Latency-Aware Joint Transmit Beamforming and Receive Power Splitting for SWIPT Systems

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***Abstract*—This paper considers a multi-user multiple-input-single-output (MU-MISO) broadcast scenario with power splitting (PS) based simultaneous wireless information and power transfer (SWIPT). Specifically, we propose a novel joint transmit beamforming and receive PS strategy aiming to minimize the total transmit power of the base station (BS) under user-specific latency constraints. We use the Lyapunov optimization framework and derive a dynamic control algorithm to transform the long-term time-average sum-power minimization problem into a sequence of deterministic and independent subproblems. Furthermore, the combinations of coupled and non-convex constraints are handled using semidefinite relaxation (SDR) and fractional programming (FP) techniques. The numerical examples illustrate the trade-offs between average transmit power and harvested power while ensuring the user-specific latency requirements.**

I. Introduction

The simultaneous wireless information and power transfer (SWIPT) is an emerging paradigm that contributes to realize green wireless Internet-of-Things (IoT) networks [1]. A SWIPT system enables the maximal utilization of radio resources by not only conveying useful information but also providing power over-the-air to energy-constrained and/or battery-limited wireless devices [2].

Due to relatively low power transfer and short operating distance, the downlink multi-antenna broadcast SWIPT scenario is attractive and has been widely studied in the literature, e.g., [3], [4]. More specifically, a multi-antenna base-station (BS) communicates with several user equipments (UEs), where each UE can perform energy harvesting (EH) as well as an information decoding (ID) functions, i.e., either by applying time-switching (TS) [3] or power splitting (PS) [3], [4] techniques. As an example, the early pioneering work [3] considers the broadcast SWIPT scenario with joint energy and information decoding receivers, and characterizes the rate-energy trade-offs under TS and PS mechanisms. Though a TS scheme simplifies the receiver design, it hinders the full exploitation of the SWIPT system, and thus motivates the use of PS schemes [4]–[8].

In literature, the joint optimization of downlink beamforming vectors and receive PS ratios has gained great interest [5]–[8]. The authors in [5]–[8] minimized the total transmit power in a downlink multi-user system with EH and quality-of-service (QoS) requirements. However, the SWIPT techniques in [5]–[8] were not originally designed for the stringent latency requirements of, e.g., industrial-grade delay bound applications, and thus motivating the current work.

In this paper, we provide a novel joint transmit beamforming and receive PS strategy that concurrently satisfies the user-specific harvested power and latency requirements of a SWIPT system. Specifically, we consider a time-average sum-power minimization objective subject to a minimum harvested power constraint and a maximum allowable queue length constraint for each user. We employ the Lyapunov optimization framework [9], specifically the *drift-plus-penalty* function, to transform the long-term time-average problem into a sequence of deterministic and independent subproblems. Furthermore, in each subproblem, the non-convex and coupled constraints are handled by applying the techniques of semidefinite relaxation (SDR) [10] and fractional programming (FP) [11]. The proposed method provides insights into the trade-offs between achievable harvested power at UE and required transmit power at BS, while ensuring the user-specific latency requirements.

II. System Model

We consider a multi-user multiple-input single-output (MU-MISO) SWIPT system where K single antenna UEs are served by a BS equipped with N_t transmit antenna elements. We use $\mathcal{K} = \{1, 2, \ldots, K\}$ to denote the set of all UEs. For simplicity, but without loss of generality, we assume that the network operates in a time-slotted manner, and time slots are normalized to an integer value, e.g., $t \in \{1, 2, \ldots\}$. Then, the downlink received signal during time slot t at k-th UE can be expressed as

$$\begin{aligned} y_k(t) = \ & \mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_k(t)d_k(t) \\ & + \sum_{u\in\mathcal{K}\setminus k} \mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_u(t)d_u(t) + w_k(t), \end{aligned} \tag{1}$$

where $\mathbf{h}_k(t) \in \mathbb{C}^{N_t\times 1}$ and $\mathbf{f}_k(t) \in \mathbb{C}^{N_t\times 1}$ denote the channel vector and the transmit beamforming vector, respectively. In expression (1), $w_k \in \mathcal{CN}(0, \sigma_k^2)$ represents the circularly symmetric additive white Gaussian noise (AWGN), and d_k is the transmitted data symbol for k-th UE. Moreover, we assume that the transmitted data symbols are independent and normalized, i.e., $\mathbb{E}\{d_k d_u^*\} = 0$ and $\mathbb{E}\{|d_k|^2\} = 1,\ \forall k, u \in \mathcal{K}$.

