Joint Optimization of Energy Transfer Scheduling and Power Control in MIMO Wireless Powered Communication Networks

Ibrahim Pehlivan and Sinem Coleri, *Senior Member, IEEE*

***Abstract*—Hybrid beamforming is a low-cost alternative to digital beamforming with its capability to operate with fewer radio frequency (RF) chains than antennas. However, the diminishing degree of freedom from utilizing fewer RF chains results in considerable performance degradation. To circumvent this setback, scheduling of energy harvesting (SEH) has been recently proposed to provide an additional degree of freedom. In this paper, we study the optimization of SEH together with the beamforming weights, energy and data transfer intervals, and uplink transmit power. The objective is minimizing the total duration of uplink and downlink transmission, whereas the constraints include minimum data transfer, maximum allowed transmit power and hybrid beamforming requirements. We formulate the non-convex optimization problem and convert it to the equivalent rank constrained semidefinite programming problem. We then propose efficient solution methodologies based on iteratively moving the rank constraints to the objective function as a penalty. Extensive simulations demonstrate that SEH is an effective circumvention to the RF chain scarcity, culminating in up to 26% delay performance gain.**

***Index Terms*—RF energy harvesting, wireless powered communication network, hybrid beamforming, scheduling, optimization.**

I. Introduction

Energy harvesting technologies have recently drawn a lot of attention with the increasing demand for wireless communication devices and the stagnant development of power storage units. Energy can be harvested from natural sources such as sun, vibration as well as radio frequency (RF), magnetic and inductive coupling. Among these methods, RF energy harvesting, where energy is harvested from the RF signals emitted from a dedicated base station, stands out with a long-range and controllable power supply [1].

Wireless powered communication networks (WPCN) are one of the principal research areas of RF energy harvesting networks. It comprises nodes that harvest energy from the base station in the downlink and transmit information with the harvested energy at the uplink. In multiple-antenna WPCN architectures, digital beamforming weights along with uplink-downlink time allocation have been optimized to maximize the overall SNR or sum-throughput of WPCNs [2], [3]. However, digital beamforming requires a separate RF chain for each antenna, resulting in excessive cost and power consumption.

Ibrahim Pehlivan and Sinem Coleri are with the department of Electrical and Electronics Engineering, Koc University, Istanbul, Turkey, e-mail: {ipehlivan, scoleri}@ku.edu.tr. This work is supported by Scientific and Technological Research Council of Turkey Grant #117E241.

Hybrid beamforming is a low-cost alternative to digital beamforming with the capability of utilizing fewer RF chains than the number of antennas. The optimization of multiple antenna WPCN considering hybrid beamforming, however, suffers from performance degradation due to limited control over beamforming weights [4]. To circumvent this setback, SEH has been proposed [5] based on the idea of providing an additional degree of freedom over time, similar to the scheduling of information transfer [6]. In SEH, the downlink time slot is subdivided into multiple, variable-length subslots and different beamforming weights are assigned to each subslot. However, the initial investigation of SEH only focuses on the downlink energy transfer parameters, including scheduling and beamforming weights, and omits the effect of uplink information transmission parameters.

In this article, we investigate the effect of the SEH on the delay performance of WPCNs based on the optimization of beamforming weights, energy and data transfer intervals, and uplink transmit power. To the best of our knowledge, this is the first complete inquiry of the SEH considering both downlink energy transfer and uplink information parameters.

II. System Model and Assumptions

WPCN comprises N nodes equipped with R antennas and a single base station possessing M antennas. Base station has access to a power supply and provides energy to the nodes in downlink transmission. Nodes do not possess energy storage unit and rely on harvested energy provided by the base station in downlink transmission.

Half-duplex dynamic time-division multiple access (TDMA) is used as a communication protocol. Each time frame is divided into two slots, one for downlink energy transfer from the base station to the nodes and one for the uplink information transfer from the nodes to the base station. The slot for the downlink energy transfer is subdivided into S subslots, each subslot with variable duration $t_s^{dl},\ s \in [1, S]$ and different beamforming weight. The following slot for the uplink transmission is subdivided into N subslots, each subslot dedicated to a single user n, $n \in [1, N]$, with variable duration t_n^{ul}. We assume that the data demand of each user n is $\Omega_n,\ n \in [1, N]$.

We assume channels between the base station and nodes are block fading. The channel gain matrix between the base station and user n is fixed during each uplink and downlink cycle, equal to $\mathbf{H_n} \in \mathbb{C}^{\mathbf{R}\times\mathbf{M}}$ for $n \in [1, N]$, and perfectly known by the base station and nodes [2], [3].

