Power-efficient Antenna Switching and Beamforming Design for Multi-User SWIPT with Non-Linear Energy Harvesting

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***Abstract*—This paper considers the effective power in downlink a multi-antenna, multi-user single-cell network enabled with simultaneous wireless information and power transfer (SWIPT). The proposed power efficiency problem aims to maximize the harvested energy and minimize transmission power consumption simultaneously. Specifically, the beamforming and antenna selection procedures at the receivers are optimized under minimum data rate requirements. The underlying optimization problem is shown to be an intractable non-linear programming problem. As a result, a joint beamforming design and antenna selection is performed based on the scheduling chosen for information decoding and energy harvesting. The main problem is decomposed into two subproblems: antenna selection and beamforming, which yields a locally optimal solution. The first subproblem is solved based on the maximum channel gain across all antennas. While the second subproblem is solved via a two-layer iterative structure based on the sum of ratio programming. Simulation results show that the proposed scheme not only improves power efficiency but also enhances energy efficiency. The results also unveil an interesting tradeoff between power and energy efficiency.**

I. Introduction

Simultaneous wireless information and power transfer (SWIPT) has recently emerged as a promising solution to enhance wireless devices' energy efficiency (EE) and battery lifetime jointly [1]. Some current research works focus on maximizing harvested energy or throughput [2], [3]. However, solely maximizing throughput can increase network power consumption, whereas maximizing harvested energy using SWIPT can adversely affect the information transfer, resulting in the degradation of system quality-of-service (QoS). To this end, EE is an introduced metric that can efficiently handle the tradeoff between power consumption and achievable throughput.

The problem of energy-efficient resource allocation in a SWIPT network is addressed in several research works [4]–[10]. For instance, to maximize the harvested energy, the authors in [4] explore the beamforming design in a multi-cell multi-user SWIPT network. Moreover, the authors in [5] maximize EE via beamforming design for a network based on OFDMA [4]. In [6], a SWIPT network based on non-orthogonal multiple access (NOMA) is considered in which joint power allocation and time switching (TS) control are performed in a TS-based SWIPT system. The authors in [7] assume a SWIPT heterogeneous NOMA network and propose a solution for an EE maximization problem based on the matching concept and using Lagrangian duality. In [8], the authors propose an EE optimization scheme via subcarrier allocation that achieves green communication performance in the wireless sensor networks using the SWIPT technology. A multiple-input single-output (MISO)-SWIPT network is considered in [9] with a non-linear energy harvesting model, where a global EE maximization problem is formulated by jointly optimizing power-splitting ratios and beamforming design. The work in [10] introduces an energy efficiency indicator (EEI) in order to balance between data rate and harvested energy. Remarkably, none of the previous works considered the antenna switching (AS) technique at the receivers balance the tradeoff between information decoding (ID) and energy harvesting (EH) [4]–[10]. Intuitively, multiple receive antennas could improve harvested energy and information transfer. Also, antenna selection can provide an efficient tradeoff between cost, complexity, and performance. The receiver antenna selection process is a generalization of the AS scheme in a co-located SWIPT-based network. Each user antenna could potentially be assigned for ID or EH according to the channel state information (CSI). We refer to this methodology as *"generalized AS technique"* in SWIPT-based networks because, here, the AS acts as a "switch": It selects the antennas' operation modes, although each antenna is capable of both EH and ID, as shown in Fig 1.

A limited number of prior works focused on AS SWIPT systems, where each antenna switches performance between ID and EH [11]–[14]. In [13], the authors consider a pair of multi-antenna receiver and transmitter and propose a novel antenna-clustering method based on the hybrid deep reinforcement learning (DRL) to maximize the average data rate. The authors in [14] consider an AS strategy for a multi-antenna secondary receiver in the cognitive-based network using a thresholding-based method. However, [3], [11], [13], and [14] did not consider the EE perspective of the network, whereas [12] evaluates the EE in a point-to-point multiple-input and multiple-output (MIMO) SWIPT system. Motivated by the practical scenarios, reducing the power consumption while

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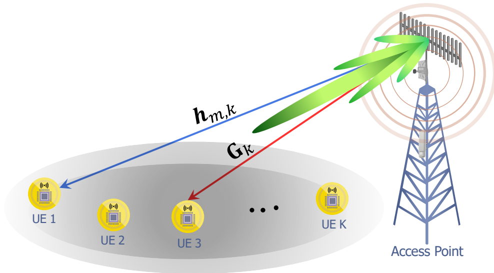

Fig. 1. Generalized AS approach to realize SWIPT architecture.

increasing the harvested power is more beneficial to satisfying the network quality conditions. To our best knowledge, power efficiency maximization with generalized AS and beamforming in a multi-user SWIPT network has not yet been studied.