Furthermore, we assume that each UE implements PS for simultaneous information decoding and radio frequency (RF) energy harvesting [3]–[8]. More specifically, the received

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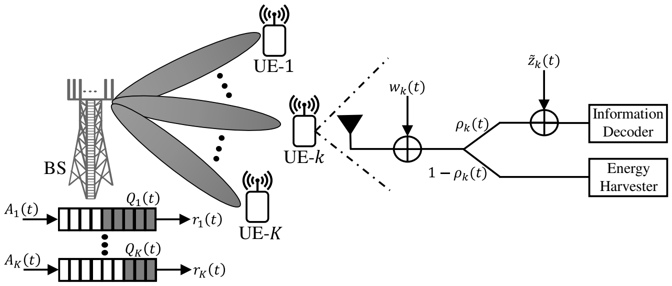

Fig. 1: SWIPT system with one BS and multiple UEs, where each UE uses PS to coordinate EH and ID simultaneously.

signal $y_k(t)$ at each user k is split to the ID and the EH circuit by a dedicated power splitter, as shown in Fig. 1. Let $\rho_k(t) \in [0,1]$ denote the PS ratio to the ID circuit, and remaining $1-\rho_k(t)$ portion to the EH circuit. Thus, the portion of the received signal split to the ID circuit of k-th UE during time slot t can be expressed as

$$y_k^{\mathrm{ID}}(t) = \sqrt{\rho_k(t)}\big(\mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_k(t)d_k(t) + \sum_{u\in\mathcal{K}\setminus k}\mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_u(t)d_u(t) + w_k(t)\big) + \tilde{z}_k(t), \quad (2)$$

where $\tilde{z}_k \in \mathcal{CN}(0,\delta_k^2)$ denotes the additive noise at the ID circuit of k-th UE. Then, the received signal-to-interference-plus-noise ratio (SINR) is given by

$$\Gamma_k(t) = \frac{\rho_k(t)|\mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_k(t)|^2}{\rho_k(t)\Big(\sum\limits_{u\in\mathcal{K}\setminus k}|\mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_u(t)|^2 + \sigma_k^2\Big) + \delta_k^2} = \frac{\rho_k(t)|\mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_k(t)|^2}{\rho_k(t)\sum\limits_{u\in\mathcal{K}\setminus k}|\mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_u(t)|^2 + \rho_k(t)\sigma_k^2 + \delta_k^2}. \quad (3)$$

Contrarily, the remaining portion of the received signal split to the EH circuit of k-th UE during time slot t can be expressed as

$$y_k^{\mathrm{EH}}(t) = \sqrt{1-\rho_k(t)}\big(\mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_k(t)d_k(t) + \sum_{u\in\mathcal{K}\setminus k}\mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_u(t)d_u(t) + w_k(t)\big). \quad (4)$$

Then, the power harvested by the EH of k-th UE is given by

$$\mathrm{E}_k(t) = \zeta_k\big(1-\rho_k(t)\big)\Big(\sum_{j\in\mathcal{K}}|\mathbf{h}_k^{\mathrm{H}}(t)\mathbf{f}_j(t)|^2 + \sigma_k^2\Big), \quad (5)$$

where $\zeta_k \in (0,1]$ represents the energy conversion efficiency. Note that we are considering a simple linear model as in [3]–[8] to allow some analytical tractability and facilitate the discussions. However, the results and the performance trends illustrated in this work should still approximately hold when considering more evolved EH models.