The base station is assumed to employ hybrid beamforming architecture with L^b RF chains and each RF chain followed by $K^b = \frac{M}{L^b}$ RF phase shifters, where K^b is an integer and $L^b \leq M$ [7]. Let us denote the transmit beamforming vector at subslot s of the base station by $\mathbf{v_s} \in \mathbb{C}^{\mathbf{M}}$ and the uplink receive combining vector of the base station dedicated to a node n by $\mathbf{q_n} \in \mathbb{C}^{\mathbf{M}}$. Let us denote the digital beamforming weight of the l-th RF chain at subslot s by $v_s^{G_l^b}$ and the group of antennas corresponding to the l-th RF chain by the phase shifter group $G_l^b = \{(l-1)K^b, (l-1)K^b + 1, ..., (l-1)K^b + K^b - 1\}$, for $l \in [1, L^b]$. This antenna group linked to the same RF chain with phase shifter group at subslot s shares the same magnitude, i.e. $\mathbf{v_s}(j) = v_s^{G_l^b} e^{j\theta_j}$, where $\mathbf{v_s}(j)$ is the j-th element of vector $\mathbf{v_s}$ and θ_j is phase shift introduced by the j-th phase shifter following the corresponding RF chain, thus, $|\mathbf{v_s}(j)| = |v_s^{G_l^b}|$ for $j \in G_l^b$. This is equivalent to $|\mathbf{v_s}(j)| = |\mathbf{v_s}(i)|, \quad i, j \in G_l^b$. Likewise, uplink receive combining vector of the base station $\mathbf{q_n}$ dedicated to a node n possesses same structure, $|\mathbf{q_n}(j)| = |\mathbf{q_n}(i)|$, $i, j \in G_l^b$ with unit norm, $\|\mathbf{q_n}\| = 1$.

Every user $n \in [1, N]$ is assumed to have digital beamforming architecture to simplify the problem and focus on the effect of SEH in the first step of the study. Transmit beamforming vector for user n is denoted by $\mathbf{c_n} \in \mathbb{C}^{\mathbf{R}}$ and receive combining vector is denoted by $\mathbf{z_{n,s}} \in \mathbb{C}^{\mathbf{R}}$ for the subslot $s = 1, \cdots, S$ with unit norms $\|\mathbf{z_{n,s}}\| = 1$ and $\|\mathbf{c_n}\| = 1$.

In downlink transmission, the output of the base station at subslot s is given by $\mathbf{x_s^{dl}} = \mathbf{v_s} y_s^{dl}$, where $y_s^{dl} \in \mathbb{C}$ is the information carrying signal. y_s^{dl} can be a random signal with certain restrictions on its power spectral density as no information is transferred in the downlink transmission. We assume that y_s^{dl} is a random process with $\mathbb{E}(\|y_s^{dl}\|^2) = 1$. Maximum allowed power of the base station is denoted by P_{dl}. Therefore, the following equation of energy beamforming vector $\mathbf{v_s}$ at subslot s must be satisfied: $\mathbb{E}(\mathbf{x_s^{dl H} x_s^{dl}}) = \|\mathbf{v_s}\|^2 = \mathbf{v_s^H v_s} \leq P_{dl}$.

Users are assumed to harvest energy only from the base station in the downlink as the energy accumulated from the information transfer of previous users is negligible. Then, the harvested energy by user n at subslot s is given by $\psi t_s^{dl} \mid \mathbf{z_{n,s}^H H_n v_s} \mid^2$, where $0 < \psi \leq 1$ is the energy harvesting efficiency [2], [3]. As nodes only rely on the harvested energy for all their operation, only a fraction $0 < \eta \leq 1$ of the harvested energy is available for transmission [8].Then, the available energy for transmission E_n^{avail} of the node n is defined as $E_n^{avail} = \eta E_n^{harv} = \eta \sum_{s=1}^{S} \psi t_s^{dl} \mid \mathbf{z_{n,s}^H H_n v_s} \mid^2$.

In uplink transmission, the output of node n is given by $\mathbf{x_n^{ul}} = \sqrt{\overline{P_n}} \mathbf{c_n} y_n^{ul}$, where $y_n^{ul} \in \mathbb{C}$ is the information carrying signal, $\overline{P_n}$ is the transmit power with $\overline{P_n} \leq P_{ul}$, and P_{ul} is the maximum allowed uplink transmit power. y_n^{ul} is assumed to be independent symmetric complex gaussian random variable with unit variance and zero mean, $y_n^{ul} \sim \mathcal{CN}(0, 1)$. To operate, each user n must acquire enough energy for transmission, therefore, following equation must hold: $\overline{\psi} E_n^{avail} = \overline{\psi} \eta \sum_{s=1}^{S} \psi t_s^{dl} \mid \mathbf{z_{n,s}^H H_n v_s} \mid^2 \geq \overline{P_n} t_n^{ul}$, where $0 < \overline{\psi} \leq 1$ is the energy conversion efficiency.

