(0, \sigma^2)$ and $n_{ED_j} \sim \mathcal{CN}(0, \sigma^2 \mathbf{I}_{n_R})$ represent the Gaussian noises at the ID and ED$_j$, respectively, with σ^2 being the power noise of IoT receivers. We denote $\mathbf{h} \in \mathbb{C}^{n_T \times 1}$ and $\mathbf{G}_j \in \mathbb{C}^{n_T \times n_R}$ the channel vector between the IG and the ID, and the channel matrix between the IG and ED$_j$, respectively.

2.1. Channel State Information (CSI) Model

In this work, we consider a practical channel assumption, where the IG does not have the perfect CSI knowledge. In particular, the channel vector $\mathbf{h}$ between the IG and the ID, and the channel matrix $\mathbf{G}$ between the IG and the EDs can be written as

$$\mathbf{h} = \hat{\mathbf{h}} + \Delta\mathbf{h} \tag{3}$$
$$\mathbf{G}_j = \hat{\mathbf{G}}_j + \Delta\mathbf{G}_j, \tag{4}$$

where $\hat{\mathbf{h}}$ and $\hat{\mathbf{G}}_j$ stand for the channel estimates of $\mathbf{h}$ and $\mathbf{G}$, respectively. Herein, $\Delta\mathbf{h}\left(\|\boldsymbol{\Delta}\mathbf{h}\|_2^2 \leq \rho^2\right)$ and $\Delta\mathbf{G}_j\left(\|\boldsymbol{\Delta}\mathbf{G}_j\|_F^2 \leq v_j^2\right)$ denote the resulting channel errors, where the constants ρ and v_j are defined as the maximum value of the norm of $\boldsymbol{\Delta}\mathbf{h}$ and of $\boldsymbol{\Delta}\mathbf{G}_j$, respectively.

2.2. Energy Harvesting Model

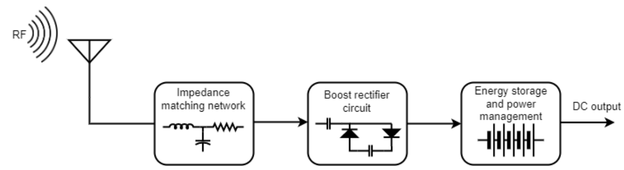

Fig. 2: Block diagram of a energy harvesting circuit.

Fig. 2 illustrates the block diagram of a general energy harvesting circuit. The antenna is connected with matched input impedance; the boost rectifier circuit; and energy storage and power management. All are connected to each other. The impedance matching circuit and the boost rectifier circuit amplify the weak input radio frequency (RF) signal to store and supply the DC output voltage. The RF power received at ED$_j$ is provided by

$$P_{ED_j}(\mathbf{w}) = \mathrm{Tr}\left(\mathbf{w}^{\mathrm{H}}\mathbf{G}_j\mathbf{G}_j^{\mathrm{H}}\mathbf{w}\right). \tag{5}$$

The total harvested power at ED$_j$ is modeled by

$$\Phi_{ED_j} = \eta_j P_{ED_j} = \eta_j \mathrm{Tr}\left(\mathbf{w}^{\mathrm{H}}\mathbf{G}_j\mathbf{G}_j^{\mathrm{H}}\mathbf{w}\right), \tag{6}$$

where the constant $\eta_j \in [0, 1]$ is the energy factor for converting RF energy to electrical energy at wireless powered ED j.