A. Network Queueing & Delay Model

We assume that the BS maintains a set of finite-length queues for storing the network-layer data of all served UEs [9, Ch. 5]. We use $Q_k(t)$ to represent the current queue backlog of k-th UE, while $A_k(t)$ denotes the amount of data arriving during time slot t with a mean arrival rate of $\mathbb{E}[A_k(t)] = \alpha_k$ bits for all $k \in \mathcal{K}$. Then, the queue dynamics of k-th UE can be expressed as

$$Q_k(t+1) = \big[Q_k(t) - r_k(t) + A_k(t)\big]^+, \quad \forall k, \quad (6)$$

where $r_k(t) \triangleq \log_2(1+\gamma_k(t))$ is the downlink rate and $\gamma_k(t)$ denotes the achievable SINR of k-th UE during time slot t.

According to Little's law, the average delay is directly proportional to the long-term average queue length [12, Ch. 1.4]. Thus, the user-specific latency requirements can easily be achieved by imposing the constraint on the user's queue length for each time slot. Similar to [13], here we also use a probabilistic queue length constraint, which is defined as

$$\Pr\big\{Q_k(t) \geq Q_k^{\mathrm{th}}\big\} \leq \epsilon, \quad \forall t, \quad (7)$$

where Q_k^{th} is the maximum allowable queue length for k-th UE and $\epsilon \ll 1$ is the tolerable queue length violation probability.

B. Problem Formulation

Our objective is to develop a power-efficient transmit beamforming and receive PS scheme which jointly satisfies the user-specific latency and EH requirements. Specifically, we jointly optimize the downlink beamforming vectors and PS ratios so as to minimize the BS average transmit power subject to a maximum allowable queue length constraint and a minimum harvested power constraint for each user. The optimization problem can be formulated as

$$\min_{\mathbf{f}_k(t),\gamma_k(t),\rho_k(t),\ \forall t} \quad \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\Big(\sum_{k\in\mathcal{K}}\mathbb{E}\big[\|\mathbf{f}_k(t)\|^2\big]\Big) \quad (8a)$$

$$\text{s.t.} \quad \Pr\big\{Q_k(t) \geq Q_k^{\mathrm{th}}\big\} \leq \epsilon, \quad \forall k,\ \forall t, \quad (8b)$$

$$\gamma_k(t) \leq \Gamma_k(t), \quad \forall k,\ \forall t, \quad (8c)$$

$$\mathrm{e}_k(t) \leq \mathrm{E}_k(t), \quad \forall k,\ \forall t, \quad (8d)$$

$$0 \leq \rho_k(t) \leq 1, \quad \forall k,\ \forall t, \quad (8e)$$

where $\mathrm{e}_k(t)$ denotes the minimum harvested power requirement of k-th UE to support its receiver operations at each time slot t. Note that constraint (8b) guarantees that the queue backlog of k-th UE at each time slot t is less than Q_k^{th} with probability $1-\epsilon$, e.g., ensures the latency requirements.

III. Dynamic Control Algorithm via Lyapunov Optimization Framework

Problem (8) is intractable as it consists of a long-term time-average sum-power objective function (8a), a non-linear probabilistic latency constraint (8b), and non-convex coupled expressions (8c), (8d). Thus, to find a solution for problem (8), this section provides a dynamic control algorithm, specifically, the *drift-plus-penalty* function using the Lyapunov optimization framework [9].

First, by using the Markov's inequality, we transform the probabilistic queue-length constraint into a time-average constraint as $\Pr\big\{Q_k(t) \geq Q_k^{\mathrm{th}}\big\} \leq \mathbb{E}[Q_k]/Q_k^{\mathrm{th}} \leq \epsilon,\ \forall k$, where the expectation is with respect to arrivals and random channel states [12], [13]. Thereby, problem (8) can be rewritten as

$$\min_{\mathbf{f}_k(t),\gamma_k(t),\rho_k(t),\ \forall t} \quad \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\Big(\sum_{k\in\mathcal{K}}\mathbb{E}\big[\|\mathbf{f}_k(t)\|^2\big]\Big) \tag{9a}$$

$$\text{s.t.} \quad \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\big[Q_k\big]\le \epsilon Q_k^{\text{th}}, \quad \forall k, \tag{9b}$$

$$\text{constraints} \quad (8\text{c})-(8\text{e}).$$

Next, we address the time-average inequality constraint (9b) by transforming it into a queue stability problem [9, Ch. 5]. For this, we define a virtual queue $Z_k(t)$ associated with (9b) for each user k during time slot t, and we update $Z_k(t)$ as

$$Z_k(t+1)=\big[Z_k(t)+Q_k(t+1)-\epsilon Q_k^{\text{th}}\big]^+, \quad \forall k. \tag{10}$$