Received signal by the base station is given by $r_n = \mathbf{q_n^H H_n^H x_n^{ul}} + \mathbf{q_n^H n}$, where $\mathbf{n} \in \mathbb{C}^M$ is the additive white gaussian noise with $\mathbf{n} \sim \mathcal{CN}(0, \mathbf{I}\sigma^2)$, where σ^2 is the variance of the noise. Then, the corresponding SNR for node n, SNR^n, is calculated as $SNR^n = \frac{\overline{P_n} \mid \mathbf{q_n^H H_n^H c_n} \mid^2}{\sigma^2}$. Consequently, channel capacity C^n for node n is given by $C^n = \beta log_2(1 + \frac{\overline{P_n} \mid \mathbf{q_n^H H_n^H c_n} \mid^2}{\sigma^2})$, where β is the bandwidth.

III. Optimization Problem formulation

The optimization problem aims to minimize the total duration of the downlink energy and uplink information transmission while satisfying the minimum data transfer constraint for each user, maximum allowed power constraint for both uplink and downlink transmission and hybrid beamforming constraint for the base station.

minimize

$$\sum_{s=1}^{S} t_s^{dl} + \sum_{n=1}^{N} t_n^{ul} \tag{1a}$$

subject to

$$\overline{\psi}\eta \sum_{s=1}^{S} \psi \mid \mathbf{z_{n,s}^H H_n w_s} \mid^2 \geq \overline{P_n} t_n^{ul}, \quad n = 1, \cdots, N \tag{1b}$$

$$\mathbf{w_s^H w_s} \leq P_{dl} t_s^{dl}, \quad s = 1, \cdots, S \tag{1c}$$

$$\overline{P_n} \leq P_{ul}, \quad n = 1, \cdots, N \tag{1d}$$

$$t_n^{ul} \beta \ln(1 + \frac{\overline{P_n} \mid \mathbf{q_n^H H_n^H c_n} \mid^2}{\sigma^2}) \geq \Omega_n, \quad n = 1, \cdots, N \tag{1e}$$

$$\mid \mathbf{w_s}(j) \mid = \mid \mathbf{w_s}(i) \mid, \quad i, j \in G_l^b \quad l = 1, \cdots, L^b, \quad s = 1, \cdots, S \tag{1f}$$

$$\mid \mathbf{q_n}(j) \mid = \mid \mathbf{q_n}(i) \mid, \quad i, j \in G_l^b \quad l = 1, \cdots, L^b, \quad n = 1, \cdots, N \tag{1g}$$

$$\|\mathbf{z_{n,s}}\| = \|\mathbf{q_n}\| = \|\mathbf{c_n}\| = 1, \quad n = 1, \cdots, N, \quad s = 1, \cdots, S \tag{1h}$$

variables

$$t_s^{dl}, t_n^{ul}, \overline{P_n} \in \mathbb{R}_+, \ \mathbf{w_s}, \ \mathbf{q_n} \in \mathbb{C}^M, \mathbf{c_n}, \ \mathbf{z_{n,s}} \in \mathbb{C}^R, \quad n = 1, \cdots, N, \quad s = 1, \cdots, S \tag{1i}$$

where $\mathbf{w_s}$ is defined as $\mathbf{v_s}\sqrt{t_s^{dl}}$ for $t_s^{dl} > 0$, $s \in [1, S]$. The definition of $\mathbf{w_s}$ allows the removal of the coupling of the variables t_s^{dl} and $\mathbf{v_s}$ in constraint (1b).

Eqn. (1a) corresponds to the objective function, minimization of the total duration of uplink and downlink transmission. Eqn. (1b) corresponds to the minimum required harvested energy constraint for each user. Eqns. (1c) and (1d) represent maximum allowed power constraints for downlink energy and uplink information transmission, respectively. Eqn. (1e) represents the minimum data transfer constraint for each user. Eqns. (1f)-(1g) enforce the hybrid beamforming transceiver limitations. Eqn. (1h) ensures that beamforming vectors have unit norm.

Problem (1) is non-convex. Non-convexity stems from the coupled variables in Eqns. (1b) and (1e) and the hybrid beamforming constraints (1f)-(1g).