The main contribution of this paper is the use of generalized AS and beamforming design for a multi-user SWIPT system to optimize the network power efficiency. In particular, we consider the system's power efficiency, defined as the ratio of the total harvested energy to the total power dissipated [15]. Consequently, we aim to optimize the effective power of the network by considering beamforming design for the information and energy signal in a MIMO generalized AS SWIPT system. We also guarantee each user's minimum QoS in the studied scenario in order to balance the tradeoff between ID and EH. We maximize the effective power throughput subject to minimum data rate and maximum power transfer constraints. This is achieved by selecting the receiver antennas and optimizing the beamforming according to the network features. The considered problem is shown to be intractable and non-linear. To tackle this, we decompose the original problem into two subproblems and provide a locally optimal solution for the main problem. In particular, the first sub-problem is solved via searching for the best channel gain across all antennas. The objective function in the second sub-problem follows the sum of objective ratio functions that will be transformed into an equivalent subtractive form. Additionally, we employ the semi-definite programming (SDP) relaxation technique and the one-dimensional search method to obtain an optimal solution iteratively. Simulation results demonstrate the efficacy of the proposed algorithm in terms of effective power efficiency and EE for a different number of antennas and sensor users. Additionally, simulations reveal the tradeoff between EE and effective power efficiency.

II. System Model and Problem Formulation

We consider a downlink (DL) OFDM network in which an access point (AP) covers multiple sensor user equipment (UE)s. The AP and sensor users are equipped with N_T and M antennas. The set of k sensor users in the coverage area is represented by $\mathcal{K} = \{1, 2, ..., K\}$. We assume that the perfect CSI is available at the central resource allocator to design the resource allocation policy[1].

[1]It is assumed that the AP has perfect CSI through a feedback channel. In particular, the AP sends some orthogonal preambles in the downlink to the sensor users and obtains the CSI by listening to the sounding reference signals transmitted by the sensor users.

Table I. Summary of our main notations.

Symbol	Definition
$\boldsymbol{h}_{m,k} \in \mathbb{C}^{N_t \times 1}$	The DL channel gain vector for the information transfer from the AP to the m^{th} antenna of user k.
$\mathbf{G}_k \in \mathbb{C}^{N_t \times M}$	The DL channel matrix for the wireless power transfer from the AP to the user k.
$b_{m,k} \in \{0, 1\}$	Binary indicator that selects the m^{th} antenna from the AP to the k^{th} user for data transmission.
$\boldsymbol{w}_k \in \mathbb{C}^{N_t \times 1}$	The transmit information beamforming of the AP for the k^{th} user.
$\boldsymbol{w}_e \in \mathbb{C}^{N_t \times 1}$	The transmit energy signal of the AP broadcasted to all sensor users.

With multiple antennas available at each user, the best antenna can be selected for either ID or EH based on the resource allocation policy. This means ID and EH can be performed by the same user simultaneously, but not over the same antenna. In particular, the best antenna (from the set $\mathcal{M}$) would be selected for ID while the remaining antennas will be assigned for EH purposes. For the readability, we summarized some of the essential variables used to describe the system model in **Table I**. We further assume that the AP transmits both the information and energy signals simultaneously. Thus, the discrete-time AP transmitted signal will be:

$$\boldsymbol{x} = \sum_{k \in \mathcal{K}} \boldsymbol{w}_k s_k + \boldsymbol{w}_{\boldsymbol{e}}, \tag{1}$$

where $s_k \in \mathbb{C}$ is a unit-energy information carrying symbol. We also note that the energy signal is known to all users, as it is generated at the AP by a deterministic pseudo-random sequence with a predefined seed of zero mean and the covariance matrix of $\mathbf{W_e}$ i.e., $\boldsymbol{w}_e \sim \mathcal{CN}(\mathbf{0}, \mathbf{W}_e)$.

For simplicity, we consider a narrow-band block-fading propagation channel as in [16], [17], which yields the following received ID and EH signals:

$$y_k^{\text{ID}} = \sum_{j \in \mathcal{K}} \boldsymbol{h}_{m,k}^H (b_{m,k} \boldsymbol{w}_j s_j + \boldsymbol{w}_{\boldsymbol{e}}) + n_k^{\text{ID}}, \tag{2}$$

$$\boldsymbol{y}_k^{\text{EH}} = (\mathbf{I}_M - \text{diag}(\boldsymbol{b}_k)) \sum_{j \in \mathcal{K}} \mathbf{G}_k^H (\boldsymbol{w}_j s_j + \boldsymbol{w}_{\boldsymbol{e}}) + \boldsymbol{n}_k^{\text{EH}}, \tag{3}$$