The achievable rate at the ID can be expressed as

$$r_I = \log(1 + \gamma), \tag{7}$$

where γ is the signal-to-interference-and-noise ratio (SINR) at the ID, which is defined by

$$\gamma = \frac{\mathbf{w}^{\mathrm{H}}\mathbf{h}\mathbf{h}^{\mathrm{H}}\mathbf{w}}{\sigma^2}. \tag{8}$$

3. Formulated Problem

In this section, we aim to maximize the total harvested power of the system while satisfying the quality-of-service (QoS) condition under the imperfect CSI assumption. In particular, we formulate the max-min optimization problem as follows

$$P1: \quad \max_{\mathbf{w}} \quad \min \Phi_{ED_j} \tag{9a}$$
$$\text{s.t.} \quad \|\mathbf{w}\|_2^2 \leq P_{max} \tag{9b}$$
$$\log\left(1 + \frac{\mathbf{w}^{\mathrm{H}}\mathbf{h}\mathbf{h}^{\mathrm{H}}\mathbf{w}}{\sigma^2}\right) \geq r_{\mathrm{req}}, \tag{9c}$$
$$\|\boldsymbol{\Delta}\mathbf{h}\|_2^2 \leq \rho^2, \|\boldsymbol{\Delta}\mathbf{G}_j\|_F^2 \leq v_j^2, \tag{9d}$$

where P_{max} represents the maximum transmit power at the ID while r_{req} denotes its minimum required information rate. Because γ is a positive number, $\log(1+\gamma)$ is a monotonically increasing function. Problem (P1) can be rewritten as follows

$$P2: \quad \max_{\mathbf{w}} \ \min \ \Phi_{ED_j} \tag{10a}$$
$$\text{s.t.} \quad |\mathbf{w}\mathbf{w}^{\mathrm{H}}| \leq P_{max} \tag{10b}$$
$$|\mathbf{w}^{\mathrm{H}}\mathbf{h}|^2 \geq \sigma^2\left(2^{r_{\mathrm{req}}}-1\right), \tag{10c}$$
$$\|\boldsymbol{\Delta}\mathbf{h}\|_2^2 \leq \rho^2, \|\boldsymbol{\Delta}\mathbf{G}_j\|_F^2 \leq v_j^2 \tag{10d}$$

Assume that the channel estimation errors $\boldsymbol{\Delta}\mathbf{h}$ and $\boldsymbol{\Delta}\mathbf{G}_j$ are independent with $\mathbf{h}$ and $\mathbf{G}_j$, respectively, we have

$$\begin{aligned}\Phi_{ED_j} &= \eta_j \mathrm{Tr}\left(\mathbf{w}^{\mathrm{H}}\left(\hat{\mathbf{G}}_j+\boldsymbol{\Delta}\mathbf{G}_j\right)\left(\hat{\mathbf{G}}_j+\boldsymbol{\Delta}\mathbf{G}_j\right)^{\mathrm{H}}\mathbf{w}\right)\\ &= \eta_j\left\{\mathrm{Tr}\left(\mathbf{w}^{\mathrm{H}}\hat{\mathbf{G}}_j\hat{\mathbf{G}}_j^{\mathrm{H}}\mathbf{w}\right)+\mathrm{Tr}\left(\mathbf{w}^{\mathrm{H}}\boldsymbol{\Delta}\mathbf{G}_j\boldsymbol{\Delta}\mathbf{G}_j^{\mathrm{H}}\mathbf{w}\right)\right\},\\ &\leq \eta_j\left\{\mathrm{Tr}\left(\mathbf{w}^{\mathrm{H}}\hat{\mathbf{G}}_j\hat{\mathbf{G}}_j^{\mathrm{H}}\mathbf{w}\right)+v_j^2P_{max}\right\},\end{aligned}$$

and

$$\begin{aligned}|\mathbf{w}^{\mathrm{H}}\mathbf{h}| &= |\mathbf{w}^{\mathrm{H}}\hat{\mathbf{h}}+\mathbf{w}^{\mathrm{H}}\Delta\mathbf{h}|\\ &\geq |\mathbf{w}^{\mathrm{H}}\hat{\mathbf{h}}|-|\mathbf{w}^{\mathrm{H}}\Delta\mathbf{h}|\\ &\geq |\mathbf{w}^{\mathrm{H}}\hat{\mathbf{h}}|-\rho^2P_{max}.\end{aligned} \tag{11}$$