IV. Solution Method

We first investigate the variables that can be solved independently from the remaining variables in the optimal solution. As a result, we formulate the optimization problem for the uplink beamforming weights of each user n separately. Then, by using these optimal values, we rewrite the remaining problem as a semidefinite programming problem with additional rank constraints. With this conversion, non-convexity is reduced only to the rank constraints. To achieve near-optimal solutions, the Alternating minimization (AM) algorithm moves the rank constraints to the objective function as a penalty and solves the problem iteratively [4]. We propose the Project and Alternate (PA) algorithm that improves the performance of the AM algorithm by introducing rank 1 approximation in each iteration.

A. Identification of Independent Subproblem

The subproblem for user n for the optimization of the variables $\mathbf{q_n}$ and $\mathbf{c_n}$ within problem (1) can be formulated separately based on the following lemma.

Lemma 1. *The optimal values of* $\mathbf{q_n}$ *and* $\mathbf{c_n}$, $n \in [1, N]$, *for the optimization problem given by*

maximize

$$| \mathbf{q_n^H H_n^H c_n} |^2 \tag{2a}$$

subject to

$$\|\mathbf{q_n}\| = \|\mathbf{c_n}\| = 1 \tag{2b}$$

$$| \mathbf{q_n}(j) | = | \mathbf{q_n}(i) |, \quad i, j \in G_l^b \quad l = 1, \cdots, L^b \tag{2c}$$

variables

$$\mathbf{q_n} \in \mathbb{C}^M, \ \mathbf{c_n} \in \mathbb{C}^R \tag{2d}$$

are also optimal for optimization problem (1).

Proof. Let us denote the optimal variables of problem (1) as $\mathbf{q_n^*}, \mathbf{c_n^*}, (t_n^{ul})^*, (t_s^{dl})^*, (\overline{P_n})^*, \mathbf{w_s}^*, \mathbf{z_{n,s}}^*, s \in [1, S], n \in [1, N]$ and optimal variables of problem (2) for user n as $\mathbf{q_n^{**}}, \mathbf{c_n^{**}}$. We will prove the lemma by showing that $\forall n$ using $\mathbf{q_n^{**}}, \mathbf{c_n^{**}}$ instead of $\mathbf{q_n^*}, \mathbf{c_n^*}$ will yield the same objective value while satisfying the constraints for problem (1). First, $\forall n$, $| (\mathbf{q_n^{**}})^\mathbf{H} \mathbf{H_n^H c_n^{**}} |^2 \geq | (\mathbf{q_n^*})^\mathbf{H} \mathbf{H_n^H c_n^*} |^2$ as $\mathbf{q_n^{**}}, \mathbf{c_n^{**}}$ are optimal and $\mathbf{q_n^*}, \mathbf{c_n^*}$ are feasible for problem (2). Hence, $\forall n$, $\mathbf{q_n^{**}}$, $\mathbf{c_n^{**}}$ together with $(t_n^{ul})^*, (\overline{P_n})^*$ satisfy the constraints in Eqns. (1e) and (1h). Since $\mathbf{q_n^{**}}$, $\mathbf{c_n^{**}}$ are not present in any other constraints and objective value remains the same, $\mathbf{q_n^{**}}, \mathbf{c_n^{**}}, (t_n^{ul})^*, (t_s^{dl})^*, (\overline{P_n})^*, \mathbf{w_s}^*, \mathbf{z_{n,s}}^*, s \in [1, S], n \in [1, N]$ are optimal for problem (1). □

Problem (2) is non-convex because of hybrid beamforming constraint in Eqn. (2c) and the coupled variables in the objective function in Eqn. (2a). We can employ the maximum the ratio combining principle (MRC) for the coupled variables. According to the MRC principle, problem (2) is maximized if and only if $\mathbf{c_n} = \dfrac{\mathbf{H_n q_n}}{\|\mathbf{H_n q_n}\|}$. Then, the objective function in Eqn. (2a) can be simplified to $\|\mathbf{H_n q_n}\|^\mathbf{2}$ [2].

Problem (2) is still non-convex as a result of hybrid beamforming constraint in Eqn. (2c). Observe that $\|\mathbf{H_n q_n}\|^\mathbf{2} = \mathrm{Tr}(\mathbf{q_n^H H_n^H H_n q_n}) = \mathrm{Tr}(\mathbf{H_n^H H_n q_n q_n^H})$ then by renaming $\mathbf{Q_n} = \mathbf{q_n q_n^H}$ and including a non-convex rank constraint, problem (2) can be rewritten as an equivalent semidefinite programming problem [9].