where n_k^{ID} and $\boldsymbol{n}_k^{\text{EH}}$ are additive white Gaussian noise (AWGN) terms with a circularly symmetric Gaussian distribution, i.e., $n_k^{\text{ID}} \sim \mathcal{CN}(0, \sigma_k^{\text{ID}^2})$ and $\boldsymbol{n}_k^{\text{EH}} \sim \mathcal{CN}(\mathbf{0}, \sigma_k^{\text{EH}^2} \mathbf{I}_M)$, respectively. It is assumed that the generalized AS technique can distinguish between the information and power transfer signals. Through this methodology, one group of the receiver antennas can be used for harvesting energy, whereas the other group are responsible for the wireless information processing [18]. The data rate of user k through the received antenna m will be:

$$R_{m,k}(b_{m,k}, \boldsymbol{w}_k) = \log_2 \left(1 + \frac{b_{m,k} |\boldsymbol{h}_{m,k}^H \boldsymbol{w}_k|^2}{\sigma_k^{\text{ID}^2} + I_{m,k}} \right), \tag{4}$$

where the AWGN is considered at the k^{th} user with zero mean and variance $\sigma_k^{\text{ID}^2}$ and $I_{m,k} = \sum_{k' \neq k, k' \in \mathcal{K}} b_{m,k} |\boldsymbol{h}_{m,k}^H \boldsymbol{w}_{k'}|^2$, indicates the multi-user interference. We should note that the EH beams may cause interference in the data rate function in (4). However, since the energy signals are known to the sensor users, the users can remove these undesired signals (even before decoding the information-bearing signals) based on successive interference cancellation [19]. For facilitating the presentation, we define $\boldsymbol{b}_k = [b_{1,k}, ..., b_{M,k}]^T \in \mathbb{Z}^{1\times M}$ as the vector of the antenna selection optimization problem. Consequently, the achievable data rate of user k can be written as:

$$R_k(\boldsymbol{b}_k, \boldsymbol{w}_k) = \sum_{m\in\mathcal{M}} R_{m,k}(b_{m,k}, \boldsymbol{w}_k). \tag{5}$$

We now define a new performance metric, $\mathcal{P}^{\text{eff}}(\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W_e})$, for the wireless power transfer efficiency which is given by [10], [15]:

$$\mathcal{P}^{\text{eff}}(\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W_e}) = \frac{\sum_{k\in\mathcal{K}} P^{\text{EH}}_{\text{NL}_k}(\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W_e})}{P_{\text{T}}(\boldsymbol{w}_k, \mathbf{W_e})}. \tag{6}$$

The denominator of (6), $P_{\text{T}}(\boldsymbol{w}_k, \mathbf{W_e})$, is the total power dissipated in the system in [Joule/Second] given by:

$$P_{\text{T}}(\boldsymbol{w}_k, \mathbf{W_e}) = \frac{\sum_{k\in\mathcal{K}} ||\boldsymbol{w}_k||^2 + \text{Tr}(\mathbf{W_e})}{\beta} + N_T P_{\text{ant}} + P_c, \tag{7}$$

where P_{ant} and P_c are the dissipated power in each transmit antenna and fixed consumed power for baseband signal processing, respectively [20]. We note the first term in (7) is the so-called radio frequency (RF)'s transmit power consumption that is divided by $0 < \beta \leq 1$, the constant AP power amplifier efficiency. The numerator in (6), $P^{\text{EH}}_{\text{NL}_k}(\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W_e})$ is the total harvested energy in the network topology. The harvesting is realized using the active EH antennas for each user. The total harvested energy is then given by [15], [19]:

$$P^{\text{EH}}_{\text{NL}_k}(\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W_e}) = \frac{[\Theta_k - \Omega_k \Delta_k]}{1 - \Delta_k}, \ \Delta_k = \frac{1}{1 + \exp(\alpha_k \zeta_k)}, \tag{8}$$

$$\Theta_k = \frac{\Omega_k}{1 + \exp\big(-\alpha_k (P^{\text{EH}}_{\text{L}_k}(\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W_e}) - \zeta_k)\big)}. \tag{9}$$

The constant Δ_k is introduced to guarantee a zero-input/zero-output response for EH [19]. In the traditional logistic function (9), the linear factor is given by

$$P^{\text{EH}}_{\text{L}_k}(\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W_e}) = \epsilon_k \text{Tr}\Big(\sum_{j\in\mathcal{K}} \tilde{\mathbf{G}}^{\text{H}}_k (\boldsymbol{w}_j \boldsymbol{w}_j^H + \mathbf{W_e}) \tilde{\mathbf{G}}_k\Big), \tag{10}$$

where $\tilde{\mathbf{G}}_k = \Big(\mathbf{I} - \text{diag}(\boldsymbol{b}_k)\Big)\mathbf{G}_k$. In the total linear received RF power formula (10), $0 < \epsilon_k < 1$ is the power conversion efficiency for the m^{th} active EH antenna of the k^{th} receiver. Ω_k is a constant parameter defined as the maximum harvested power at user k when the EH circuit becomes saturated. α_k and ζ_k are constant parameters that can be obtained by a curve fitting tool. We should note that the contribution of the noise power to the $P^{\text{EH}}_{\text{NL}_k}(\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W_e})$ formula can be neglected, as it is very small compared to the main term.