The inequation (10c) can be rewritten as

$$|\mathbf{w}^{\mathrm{H}}\hat{\mathbf{h}}|-\rho^2P_{max} \geq \sqrt{\sigma^2\left(2^{r_{\mathrm{req}}}-1\right)}. \tag{12}$$

Then in order to meet this constraint, we just need to satisfy the following

$$|\mathbf{w}^{\mathrm{H}}\hat{\mathbf{h}}| \geq \rho^2P_{max}+\sigma\sqrt{2^{r_{\mathrm{req}}}-1}. \tag{13}$$

In the end, the robust beamforming problem (10) can be reformulated as shown next

$$P3: \quad \max_{\mathbf{w}} \ \min \ \mathrm{Tr}\left(\mathbf{w}^{\mathrm{H}}\hat{\mathbf{G}}_j\hat{\mathbf{G}}_j^{\mathrm{H}}\mathbf{w}\right) \tag{14a}$$
$$\text{s.t.} \quad |\mathbf{w}\mathbf{w}^{\mathrm{H}}| \leq P_{max} \tag{14b}$$
$$|\mathbf{w}^{\mathrm{H}}\hat{\mathbf{h}}|^2 \geq \left(\rho^2P_{max}+\sigma\sqrt{2^{r_{\mathrm{req}}}-1}\right)^2, \tag{14c}$$
$$\|\boldsymbol{\Delta}\mathbf{h}\|_2^2 \leq \rho^2, \|\boldsymbol{\Delta}\mathbf{G}_j\|_F^2 \leq v_j^2. \tag{14d}$$

4. Semidefinite programming for precoders design

In problem (P3), the constraint in (14b) is convex, while the objective function in (14a) and the constraint (14c) are not concave, leading to the nonconvexity of the problem. To solve it, one may relax it as a semi-definite programming (SDP) problem [8] as follows.

We first define $\tilde{\mathbf{H}} = \hat{\mathbf{h}}\hat{\mathbf{h}}^{\mathrm{H}}$, $\tilde{\mathbf{G}}_j = \hat{\mathbf{G}}_j\hat{\mathbf{G}}_j^{\mathrm{H}}$, and $\mathbf{W} = \mathbf{w}\mathbf{w}^{\mathrm{H}}$, wherein the following problem (P4) is a relaxed version of (P3) and the rank-one constraint can be naturally dropped as in [5]:

$$P4: \quad \min_{\mathbf{W}} \ -t \tag{15a}$$
$$\text{s.t.} \quad \mathrm{Tr}\left(\tilde{\mathbf{G}}_j\mathbf{W}\right) \geq t \tag{15b}$$
$$\mathrm{Tr}\left(\mathbf{W}\right) \leq P_{max} \tag{15c}$$
$$\mathrm{Tr}\left(\tilde{\mathbf{H}}\mathbf{W}\right) \geq \left(\rho^2P_{max}+\sigma\sqrt{2^{r_{\mathrm{req}}}-1}\right)^2, \tag{15d}$$
$$\|\boldsymbol{\Delta}\mathbf{h}\|_2^2 \leq \rho^2, \|\boldsymbol{\Delta}\mathbf{G}_j\|_F^2 \leq v_j^2, \tag{15e}$$
$$\mathbf{W} \succeq 0, \tag{15f}$$

where t is introduced as a new variable to deal with the non-convex objective function. Note that, in case $\mathbf{W}$ is rank-one, one can obtain the optimal beamformer by using eigenvalue decomposition. On the other hand, solving problem (P4) leads to an upper bound of (P3) [5].

The problem (15) has the standard form of a SDP problem which is convex and can be efficiently solved using the software package cvx [9].

5. SOS for precoders design

In this section, we develop an advanced metaheuristic algorithm based on the so-called symbiotic organisms search (SOS) algorithm [10], known as a powerful and simple metaheuristic algorithm, to address the problem (10). As a general rule, organisms develop symbiotic relationships as a strategy for sustaining life in ecosystems. Based on the behaviors of organisms in nature, this SOS algorithm mimics the three stages of a symbiotic system, namely mutualism, commensalism, and parasitism. Finally, the last remaining organism in the ecosystem is recognized as the best organism.