Note that the stability of the associated virtual queues strictly ensures that the constraint (9b) is satisfied [9, Theorem 2.5]. Thus, in order to stabilize $\{Z_k(t)\}_{\forall k}$, we now define Lyapunov function $\mathcal{L}(\mathbf{\Psi}(t))\triangleq\frac{1}{2}\sum_{k\in\mathcal{K}}Z_k(t)^2$, and its drift as

$$\triangle(\mathbf{\Psi}(t))=\frac{1}{2}\mathbb{E}\Big[\sum_{k\in\mathcal{K}}\big(Z_k(t+1)^2-Z_k(t)^2\big)\big|\mathbf{\Psi}(t)\Big], \tag{11}$$

where $\mathbf{\Psi}(t)=[Z_1(t),\dots,Z_K(t),Q_1(t),\dots,Q_K(t)]^{\text{T}}$ denotes a collection of virtual and actual queues. Intuitively, we can observe that the queues $\{Z_k(t)\}_{\forall k}$ can be stabilized by minimizing the drift between two consecutive slots (11). Next, by using (6) and (10), and after some algebraic simplifications, an upper bound for the drift $\triangle(\mathbf{\Psi}(t))$ is obtained as

$$\triangle(\mathbf{\Psi}(t))\le\Phi-\mathbb{E}\Big[\sum_{k\in\mathcal{K}}\big(Q_k(t)+A_k(t)+Z_k(t)\big) \times\log_2(1+\gamma_k(t))\big|\mathbf{\Psi}(t)\Big], \tag{12}$$

where Φ is a positive constant term (we refer the reader to [13] for the details). We now define the *drift-plus-penalty* function [9] for problem (9) as

$$\triangle(\mathbf{\Psi}(t))+V\mathbb{E}\Big[\sum_{k\in\mathcal{K}}\|\mathbf{f}_k(t)\|^2\big|\mathbf{\Psi}(t)\Big], \tag{13}$$

where $V\ge 0$ is a trade-off parameter. Thus, by minimizing the upper bound of (13) subject to constraints (8c) - (8e) at each time slot, we can ensure the user-specific latency requirements while minimizing the sum-power objective function (8a). Here, we employ the concept of *opportunistic minimization of an expectation* [9, Ch. 1.8] to minimize the upper bound of (13), and obtain a dynamic control algorithm, as summarized in Algorithm 1. Note that feasible transmit beamforming vectors and PS ratios are computed at each time slot by solving (14).

Algorithm 1: Dynamic algorithm for problem (8)

1. For a given time slot t, observe the queue backlogs $\{Q_k(t)\}$ and $\{Z_k(t)\}$, and solve following problem:

$$\min_{\mathbf{f}_k(t),\gamma_k(t),\rho_k(t)} \quad V\sum_{k\in\mathcal{K}}\|\mathbf{f}_k(t)\|^2-\sum_{k\in\mathcal{K}}\big(Q_k(t) + A_k(t)+Z_k(t)\big)\log_2(1+\gamma_k(t)) \tag{14a}$$

$$\text{s.t.} \quad \gamma_k(t)\le\frac{\rho_k(t)|\mathbf{h}_k^{\text{H}}(t)\mathbf{f}_k(t)|^2}{\rho_k(t)\sum_{u\in\mathcal{K}\setminus k}|\mathbf{h}_k^{\text{H}}(t)\mathbf{f}_u(t)|^2+\rho_k(t)\sigma_k^2+\delta_k^2}, \quad \forall k, \tag{14b}$$

$$\text{e}_k(t)\le\zeta_k\big(1-\rho_k(t)\big) \times\Big(\sum_{j=1}^{K}|\mathbf{h}_k^{\text{H}}(t)\mathbf{f}_j(t)|^2+\sigma_k^2\Big), \quad \forall k, \tag{14c}$$

$$0\le\rho_k(t)\le 1, \quad \forall k. \tag{14d}$$

2. Update queues $Q_k(t+1)$ and $Z_k(t+1)$ by using (6) and (10), respectively, for all $k\in\mathcal{K}$
3. Set $t=t+1$, and go to step 1

IV. Optimal Beamformer and PS Ratio Design

The problem (14) is still intractable due to the non-convex SINR constraint (14b), and the coupling between beamforming vectors $\mathbf{f}_k(t)$ and PS ratios $\rho_k(t)$ in (14b) and (14c). In this paper, we adopt SDR and FP techniques to find a feasible solution for (14). In the following, we omit the time index t to simplify the notation.