Now, we formulate the main optimization problem of beamforming design with the antenna selection for the new performance metric with a generalized AS-based SWIPT framework in a single-cell multi-user network. The optimization problem can be written as follows:

$$\text{P}_1: \max_{\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W}_e} \mathcal{P}^{\text{eff}}(\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W}_e) \tag{11}$$

$$\text{s.t.}: \sum_{k\in\mathcal{K}} ||\boldsymbol{w}_k||^2 + \text{Tr}(\mathbf{W}_e) \leq p_{\max}, \tag{11a}$$

$$R_k(\boldsymbol{b}_k, \boldsymbol{w}_k) \geq R_{\min}, \ \forall k \in \mathcal{K}, \tag{11b}$$

$$\sum_{m\in\mathcal{M}} b_{m,k} = 1, \qquad \forall k \in \mathcal{K}, \tag{11c}$$

$$b_{m,k} \in \{0, 1\}, \qquad \forall k \in \mathcal{K}, \forall m \in \mathcal{M}. \tag{11d}$$

In the optimization problem P_1, constraint (11a) limits the total transmit power of the AP that should not exceed its maximum threshold ($p_{\max}$). Constraint (11b) guarantees a minimum data rate requirement, $R_{\min}$, for each user k. Constraint (11c) determines that each user utilizes only one antenna for ID. (11d) shows the antenna selection variable takes only binary values. Since the antenna selection variable is binary, the optimization problem P_1 is a mixed-integer non-linear programming (MINLP) problem, which is generally intractable [21]. We aim to propose a solution design for this proposed problem and scenario.

III. A Two-layer Optimal Solution Design

To solve this problem, we decompose the original problem into two sub-problems — antenna selection and beamforming subproblems. The first subproblem is solved based on the maximum channel gain across all antennas. The second sub-problem is optimally solved via a two-layer iterative structure based on the sum of ratio programming. In particular, we first select the best antenna for ID to satisfy the data rate requirement and assign the rest of the antennas for EH. Then, we design the beamforming policy, respecting the objective function. Please note that the Dinkelbach method or the Charnes-Cooper transformation cannot be exploited to handle sum-of-ratios objective function. In what follows, we explain each step in detail.

A. Antenna Selection

We now first carry out the antenna selection for the fixed beamforming. It can be seen that from the optimization problem only one antenna should be selected for the ID while the rest would be used for EH. The main dilemma in the optimization problem P_1 is the data rate QoS requirement for each user. One can conclude that in order to meet the data rate requirement for each user, the highest channel gain over all the antenna needs to be selected for ID as follows:

$$b_{m,k} = \begin{cases} 1, & \underset{m\in\mathcal{M}}{\text{argmax}} \ \boldsymbol{h}_{m,k}, \forall k \in \mathcal{K}, \\ 0, & \text{otherwise}. \end{cases} \tag{12}$$

In essence, we examine the channel quality between the AP and all user's antennas via (12), and subsequently select the best channel quality for ID purposes[2]. The rest of the antennas are then assigned for EH. By assigning the best channel gain to the ID antenna (not EH antennas), we are prioritizing information signals over the energy signal to ensure the practicality of our design policy. Please note that the complexity of the antenna selection algorithm will not be exponential. This is because the number of antennas is usually insignificant in a typical mobile receiver.

B. Beamfroming Design

Next, we design the information and energy beamforming to maximize the power efficiency. Let us define matrices $\mathbf{W}_k = \boldsymbol{w}_k \boldsymbol{w}_k^{\mathbf{H}}$, $\mathbf{W}_k \in \mathbb{H}^{N_T \times N_T}$ and $\mathbf{H}_k = \boldsymbol{h}_{m,k} \boldsymbol{h}_{m,k}^{\mathbf{H}}$.

[2] Here, we assume that the users are sensor nodes. These nodes do not need to transmit with a high data rate and are more interested in EH.