Let $\mathbf{X}_i = \mathbf{w}_i \in \mathbb{C}^{n_T\times 1}$ be the solution beamforming vector for the energy harvested problem (10), where $\mathbf{X}_i$ is the ith position of the organism in the solution search space, then the ecosystem is a set of solution

$$\mathbb{X} = \left[\mathbf{X}_1, \ldots, \mathbf{X}_{\mathrm{n_O}}\right], \tag{16}$$

where $\mathrm{n_O}$ denotes the number of organisms in the ecosystems (i.e. ecosystem size). The organism's position is updated through the iterative phases of the SOS process described in the algorithm update phases section.

5.1. Mutualism

Mutualism implies a relationship between two organisms of different species, aiming at increasing mutual survival in the ecosystem. More specifically, assuming that $\mathbf{X}_i^{\mathrm{new}}$ and $\mathbf{X}_j^{\mathrm{new}}$ are the new candidate organisms generated from this relationship, then one can express

$$\mathbf{X}_i^{\mathrm{new}} = \mathbf{X}_i + \mathrm{rand}(0,1) * (\mathbf{X}_{\mathrm{best}} - \mathrm{MV} * \mathrm{BF}_1), \tag{17}$$
$$\mathbf{X}_j^{\mathrm{new}} = \mathbf{X}_j + \mathrm{rand}(0,1) * (\mathbf{X}_{\mathrm{best}} - \mathrm{MV} * \mathrm{BF}_2), \tag{18}$$
$$\mathrm{BF}_k = 1 + \mathrm{round}(\mathrm{rand}(0,1)), k = 1, 2, \tag{19}$$
$$\mathrm{MV} = \frac{1}{2}\sum_{k=1}^{2}\mathrm{BF}_k \tag{20}$$

where $\mathbf{X}_{\mathrm{best}}$ denotes the best organism in the ecosystem. BF_k is the k-th benefit factor, MV denotes the mutual vector of the two organisms.

5.2. Commensalism

The principle of this phase lies on a symbiotic link between two individual species, whereine one would take advantage of this relation while the other is uninfluenced. Therefore, the new candidate solution of $\mathbf{X}_i$ is updated if its new fitness value is better than its pre-interaction fitness, i.e.

$$\mathbf{X}_i^{\text{new}} = \mathbf{X}_i + \text{rand}(-1,1) * (\mathbf{X}_{\text{best}} - \mathbf{X}_i). \tag{21}$$

5.3. Parasitism

This phase describes a symbiotic relationship between two individual species, among which one is harmful to the other while the other would benefit from this relationship. Denote $\mathbf{X}_i$ the parasite organism and $\mathbf{X}_j$ the host, which is randomly picked up from the ecosystem. Then the mechanism of parasitism can be summarized as follows. First $\mathbf{X}_i$ replicates itself to make a copy $\mathbf{PV}$, which is called as Parasite Vector. If the fitness value of $\mathbf{PV}$ is higher than that of $\mathbf{X}_j$, it will replace $\mathbf{X}_j$ in the current ecosystem. On the other hand, $\mathbf{X}_j$ will be immunned from $\mathbf{PV}$ and the parasite will be eliminated in the system of interest.

6. Constrained Symbiotic Organisms Search Algorithm to solve (P2)

It is worthy to note that finding the candidate solution in (21) is equivalent to global search solution for an unconstrained optimization problem. On the other hand, the original problem (10) is considered as a constrained optimization one, which requires further processing on transforming the constrained problem.

The search space in constrained optimization problems consists of both feasible and infeasible points. The feasible points satisfy all the constraints, while the non-viable points violate at least one of them. Among the proposed solutions for constraint optimization problems [11], this paper utilizes the penalty function (PF) method [12] to solve problem (10). Basically, the PF method uses a sequence of unconstrained optimization problems to solve the constrained optimization problem [12].