To begin with, let us define $\mathbf{F}_k\triangleq\mathbf{f}_k\mathbf{f}_k^{\text{H}}$ for all $k\in\mathcal{K}$. The idea of SDR is to replace each rank-one matrix $\mathbf{F}_k$ by a general-rank positive semidefinite matrix, i.e., $\mathbf{F}_k\succeq 0,\forall k$ [10]. Thus, by applying the SDR technique to (14), and after some algebraic manipulations, we obtain the following problem

$$\min_{\mathbf{F}_k,\gamma_k,\rho_k} \quad V\sum_{k\in\mathcal{K}}\text{Tr}\big(\mathbf{F}_k\big)-\sum_{k\in\mathcal{K}}\big(Q_k + A_k+Z_k\big)\log_2(1+\gamma_k) \tag{15a}$$

$$\text{s.t.} \quad \frac{1}{\gamma_k}\mathbf{h}_k^{\text{H}}\mathbf{F}_k\mathbf{h}_k-\sum_{u\in\mathcal{K}\setminus k}\mathbf{h}_k^{\text{H}}\mathbf{F}_u\mathbf{h}_k\ge\sigma_k^2+\frac{\delta_k^2}{\rho_k}, \quad \forall k, \tag{15b}$$

$$\sum_{j=1}^{K}\mathbf{h}_k^{\text{H}}\mathbf{F}_j\mathbf{h}_k\ge\frac{\text{e}_k}{\zeta_k(1-\rho_k)}-\sigma_k^2, \quad \forall k, \tag{15c}$$

$$0\le\rho_k\le 1, \quad \forall k, \tag{15d}$$

$$\mathbf{F}_k\succeq 0, \quad \forall k, \tag{15e}$$

where $\text{Tr}(\cdot)$ denotes the trace of a matrix. Note that problem (15) is still non-convex due to the coupling between variables $\big\{\mathbf{F}_k,\gamma_k\big\}$ in (15b). Several approaches have been outlined in the literature to handle such non-convexity [11], [13], [14]. Here, we develop the following proposition based on recently proposed FP *quadratic transform* technique [11].

Proposition 1. The coupled fractional term in constraint (15b)

$$\frac{1}{\gamma_k}\mathbf{h}_k^{\text{H}}\mathbf{F}_k\mathbf{h}_k, \quad \forall k, \tag{16}$$

is equivalent to

$$2\nu_k\sqrt{\mathbf{h}_k^{\text{H}}\mathbf{F}_k\mathbf{h}_k}-\nu_k^2\gamma_k, \quad \forall k, \tag{17}$$

when the auxiliary variable $\nu_k,\ \forall k$, has the optimal value

$$\nu_k^{(\star)}=\frac{1}{\gamma_k}\sqrt{\mathbf{h}_k^{\text{H}}\mathbf{F}_k\mathbf{h}_k}, \quad \forall k. \tag{18}$$

We refer the reader to [11, Theorem 1] for details. Specifically, the Proposition 1 can be proved by following the steps in [11, Section II], which are not included due to space limitations.