For simplicity, we ignore the constant terms in the total power consumption model in (7). Thus, using the semi-definite programming (SDP), the original optimization problem in P_1 can be reformulated as follows:

$$\mathrm{P}_2: \max_{\mathbf{W}_k,\mathbf{W}_e} \frac{\sum_{k\in\mathcal{K}} P^{\mathrm{EH}}_{\mathrm{NL}_k}(\mathbf{W}_k,\mathbf{W}_\mathbf{e})}{\sum_{k\in\mathcal{K}} \mathrm{Tr}(\mathbf{W}_k)+\mathrm{Tr}(\mathbf{W}_e)} \tag{13}$$

$$\text{s.t.}: \sum_{k\in\mathcal{K}} \mathrm{Tr}(\mathbf{W}_k)+\mathrm{Tr}(\mathbf{W}_e) \le p_{\max}, \forall k\in\mathcal{K}, \tag{13a}$$

$$\overline{R}_k(\mathbf{W}_k) \ge \mathrm{R}_{\min}, \quad \forall k\in\mathcal{K}, \tag{13b}$$

$$\mathrm{Rank}(\mathbf{W}_k) \le 1, \quad \forall k\in\mathcal{K}, \tag{13c}$$

$$\mathbf{W}_\mathbf{e} \succeq 0. \tag{13d}$$

We employ SDP relaxation by dropping the rank one constraint. Next, we handle the constraint (13b). In doing so, we restate this constraint as follows:

$$\frac{\mathrm{Tr}(\mathbf{H_k}\mathbf{W}_k)}{\gamma_{\mathrm{req}}} \ge \sum_{k'\neq k} \mathrm{Tr}(\mathbf{H}_k\mathbf{W}_{k'}) + \sigma_k^2, \tag{14}$$

where $\gamma_{\mathrm{req}} = 2^{R_{\min}} - 1$. Furthermore, the non-linear objective function is non-convex, but it is possible to set it compatible to the class of sum of ratio objective functions. To this end, we introduce a new slack variable ϱ that changes the optimization problem as follows:

$$\mathrm{P}_3: \max_{\mathbf{W}_k,\mathbf{W}_e} \frac{\sum_{k\in\mathcal{K}} P^{\mathrm{EH}}_{\mathrm{NL}_k}(\mathbf{W}_k,\mathbf{W}_e)}{\varrho}, \tag{15}$$

$$\text{s.t.}: \sum_{k\in\mathcal{K}} \mathrm{Tr}(\mathbf{W}_k)+\mathrm{Tr}(\mathbf{W}_e) = \varrho, \tag{15a}$$

$$(13\text{a}), (13\text{d}), \text{and } (14).$$

In order to solve this optimization problem, we consider an iterative algorithm in which the first subproblem determines $\mathbf{W}_k$ and $\mathbf{W_e}$ for a preset ϱ and the second subproblem updates ϱ based on new obtained beamforming vectors. In the first subproblem, the optimization problem in (15) follows the sum of objective ratio functions that Dinkelbach cannot be adopted to obtain a solution method. So, we first find an equivalent form in subtractive form which yields the same optimal solution based on the following lemma from [21].

Lemma 1 [21]: For (15), there exist two vectors $\boldsymbol{\psi^*} = [\psi^*,...,\psi_K^*]^T$ and $\boldsymbol{\beta^*} = [\beta_1^*,...,\beta_K^*]^T$ in which $\mathbf{W}_k^*$ and $\mathbf{W_e}^*$ are the optimal solutions to the following optimization problem

$$\max_{\{\mathbf{W}_k^*,\mathbf{W_e}^*\}\in\mathcal{S}} \frac{1}{\varrho}\sum_{k\in\mathcal{K}} \psi_k^*\left[\Omega_k\left(1-\Delta_k\mathit{\Gamma}_k\right)-\beta_k^*\left(\mathit{\Gamma}_k(1-\Delta_k)\right)\right], \tag{16}$$

where $\mathcal{S}$ is the set belonging to the feasible solution of P_3. In (16), $\mathit{\Gamma}_k = 1+\exp\big(-\alpha_k(P^{\mathrm{EH}}_{\mathrm{L}}(\mathbf{W}_k,\mathbf{W_e})-\zeta_k)\big)$. Note that $\{\mathbf{W}_k^*,\mathbf{W_e}^*\}$ should satisfy the following equations

$$\Omega_k\left(1-\Delta_k\mathit{\Gamma}_k\right)-\beta_k^*\left(\mathit{\Gamma}_k(1-\Delta_k)\right)=0, \tag{17}$$

$$\psi_k^*\left(\mathit{\Gamma}_k(1-\Delta_k)\right)-1=0. \tag{18}$$

Subproblem (16) can be solved with two-layer iterative structure including an inner and an outer layer. In the following, we describe these layers' functionality.