Herein, the penalty function of (10) can be defined as

$$\mathcal{F}(\mathbf{X}_i) = \min\left\{\Phi_{ED_j}(\mathbf{X}_i)\right\} - P_0(\mathbf{X}_i), \tag{22}$$

where $\mathbf{X}_i = \mathbf{w}_i$, $P_0(\mathbf{X}_i)$ is penalty term, which can be defined as

$$P_0(\mathbf{X}_i) = \sum_{j=1}^{2} \lambda_j g_j(\mathbf{X}_i)^2 H(g_j(\mathbf{X}_i)), \tag{23}$$

where $\lambda_j (j \in \{1,2\})$ is the j-th position constraint, called as penalty factor, while $H(g_j(\mathbf{X}_i))$ is the indicator function of $g_j(\mathbf{X}_i)$, and

$$H(g_j(\mathbf{X}_i)) = \begin{cases} 0, & \text{if } g_j(\mathbf{X}_i) \le 0 \\ 1, & \text{otherwise,} \end{cases} \tag{24}$$

and

$$g_1(\mathbf{X}_i) = \text{Tr}\left(\mathbf{w}\mathbf{w}^{\text{H}}\right) - P_{max},$$

$$g_2(\mathbf{X}_i) = \left(\rho^2 P_{max} + \sigma\sqrt{2^{r_{\text{req}}} - 1}\right)^2 - \text{Tr}\left(\mathbf{w}^{\text{H}}\hat{\mathbf{h}}\hat{\mathbf{h}}^{\text{H}}\mathbf{w}\right). \tag{25}$$

We then consider solving the following penalty program by non-constraint SOS-based as follow:

$$\underset{\mathbf{X}_i}{\texttt{maximize}}\ \mathcal{F}(\mathbf{X}_i) \quad \texttt{s.t.}\ \mathbf{X}_i \in \mathbb{C}^{n_T \times 1}. \tag{26}$$

The pseudo-code of the proposed SOS algorithm to solve (26) can be summarized as in Algorithm 1.

Algorithm 1 SOS-based Algorithm to solve (26)

Inputs: The maximum number of iterations n_{Iter}, the ecosystem size (the number of organisms) n_O
Outputs: The best organism in ecosystem $\mathbf{X}_{\text{best}}$
Initialization:
Set $t = 0$ and generate the random ecosystem $\mathcal{X} = \{\mathbf{X}_i\}, \forall i = 1, \ldots, n_O$.
Initiate the best organism in the ecosystem $\mathbf{X}_{\text{best}} = \text{argmax}\{\mathcal{F}(\mathbf{X}_i)\}, i = 1, \ldots, n_O$, where $\mathcal{F}(.)$ defined in (22).
while $t < n_{Iter}$ **do**
  for $i = 1 : n_O$ **do**
    Randomly choose j-th organism $\mathbf{X}_j$, $j \neq i$
    Calculate $\mathbf{X}_i^{\text{new}}$ and $\mathbf{X}_j^{\text{new}}$ by (17) and (18), respectively.
    $\mathbf{X}_i = \mathbf{X}_i^{\text{new}}$ if $\mathcal{F}(\mathbf{X}_i^{\text{new}}) \ge \mathcal{F}(\mathbf{X}_i)$
    $\mathbf{X}_j = \mathbf{X}_j^{\text{new}}$ if $\mathcal{F}(\mathbf{X}_j^{\text{new}}) \ge \mathcal{F}(\mathbf{X}_j)$
    Randomly choose j-th organism $\mathbf{X}_j$, $j \neq i$
    Calculate $\mathbf{X}_i^{\text{new}}$ by (21)
    Update $\mathbf{X}_i = \mathbf{X}_i^{\text{new}}$ if $\mathcal{F}(\mathbf{X}_i^{\text{new}}) \ge \mathcal{F}(\mathbf{X}_i)$
    Generate $\mathbf{PV}$
    $\mathbf{X}_j = \mathbf{PV}$ if $\mathcal{F}(\mathbf{PV}) \ge \mathcal{F}(\mathbf{X}_j)$
    Update $\mathbf{X}_{\text{best}}$
  end for
  $t = t + 1$
end while
return $\mathbf{X}_{\text{best}}$