We can obtain the convex semidefinite relaxation of this problem (SDR) by relaxing the rank constraint. If the relaxed solution is rank 1, we can deduce that the optimal solution of problem (2) is found. Otherwise, the relaxed problem provides an upper bound and a near-optimal solution is determined by the Alternating minimization (AM) Algorithm.

In AM algorithm, the rank constraint for user n is replaced by the equivalent constraint, $\mathrm{Tr}(\mathbf{Q_n})^2 - \mathrm{Tr}(\mathbf{Q_n}^2) \leq 0$, $n = 1, \cdots, N$, since it is proven that for every non-zero hermitian positive semidefinite matrix $\mathbf{Q}$, $\mathrm{Tr}(\mathbf{Q^2}) \leq \mathrm{Tr}(\mathbf{Q})^2$; and $\mathrm{Tr}(\mathbf{Q^2}) = \mathrm{Tr}(\mathbf{Q})^2$ if and only if $rank(\mathbf{Q}) = 1$ [4]. Then, this non-convex constraint is moved to the objective function as a *penalty*, which corresponds to the violation of the rank constraint for user n, $\xi_n(\mathrm{Tr}(\mathbf{Q_n})\mathrm{Tr}(\mathbf{Q_n}) - \mathrm{Tr}(\mathbf{Q_n Q_n}))$, where ξ_n is the penalty coefficient. Then, the AM algorithm iteratively approximates problem (2) [4], [5].

B. Main problem

We have calculated $\Psi_n = | \mathbf{q_n^H H_n^H c_n} |^2$ in the previous section. Similarly, $| \mathbf{z_{n,s}^H H_n w_s} |^2$ can be rewritten as $\|\mathbf{H_n w_s}\|^\mathbf{2}$ as the optimal $\mathbf{z_{n,s}}$ can be written as $\mathbf{z_{n,s}} = \dfrac{\mathbf{H_n w_s}}{\|\mathbf{H_n w_s}\|}$ according to the MRC principle. Therefore, problem (1) is converted to the equivalent semidefinite programming problem by renaming $\mathbf{W_s} = \mathbf{w_s w_s^H}$ and including rank constraint, as follows:

minimize

$$\sum_{s=1}^{S} t_s^{dl} + \sum_{n=1}^{N} t_n^{ul} \tag{3a}$$

subject to

$$\overline{\psi}\eta \sum_{s=1}^{S} \psi \mathrm{Tr}(\mathbf{H_n^H H_n W_s}) \geq E_n, \quad n = 1, \cdots, N \tag{3b}$$

$$\mathrm{Tr}(\mathbf{W_s}) \leq P_{dl} t_s^{dl}, \quad s = 1, \cdots, S \tag{3c}$$

$$E_n \leq t_n^{ul} P_{ul}, \quad n = 1, \cdots, N \tag{3d}$$

$$t_n^{ul} \beta \ln(1 + \frac{E_n \Psi_n}{\sigma^2 t_n^{ul}}) \geq \Omega_n, \quad n = 1, \cdots, N \tag{3e}$$

$$\mathbf{W_s}(j, j) = \mathbf{W_s}(i, i), \quad i, j \in G_l^b \quad l = 1, \cdots, L^b, \quad s = 1, \cdots, S \tag{3f}$$

$$\mathrm{rank}(\mathbf{W_s}) = 1, \quad s = 1, \cdots, S \tag{3g}$$

$$\mathbf{W_s} \geq 0, \quad s = 1, \cdots, S \tag{3h}$$

variables

$$t_s^{dl}, t_n^{ul}, E_n \in \mathbb{R}_+, \ \mathbf{W_s} \in \mathbb{C}^{M \times M}, \quad s = 1, \cdots, S, \quad n = 1, \cdots, N \tag{3i}$$

where E_n is the required energy for the user n defined as $E_n := P_n t_n^{ul}$. Problem (3) is convex except the rank constraint (3g). By relaxing the rank constraint (3g), SDR lower bound can be achieved. If the optimal solution of the relaxed problem

is rank 1, then we can deduce that we have found the optimal solution. Otherwise, approximation methods are utilized for obtaining near-optimal solutions.