Hence, by using the Proposition 1, problem (15) can be equivalently rewritten as the following convex problem

$$\min_{\mathbf{F}_k,\gamma_k,\rho_k} \quad V\sum_{k\in\mathcal{K}}\mathrm{Tr}\big(\mathbf{F}_k\big)-\sum_{k\in\mathcal{K}}\big(Q_k + A_k + Z_k\big)\log_2(1+\gamma_k) \tag{19a}$$

$$\text{s.t.} \quad 2\nu_k^{(i)}\sqrt{\mathrm{Tr}(\mathbf{F}_k\mathbf{H}_k)}-(\nu_k^{(i)})^2\gamma_k - \sum_{u\in\mathcal{K}\setminus k}\mathrm{Tr}(\mathbf{F}_u\mathbf{H}_k)\geq \sigma_k^2+\frac{\delta_k^2}{\rho_k},\quad \forall k, \tag{19b}$$

$$\sum_{j=1}^{K}\mathrm{Tr}(\mathbf{F}_j\mathbf{H}_k)\geq \frac{\mathrm{e}_k}{\zeta_k(1-\rho_k)}-\sigma_k^2,\quad \forall k, \tag{19c}$$

$$0\leq\rho_k\leq 1,\quad \forall k, \tag{19d}$$

$$\mathbf{F}_k\succeq 0,\quad \forall k, \tag{19e}$$

where $\mathbf{H}_k=\mathbf{h}_k\mathbf{h}_k^{\mathrm{H}}$ and $\mathrm{Tr}(\mathbf{F}_k\mathbf{H}_k)=\mathbf{F}_k\mathbf{h}_k\mathbf{h}_k^{\mathrm{H}}=\mathbf{h}_k^{\mathrm{H}}\mathbf{F}_k\mathbf{h}_k$ for all $k\in\mathcal{K}$. Note that (19) provides an approximate solution for (15) in the vicinity of a fixed operating point $\{\nu_k^{(i)}\}$. Thus, by iteratively solving (19) while updating $\{\nu_k^{(i)}\}$ with the solution of current iteration (18), we can find a local solution for (15) [11]. Moreover, for a fixed operating point $\{\nu_k^{(i)}\}$, the subproblem (19) can be efficiently solved, in general, using standard convex optimization tools, e.g., CVX [15].

For a given time slot t, let $\big\{\mathbf{F}_k^{\star}(t),\rho_k^{\star}(t)\big\}_{\forall k}$ denote the local solution obtained from (19). However, note that for each user k, the achievable SINR (3) and harvested power (5) is computed using the actual beamforming vector $\mathbf{f}_k^{\star}(t)$, $\forall k\in\mathcal{K}$. If $\mathbf{F}_k^{\star}(t)$ satisfies $\mathrm{Rank}\big(\mathbf{F}_k^{\star}(t)\big)=1$, $\forall k$, then we can write $\mathbf{F}_k^{\star}(t)=\mathbf{f}_k^{\star}(t)\mathbf{f}_k^{\star\mathrm{H}}(t)$, and $\mathbf{f}_k^{\star}(t)$ is a feasible (indeed optimal) solution to (14). On the contrary, if $\mathrm{Rank}\big(\mathbf{F}_k^{\star}(t)\big)>1$, additional approximation procedure is needed to extract a feasible solution. For example, we can set $\{\mathbf{f}_k^{\star}(t)\}_{\forall k}$ to be proportional to the eigen vector $\mathbf{q}_k^1(t)$ of $\{\mathbf{F}_k^{\star}(t)\}_{\forall k}$ associated with the largest eigen value $\lambda_k^1(t)$, i.e., $\mathbf{f}_k^{\star}(t)=\sqrt{\lambda_k^1(t)}\mathbf{q}_k^1(t)$, $\forall k$ [10]. The joint optimization of transmit beamforming vectors and receive PS ratios with the proposed convex approximation has been summarized in Algorithm 2.

Algorithm 2: Iterative algorithm for problem (19)

1 Set $i=1$ and initialize $\{\nu_k^{(0)}\},\forall k$, with a feasible value
2 **repeat**
3 Solve (19) with $\{\nu_k^{(i-1)}\}$, and denote the local solution as $\big\{\mathbf{F}_k^{(i)},\gamma_k^{(i)},\rho_k^{(i)}\big\}$
4 Update $\nu_k^{(i)}$ using (18) with $\big\{\mathbf{F}_k^{(i)},\gamma_k^{(i)}\big\}$
5 Set $i=i+1$
6 **until** convergence or for fixed number of iterations