7. Numerical Results

Now we examine the effectiveness of the proposed algorithms by means of simulations, where 100 independent normalized channel realizations are executed. The simulation parameters are listed in **Table** 1, wherein the maximal transmit power is normalized to have unit value, i.e. $P = 1$, and noise covariance is defined as $\sigma^2 = \text{SNR}/P$. In this work, the Rayleigh fading channel model is adopted.

TABLE 1: System simulation parameters

Parameter	Value
Number of IoT gateway transmitter antennas (n_T)	4, 8
Number of IoT information devices (n_{ID})	1
Number of IoT information device receiver antennas	1
Number of IoT energy harvesting device (n_{ED})	2, 3
Number of IoT information device receiver antennas (n_R)	2
Maximum transmit Power (P_{max})	1
Ecosystem size (n_O)	100
Maximum number of iterations (n_Iter)	20
The energy factor η_j	1

First, we investigate the system performance of the two approaches based on SDP and SOS algorithms with different requirement rates. Fig. 3 shows the average minimum energy harvested at EDs as a function of $\|\Delta\mathbf{G}_j\|_F^2$. In this setting, the system parameters are selected to facilitate the execution of SDP-based algorithm such as $\|\Delta\mathbf{h}\|_2 = 0.1$, SNR $=$ 10dB, $N_{ED} = 3, n_R = 2$, and $n_T = 8$. As one would expect, the harvested energy in the system decreases with the increasing the requirement rate for both cases. Moreover, with a relatively relaxed condition on channel estimation error, e.g. $\|\Delta\mathbf{h}\|_2 = 0.1$, the proposed algorithm based on SDP generally obtains better performance than that of the SOS-based algorithm.

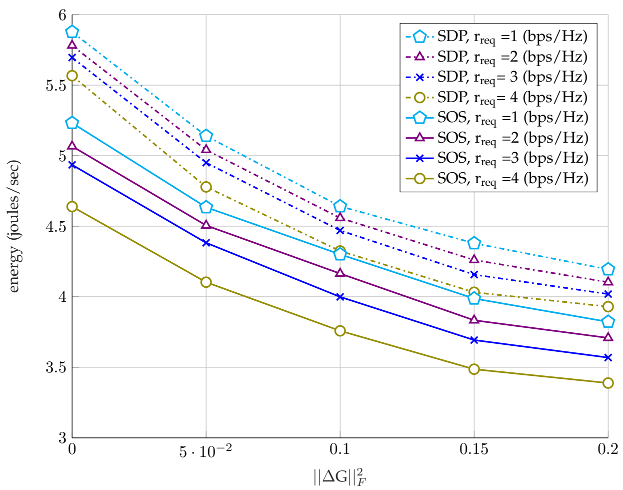

Fig. 3: The average minimum energy harvested at EDs of different algorithms as a function of $\|\Delta\mathbf{G}\|_F^2$ with $\|\Delta\mathbf{h}\|_2 = 0.1$, SNR $=$ 10dB, $N_{ED} = 3, n_R = 2$, and $n_T = 8$.