We observed that in some instances, the AM algorithm has failed to solve the problem due to solver limitations. At the q-th iteration and for every $s \in [1, S]$, the AM algorithm maximizes the projection over the previous iteration's optimal solution, $\mathbf{W_s}^{(q-1)}$, with the expression $\mathrm{Tr}(\mathbf{W_s}^{(q-1)}\mathbf{W_s})$. Since $\mathbf{W_s}^{(q-1)}$ is hermitian positive semidefinite; the expression $\mathrm{Tr}(\mathbf{W_s}^{(q-1)}\mathbf{W_s})$ is equivalent to the summation of the projections of $\mathbf{W_s}$ over orthogonal rank 1 matrices generated from the eigenvalue and eigenvectors of $\mathbf{W_s}^{(q-1)}$. In certain cases, directions introduced by rank 1 matrices with smaller eigenvalues might lead to numerical problems and extend the search. Therefore, we propose the Project and Alternate (PA) algorithm as a heuristic extension to the AM algorithm. In each iteration, we only search around the normalized rank 1 approximation of the $\mathbf{W_s}^{(q-1)}$ defined as the rank 1 matrix $\mathbf{\Theta_s}^{(q)} = \vartheta_\mathbf{1}\vartheta_\mathbf{1}^\mathbf{H}$ generated from the primal eigenvector $\vartheta_\mathbf{1}$ of $\mathbf{W_s}^{(q-1)}$ where $\|\vartheta_\mathbf{1}\| = 1$. Therefore, at the q-th iteration, the following problem is solved:

$$\begin{aligned} \min \quad & \sum_{s=1}^{S} t_s^{dl} + \sum_{n=1}^{N} t_n^{ul} \\ & + \sum_{s=1}^{S} \xi_s(\mathrm{Tr}(\mathbf{\Theta_s}^{(q)})\mathrm{Tr}(\mathbf{W_s}) - \mathrm{Tr}(\mathbf{\Theta_s}^{(q)}\mathbf{W_s})) \qquad (4a) \\ \text{s.t.} \quad & (3b - 3i) \end{aligned}$$

This approximation in the PA algorithm improves the performance and reliability of the AM algorithm, as demonstrated in Section V. The PA algorithm is provided in Algorithm 1, where $eig_1(.)$ function denotes the primal eigenvalue. We now prove that the PA algorithm converges.

Theorem 2. *The Project and Alternate algorithm converges.*

Proof. We prove the convergence by showing that objective value decreases and it is bounded below. Let us denote the objective function of the optimization problem (4) by $\mathrm{f}_q(.)$, a feasible solution of the problem at the q-th step as $\mathbf{X^q} = \{\mathbf{W_s}^{(q)}, (t_s^{(q)})\}_{s=1}^{S}$ and an optimal solution of the problem at the q-th step as $\mathbf{X^q_{opt}} = \{(\underline{\mathbf{W_s}}^{(q)}), (\underline{t_s^{(q)}})\}_{s=1}^{S}$.

Observe that $\mathbf{X^q_{opt}}$ is also a feasible solution at the $(q+1)$-th step. Then:

$$\begin{aligned} & \mathrm{f}_{q+1}(\mathbf{X^q_{opt}}) - \mathrm{f}_q(\mathbf{X^q_{opt}}) \\ & = \sum_{s=1}^{S} \xi_s(\mathrm{Tr}(\mathbf{\Theta_s}^{(q)}\underline{\mathbf{W_s}}^{(q)}) - \mathrm{Tr}(\mathbf{\Theta_s}^{(q+1)}\underline{\mathbf{W_s}}^{(q)})) \qquad (5a) \\ & = \sum_{s=1}^{S} \xi_s(\mathrm{Tr}(\mathbf{\Theta_s}^{(q)}\underline{\mathbf{W_s}}^{(q)}) - \sigma_s^q) \qquad (5b) \\ & \leq \sum_{s=1}^{S} \xi_s(\mathrm{Tr}(\mathbf{\Theta_s}^{(q)})\sigma_s^q - \sigma_s^q) \leq 0 \qquad (5c) \end{aligned}$$

where σ_s^q is the primal eigenvalue of $\underline{\mathbf{W_s}}^{(q)}$. Eqn. (5a) is obtained from direct substitution, Eqn. (5b) is obtained from the definition of $\mathbf{\Theta_s}^{(q+1)}$ and Eqn. (5c) is the direct result of the following relation that holds for every s: $\mathrm{Tr}(\mathbf{\Theta_s}^{(q)}\underline{\mathbf{W_s}}^{(q)}) = \mathrm{Tr}(\mathbf{\Theta_s}^{(q)}\underline{\mathbf{F_s\Sigma_s F_s^H}}) \leq \mathrm{Tr}(\mathbf{\Theta_s}^{(q)}\underline{\mathbf{F_s F_s^H}})\sigma_s^q \leq \mathrm{Tr}(\mathbf{\Theta_s}^{(q)})\sigma_s^q \leq \sigma_s^q$, where $\underline{\mathbf{F_s\Sigma_s F_s^H}}$ is the eigenvalue decomposition of the $\underline{\mathbf{W_s}}^{(q)}$ and $\mathrm{Tr}(\underline{\mathbf{\Theta_s}^{(q)}}) = 1$ from the definition. Therefore, it can be observed that

$$\mathrm{f}_{q+1}(\mathbf{X^{q+1}_{opt}}) \leq \mathrm{f}_{q+1}(\mathbf{X^q_{opt}}) \leq \mathrm{f}_q(\mathbf{X^q_{opt}})$$

This proves that the objective function value is decreasing. Since it is bounded below by 0, it converges.