1) Inner Layer Solution: In the inner layer, assuming the given ψ and β, the optimization problem P_4 which is convex

Algorithm 1 Resource Allocation Algorithm for Beamforming Design

1: **Initialize**
iteration index of resource allocation policy $i=1$,
limitation over two layer iteration of $I_{\max}$
define feasible set vector ϱ, and constant set $\{\alpha,\zeta,\Omega,\epsilon_k,\tau,\kappa\}$.
2: **repeat**
3: Set $\{\mathbf{W}_k^i,\mathbf{W_e}^i\} = \{\mathbf{W}_k^{s^*},\mathbf{W_e}^{s^*}\}$.
4: Solve the inner-layer of (16) to update $\{\mathbf{W}_k^{i+1},\mathbf{W_e}^{i+1}\}$.
5: Solve the outer-layer of (16) to update $\{\boldsymbol{\beta}^{i+1},\boldsymbol{\Psi}^{i+1}\}$ regarding (22) and (22).
6: **until** $i = I_{\max}$
7: Update ϱ for the obtained $\{\mathbf{W}_k^{i+1},\mathbf{W_e}^{i+1}\}$ via one dimensional search method.
8: **return** $\{\varrho,\mathbf{W}_k^{i+1},\mathbf{W_e}^{i+1}\}$

and can be solved efficiently.

$$\mathrm{P}_4: \max_{\mathbf{W}_k,\mathbf{W_e},\lambda_k} \frac{1}{\varrho}\sum_{k\in\mathcal{K}} \psi_k\Big[\Omega_k-\beta_k\big(1+\exp\big(-\alpha_k(\lambda_k-\zeta_k)\big)\big)\Big], \tag{19}$$

$$\text{s.t.}: \lambda_k \le \epsilon_k \mathrm{Tr}\Big(\sum_{j\in\mathcal{K}} \tilde{\mathbf{G}}_k^{\mathrm{H}}(\boldsymbol{w}_j\boldsymbol{w}_j^H+\mathbf{W_e})\tilde{\mathbf{G}}_k\Big), \tag{19a}$$

$$(13\text{a}), (13\text{d}), (14), \text{and } (15\text{a}),$$

where λ_k is the auxiliary optimization variable.

2) Outer-Layer Solution: For the outer layer, an iterative algorithm based on the damped Newton method is employed to obtain ψ and β. In this regard, we define

$$\phi_k(\beta_k) = \Omega_k\left(1-\Delta_k\mathit{\Gamma}_k\right)-\beta_k^*\left(\mathit{\Gamma}_k(1-\Delta_k)\right), \tag{20}$$

$$\phi_{K+k}(\psi_k) = \psi_k\left(\mathit{\Gamma}_k(1-\Delta_k)\right)-1, \tag{21}$$

where $k\in\{1,2,...,K\}$. It has been shown in [19] that the optimal solution $\{\boldsymbol{\beta^*},\ \boldsymbol{\psi^*}\}$ can be found if and only if $\phi(\boldsymbol{\beta},\ \boldsymbol{\psi}) = [\phi_1,...,\phi_{2K}]^T = 0$. As a result the update rule for ψ_k and β_k at i-th iteration are given by

$$\boldsymbol{\beta^{i+1}} = \boldsymbol{\beta^i} + \tau^i\boldsymbol{\eta}^i_{1:K}, \tag{22}$$

$$\boldsymbol{\psi^{i+1}} = \boldsymbol{\psi^i} + \tau^i\boldsymbol{\eta}^i_{K+1:2K}, \tag{23}$$

where $\boldsymbol{\eta} = [\boldsymbol{\phi'}(\boldsymbol{\beta},\ \boldsymbol{\psi})]^{-1}\boldsymbol{\phi}(\boldsymbol{\beta},\ \boldsymbol{\psi})$, and $\boldsymbol{\phi'}(\boldsymbol{\beta},\ \boldsymbol{\psi})$ is the Jacobian matrix of $\boldsymbol{\phi}(\boldsymbol{\beta},\ \boldsymbol{\psi})$. Furthermore, τ^i is the largest value of ε^l that should satisfy the following criterion

$$\|\boldsymbol{\phi}(\boldsymbol{\psi}^i+\varepsilon^l\boldsymbol{\eta}^l_{K+1:2K},\boldsymbol{\beta}^i+\varepsilon^l\boldsymbol{\eta}^i_{1:K})\| \le (1-\kappa\varepsilon^l)\|\boldsymbol{\phi}(\boldsymbol{\beta},\boldsymbol{\psi})\|, \tag{24}$$

where $l\in\{1,2,...\}$, $\varepsilon^l\in(0,1)$, and $\kappa\in(0,1)$. Since the optimization problem (16) is convex, it can be solved in an efficient manner based on the pseudo-code in **Algorithm 1**. It should be noted that one-dimensional search needs to be adopted on ϱ, where the problem P_4 should be solved for each value of ϱ[3]. It is worth mentioning that the considered problem is a convex SDP problem and can be solved by standard numerical algorithms for convex programs such as the interior point method. Now, we discuss the rank-one solution. Fortunately, it has been proven that the rank-one solution for beamforming exists [19].