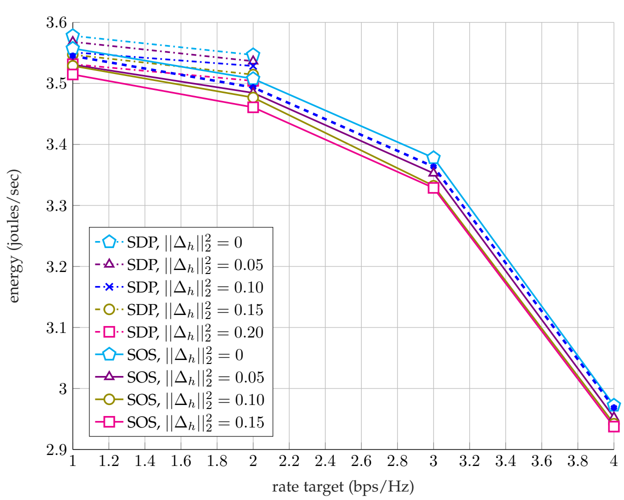

Fig. 4: The average minimum energy at EDs as a function of QoS rate target with $\|\Delta\mathbf{G}_j\|_F = 0.1$, SNR $=$ 10dB, $N_{ED} = 2, n_R = 2$, and $n_T = 4$.

Next, we plot the average harvested energy as a function of the QoS target rates in Fig. 4. Different values of channel estimation error condition $\|\Delta\mathbf{h}\|_2$ are evaluated, showing that the SDP-based approach may experience outage when the conditions on channel uncertainty or QoS required rates are relatively strict, e.g. the QoS rate targets are higher than 2 bps/Hz. This happens because the constraint (15d) is no longer satisfied with QoS target rates increasing, yielding to the failure of SDP-based algorithm in solving problem. Meanwhile, all constraints are always satisfied while executing the SOS algorithm, which makes the SOS be feasible with diverse system setting requirements.

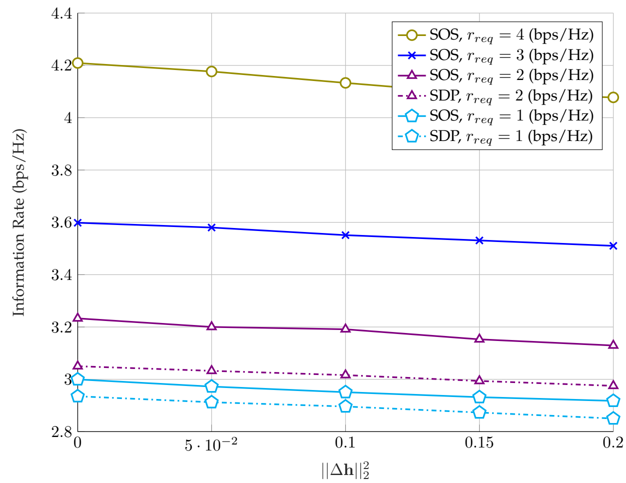

Fig. 5: Information rate at ID as a function of channel estimation error $\|\Delta_{\mathbf{h}}\|_2^2$ when $\|\Delta\mathbf{G}_j\|_F = 0.1$, SNR $= 10dB$, $N_{ED} = 2, n_R = 2$, and $n_T = 4$

The feasibility of the two approaches are further evaluated via the impact of the channel uncertainty $\|\Delta\mathbf{h}_j\|_F^2$ on the average information rate at ID. Fig. 5 shows that with the required rate higher than 2 bps/Hz, i.e. $r_{\mathrm{req}} \in \{3, 4\}$ bps/Hz, optimal solutions are not found with the SDP. On the other hand, this occurs with the SOS algorithm, where the QoS constraints are always met. In the end, the channel estimation error, a frequent source of violating the rate objective at the communication receiver in practice, does not impose any impact on the SOS performance.

8. Conclusion

In this work, we aimed to design robust beamforming for a IoT WIPT network, consisting of both information and energy harvesting receivers using SDP and SOS algorithms. The practical assumption of imperfect CSI is considered for all cases. Extensive simulations have been used to demonstrate the performance of the proposed beamforming algorithm. As a matter of fact, the SDP-based algorithm generally has better performance than that of the SOS one. However, in cases of strict system conditions such as low channel uncertainty, high QoS rate constraint or low transmit power, the traditional approach using SDP may not lead to a feasible solution, whereas SOS-based method always finds a “near optimal” solution. This makes the SOS-based approach a prominent candidate among the solvers due to its superior feasibility, which can adapt to diverse strict conditions in practical scenarios.

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