□

Algorithm 1: Project and alternate algorithm

```
Set ξ_s = 1, q = 0, W_s^0, Θ_s^(0) to zero matrices for
  s = 1, ··· , S
while (q + + ≤ q_max) do
    Solve problem (4) with Θ_s^(q−1) as input and
      W_s^q, t_s, s = 1, ··· , S as output
    if ∃s such that rank(W_s) ≠ 1 and
      eig_1(W_s) − eig_1(W_s^(q−1)) ≤ ε_1 then
        ξ_s ← 2ξ_s
    end
    if Penalty ≤ ε_2 and convergence then
        return W_s, t_s   s = 1, ··· , S
    end
    Calculate Θ_s^(q) = ϑ_1 ϑ_1^H from ϑ_1 of W_s^(q−1),
      s = 1, ··· , S.
end
```

The worst-case complexity of the PA algorithm in each step with primal-dual interior point algorithms requires $O(\sqrt{SM + S + 2N}\,\log(1/\epsilon_{alg}))$ iterations with at most $O((SM^2+S+2N)^3+(SM^2+S+2N)(2N+2S+N\sqrt{\log(1/\epsilon_{ln})}))$ arithmetic operations in each iteration, where ϵ_{alg} is the accuracy of termination [4] and ϵ_{ln} is the accuracy of the logarithmic approximation of the constraint in Eqn. (3e) [10].

V. Performance Evaluation

This section demonstrates the performance gain obtained with SEH for different hybrid beamforming configurations and scheduling scenarios, where $S = 5$ is denoted by scheduled and $S = 1$ is denoted by non-scheduled case. To assess the optimality performance, semidefinite programming relaxation is used as a lower bound and denoted by SDR.

Simulations are conducted for 150 independent random network topologies, where users are distributed randomly on a sphere of radius 5 m. This setup can be utilized for small area networks, such as intra-vehicular wireless sensor networks, intra-body communication networks. Optimization problems are solved with CVX in MATLAB [11] with the solver SDPT3 [12]. Simulation parameters are listed in Table (I).

The antenna arrays in base station and users have circular-shaped configuration with the spacing of $\lambda/4$, where λ is the wavelength of the carrier frequency. The attenuation of the links is determined by using Rayleigh fading with scale parameter set to the mean path loss value $PL(d)$ in decibels calculated by $PL(d) = PL(d_0) + 10\alpha\log(d/d_0) + Z$, where d

Table I
SIMULATION PARAMETERS

M	16	R	4	η	0.5
P_{dl}	30 dBm	P_{ul}	10 dBm	f	28 Ghz
$\psi = \overline{\psi}$	0.2	σ^2	2×10^{-9}	β	200 MHz
Ω_n	1 Knats	σ_z	1.7	α	1.2

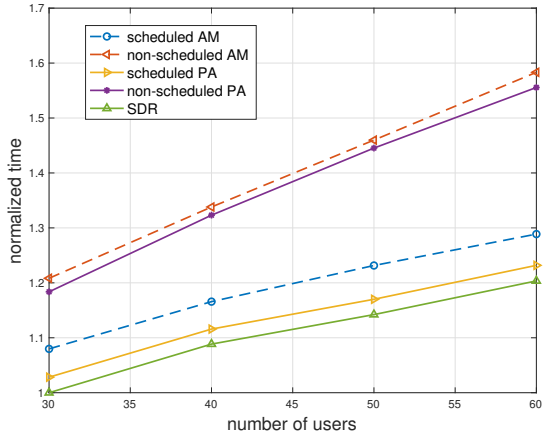


Figure 1. Normalized time for different number of users and 1 RF chain at the base station.

is the distance between the user and base station, $PL(d_0 = 1\text{ m}) = 61.39$ dB is the path loss at reference distance, $\alpha = 1.2$ is the path loss exponent and Z is a Gaussian random variable with zero mean and standard deviation $\sigma_z = 1.7$ at 28 GHz frequency band for line of sight (LOS) transmission [13].