V. Simulation Results

In this section, we provide numerical results to validate the performance of the proposed joint transmit beamforming and receive PS algorithm with the user-specific latency and EH requirements. We assume the BS is equipped with a uniform linear array (ULA) of $N_t=4$ antennas, and serves $K=4$ single antenna UEs. Without loss of generality, we assume identical parameters for all UEs, i.e., noise variance $\sigma_k^2=-70$ dBm, $\delta_k^2=-50$ dBm, energy conversion efficiency $\zeta_k=0.5$, and harvested power $\mathrm{e}_k(t)=\mathrm{e}$, $\forall t,k$ [8]. Moreover, we set $A_k\sim\mathrm{Pois}(\alpha)$ with $\alpha=5$ bits/slot, maximum allowable queue length $Q_k^{\mathrm{th}}=5$ bits, and tolerable queue length violation probability $\epsilon=10\%$ in problem (8) [13].

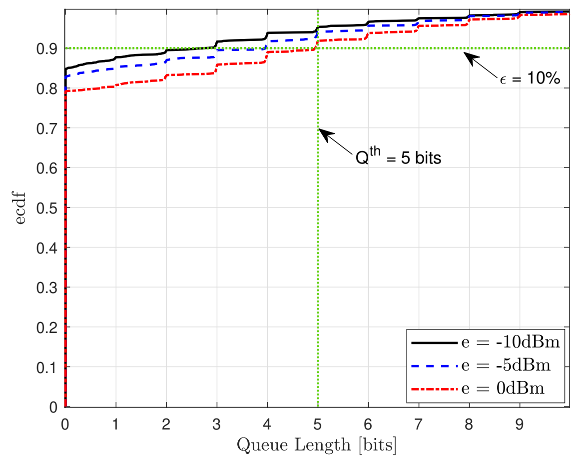

Fig. 2: Queue backlog performance of each user with $V=20$.

The radio channel $\mathbf{h}_k\in\mathbb{C}^{N_t\times 1}$ for each user k is assumed to undergo uncorrelated Rician fading, which consists of a deterministic line-of-sight (LOS) component $\mathbf{h}_k^{\mathrm{L}}$ and a spatially uncorrelated non-LoS (NLoS) component $\mathbf{h}_k^{\mathrm{NL}}$ as

$$\mathbf{h}_k(t)=\sqrt{\frac{\kappa}{1+\kappa}}\mathbf{h}_k^{\mathrm{L}}(t)+\sqrt{\frac{1}{1+\kappa}}\mathbf{h}_k^{\mathrm{NL}}(t),\quad \forall t,k, \tag{20}$$

where κ is the Rician factor, which we set to 5 dB. The NLoS component for each time slot t is independently modeled using Rayleigh fading with zero mean and covariance of -40 dB. For the LoS component, we use far-field ULA model, e.g., $\mathbf{h}_k^{\mathrm{L}}(t)=10^{-4}\big[1,\ e^{-\mathrm{j}\pi\sin(\theta_k(t))},\ldots,e^{-\mathrm{j}(N_t-1)\pi\sin(\theta_k(t))}\big]^{\mathrm{T}}$, where $\theta_k(t)$ is the azimuth angle of k-th UE during time slot t relative to the boresight of the BS antenna array. The azimuth angles $\theta_k(t)\in[-\pi/2,\ \pi/2]$, $\forall t,k$, are randomly generated.

Fig. 2 illustrates the user-specific latency performance with the trade-off parameter $V=20$. Result shows that, irrespective of the minimum harvested power constraint (8d), our proposed method ensures the maximum backlogs of each user k (i.e., $Q_k^{\mathrm{th}}=5$) within the allowable violation probability $\epsilon=10\%$. Thus, the proposed convex relaxations to problem (8) still allow to satisfy the desired latency requirements (i.e., constraint (8b) is strictly met).