[3]The upper bound for ϱ is $p_{\max}$ which restricts the search problem.

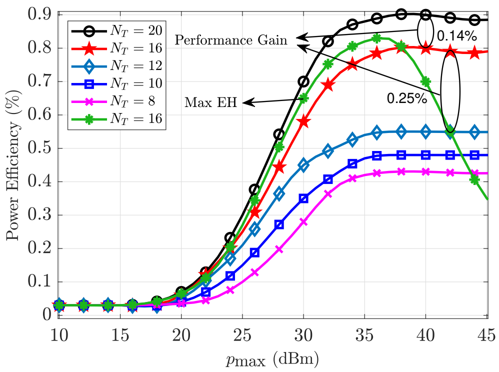

Fig. 2. Power efficiency versus maximum allowed transmit power.

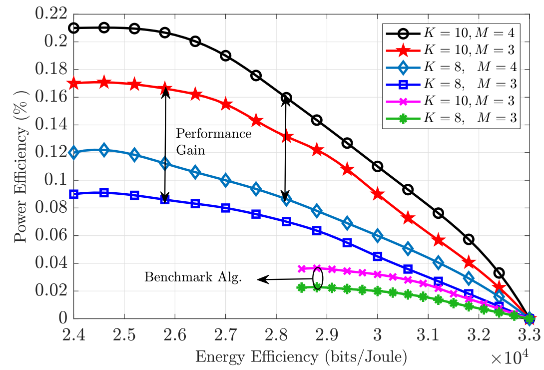

Fig. 3. System performance tradeoff between power efficiency and EE for $p_{\max} = 40$ dBm.

IV. Simulation Results

This section presents simulation results to demonstrate the system performance of power-efficient antenna switching and beamforming design for a multi-user SWIPT system. In evaluating the achievable power-efficiency of the proposed scheme, eight sensor users, $K = 8$, are uniformly located in one cell, where maximum coverage of the cell is $d_{\max} = 20$ meters. The AP and sensor users are each equipped with four and three antennas, respectively ($N_T = 4$, $M = 3$). The AP antenna power consumption is, $P_{\text{ant}} = 30$ dBm, and the static circuit power consumption is $P_c = 40$ dBm. The background noise on all antennas of each receiver is $|\sigma_k^{\text{ID}}|^2 = \sigma_k^2 = \sigma^2 = -120$dBm. We consider a frequency-selective fading channel, and since the users are close to the transmitter, line-of-sight communication channels are expected, and a small-scale fading channel is modeled as Rician fading with Rician factor $\rho = 3$ dB. The Rician flat fading channel gains include a distance-dependent path loss component and a log-normal shadowing component with 8 dB standard deviation, where the path loss exponent is equal to $\alpha = 2.8$ [18]. The power conversion efficiency of all active EH antennas is $\epsilon_k = \epsilon = 0.3$. The power amplifier efficiency of the AP is $\beta = 0.2$. The target transmission rate for each user is $\gamma_{\text{req}} = 10$ dB. Furthermore, we conduct Monte Carlo simulations by generating random realizations of the channel gains to obtain the average EE [18].

Fig. 2 demonstrates that increasing the maximum allowable power budget increases the power efficiency of the network non-linearly. This incremental process is entirely significant for the higher values of available $p_{\max}$. Clearly, there is no sensible change in the power efficiency between 5 dBm and 20 dBm of the $p_{\max}$. For a power budget from 20 dBm to 35 dBm, the power efficiency increases moderately for a small number of antennas whereas sharply for a large number of antennas. However, between approximately 35 dBm and 45 dBm values of $p_{\max}$, the power efficiency is saturated by increasing the power budget. This is because the power efficiency is dominated by the fixed circuit power consumption when transmit power is small, which translates into a gradually increasing power efficiency rate. As the transmit power budget of the AP increases, the RF's transmit power consumption becomes significantly larger compared to the fixed circuit power. Therefore, the power efficiency becomes more sensitive to increases in transmit power budget once a threshold of $p_{\max}$ is reached. This figure also investigates that increasing the number of transmit antennas, N_T, enhances the effective power efficiency, which is predictable as power efficiency is a quasi-linear function with respect to both transmit information and energy beamforming vectors. For comparison, we considered the EH maximization, Max EH, as a baseline scheme in which the numerator of power efficiency is maximized via the same approach as power efficiency optimization. We can see that our proposed algorithm outperforms the baseline scheme since we also minimized the total power consumption in power efficiency maximization. Also, the results show that for the case we solely maximized EH, the power efficiency increases for a small to moderate value of the maximum transmit power. However, power efficiency declines significantly for the high values of $p_{\max}$. This is because once the maximum EH is achieved, a further increase in the total transmitted power increases the denominator of the power efficiency, which likewise results in the degradation of the power efficiency.