Next, we investigate the impact of different values of trade-off parameter V on the average sum-power performance in Fig. 3. The result shows that, for a fixed minimum harvested power constraint, the average BS transmit power decreases with the increase of V. This behavior is expected since higher values of V emphasize the minimization of the sum-power objective function over the queue-length (see (19a)). Moreover, the transmit power increases with the increase in the minimum harvested power requirements. This is due to the increase in the total network power consumption in order to satisfy the constraint (8d). More specifically, the solution, even after convex relaxation, strictly achieves the minimum harvested

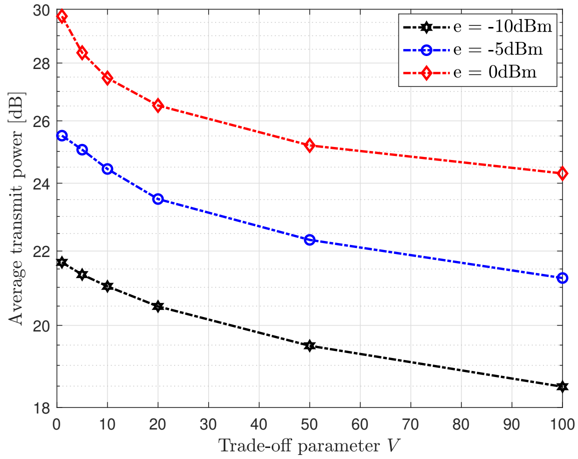

Fig. 3: Average transmit power of BS with increasing trade-off parameter V and different harvested power requirements.

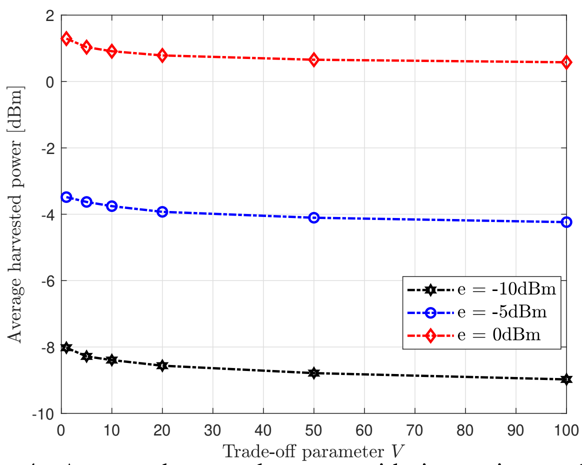

Fig. 4: Average harvested power with increasing trade-off parameter V for each user.

power requirements of each user in order to ensure the receiver operation, as shown in Fig. 4.

Finally, we examine the PS ratios with the different minimum harvested power requirements (i.e., constraint (8d)). It can be concluded from Fig. 5 that PS ratios to the EH $(1-\rho_k)$, linearly increase as the harvested power requirements become more stringent. Thus, a large portion of the received signal power is split into the EH circuit to satisfy the constraint (8d). Therefore, the proposed relaxations to problem (8) strictly achieve the desired user-specific latency and EH requirement, and lead to a power-efficient solution.

VI. Conclusion

In this paper, we explored the trade-offs between the required transmit power and achievable harvested power under user-specific latency requirements. We considered a time-average sum-power minimization problem subject to a probabilistic queue length and a minimum harvested power constraint for each user. We have adopted the drift-plus-penalty function and Lyapunov optimization framework to derive a dynamic control algorithm for the time-average stochastic problem. The non-convex and coupled constraints are handled

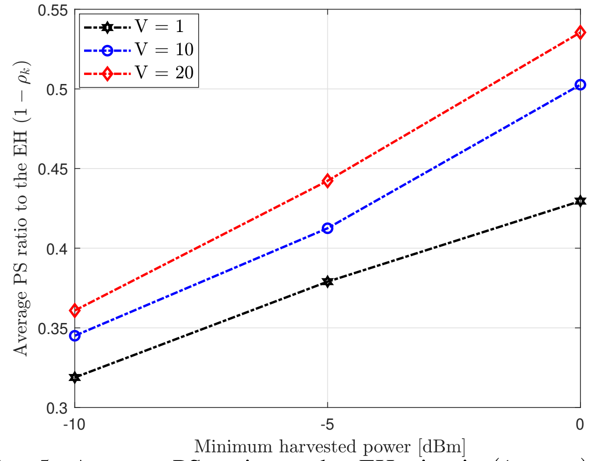

Fig. 5: Average PS ratio to the EH circuit $(1-\rho_k)$ with increasing harvested power requirements for each user.

by applying techniques of the SDR and FP quadratic transformation. The simulation results manifested the robustness of the proposed design to realize a power-efficient SWIPT system.

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