There exists an inevitable tradeoff between power and EE. Generally, a resource allocation policy maximizing power efficiency cannot simultaneously maximize the EE in the considered system since data rate and power consumption are conflicting design objectives. To verify this statement, we first define EE as the ratio of achievable data rate (5) to total network's power consumption (7) as follows

$$\mathcal{E}^{\text{eff}}(\boldsymbol{b}_k, \boldsymbol{w}_k, \mathbf{W_e}) = \frac{\sum_{k\in\mathcal{K}} R_k(\boldsymbol{b}_k, \boldsymbol{w}_k)}{P_{\text{T}}(\boldsymbol{w}_k, \mathbf{W_e})}. \tag{25}$$

In Fig. 3, we observe a tradeoff region between power and energy efficiencies by maximizing EE (25). As can be seen, power efficiency (EE) is a monotonically decreasing function with respect to EE (power efficiency). Fig. 3 shows that an increase in the number of receiver antennas improves the power efficiency as receiver antennas help harvest more energy in a network. The number of sensor users also affects the network's throughput and power efficiency. Increasing the number of sensor users not only enlarges the performance tradeoff gap between the power and energy efficiencies it also improves the power efficiency with a fixed value of EE. This is because more sensor users mean more harvesting antennas, i.e., more of the emitted power from the AP can be

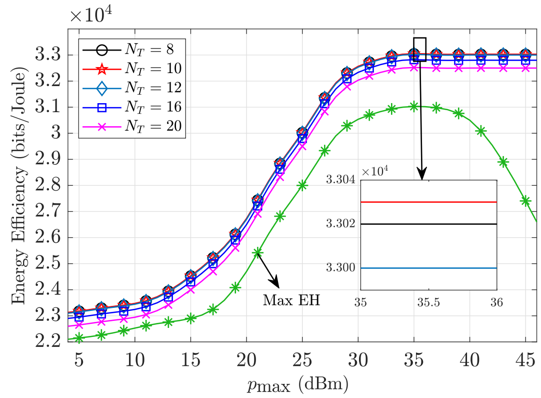

Fig. 4. EE versus maximum allowed transmit power.

harvested when more receivers (more EH antennas) partake in the energy harvesting. For comparison, we also plot the tradeoff region for the case the energy signal ($\mathbf{W}_E$) is set to zero, and maximum ratio transmission is adopted to optimize the information beamforming as a benchmark algorithm.

Fig. 4 shows that increasing the power budget increases the EE monotonically up to certain values of $p_{\max}$. But the EE reaches to its maximum value and then saturates for the high value of transmit power at about $p_{\max} \approx 30$ dBm. This reveals when maximum EE is reached via transmitting a large power budget, any additional increase in $p_{\max}$ will not further increase the EE since the interference power level arising from the AP dramatically impacts received ID signal quality and limits the data rate value. Finally, although the number of transmit antennas improves power efficiency significantly, it has a limited effect on EE. This is because the data rate function in (25), is a logarithmic function of N_T. However, the EE gain associated with extra transmit antennas is insufficient to compensate for the boosted energy cost since the circuit power grows linearly with N_T. Thus, embracing a considerably large N_T may not be viable for improving ID, as is the case for EH. Fig. 4 also explores the superiority of our proposed algorithm compared to the baseline Max EH scheme.

V. Conclusion

In this paper, we have proposed a new optimization problem for the MIMO-OFDM network with generalized AS-based receivers using SWIPT. Considering a practical non-linear power model for EH, the proposed solution aims to maximize a new wireless communication metric, the so-called power efficiency. The optimization problem, which involves a joint optimization of the antenna selection and beamforming, was non-convex and non-linear with binary variables. This made the optimization problem challenging to tackle. To obtain a feasible solution, an optimization problem with a transformed objective function was designed based on an iterative algorithm which yields a locally optimal solution. In particular, the antenna selection problem was solved based on maximum channel gain across all antennas. The second sub-problem was solved based on a two-layer method. Simulation results revealed the superiority of the generalized AS scheme by demonstrating a good balance of improvement in terms of power and EE.

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