The AM algorithm achieves rank 1 solutions to problem (1) with $[90.50 - 96]\%$ accuracy for $[40 - 60]$ users, whereas the PA algorithm achieves rank 1 solutions for all cases. This result demonstrates the reliability of the PA algorithm. The following results only cover instances where both AM and PA algorithms have obtained rank 1 solutions. Furthermore, sub-optimal Ψ_n is calculated from problem (2) with the AM algorithm with at most 0.6% loss.

Fig. (1) shows the normalized total uplink and downlink transmission time of different number of users for 1 RF chain at the base station. PA algorithm outperforms AM algorithm up to 4% for all number of users. Furthermore, the performance gain by SEH increases substantially with the number of users, highlighting the importance of the SEH in dense networks.

Fig. (2) demonstrates the normalized total uplink and downlink transmission time for different number of base station RF chains in a 60-node network. SEH is observed to yield $[12, 26]\%$ performance gain compared to the non-scheduled case due to the additional degree of freedom introduced by the SEH. This gain demonstrates that optimizing uplink information parameters together with downlink energy transfer has increased the importance of the SEH further since maximum 8% gain has been previously observed when uplink information parameters had been omitted [5].

VI. CONCLUSION

We investigate the effect of the SEH on the delay performance of the WPCN when the beamforming weights, energy and data transfer intervals, and uplink transmit power are optimized with the objective of minimizing the total duration of downlink energy transfer and uplink information transmission. We illustrate that SEH yields considerable performance gain, and the gain is substantially increased when the uplink information parameters are optimized together with the downlink energy transfer parameters.

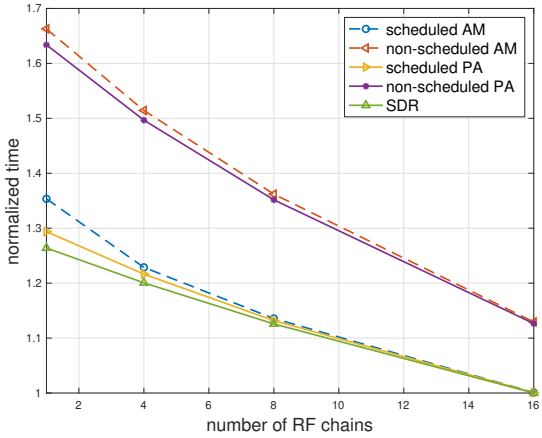


Figure 2. Normalized time for different number of RF chains in a 60 node network.

REFERENCES

[1] L. Xie, Y. Shi, Y. T. Hou, and A. Lou, "Wireless power transfer and applications to sensor networks," *IEEE Wireless Communications*, vol. 20, pp. 140–145, August 2013.

[2] A. Almradi, "Information and energy beamforming in mimo wireless powered systems," in *2016 IEEE Global Communications Conference (GLOBECOM)*, pp. 1–7, Dec 2016.

[3] L. Liu, R. Zhang, and K. C. Chua, "Multi-antenna wireless powered communication with energy beamforming," *IEEE Transactions on Communications*, vol. 62, pp. 4349–4361, December 2014.

[4] O. T. Demir and T. E. Tuncer, "Antenna selection and hybrid beamforming for simultaneous wireless information and power transfer in multi-group multicasting systems," *IEEE Transactions on Wireless Communications*, vol. 15, pp. 6948–6962, Oct 2016.

[5] I. Pehlivan and S. Coleri Ergen, "Scheduling of energy harvesting for mimo wireless powered communication networks," *IEEE Communications Letters*, vol. 23, pp. 152–155, Jan 2019.

[6] Y. Sadi and S. Coleri Ergen, "Minimum length scheduling with packet traffic demands in wireless networks," *IEEE Transactions on Wireless Communications*, vol. 13, pp. 3738–3751, July 2014.

[7] S. Han, I. Chih-Lin, Z. Xu, and C. Rowell, "Large-scale antenna systems with hybrid analog and digital beamforming for millimeter wave 5g," *IEEE Communications Magazine*, vol. 53, pp. 186–194, January 2015.

[8] K. Chi, Y. Zhu, Y. Li, L. Huang, and M. Xia, "Minimization of transmission completion time in wireless powered communication networks," *IEEE Internet of Things Journal*, vol. 4, pp. 1671–1683, Oct 2017.

[9] Z. Q. Luo, W. K. Ma, A. M. C. So, Y. Ye, and S. Zhang, "Semidefinite relaxation of quadratic optimization problems," *IEEE Signal Processing Magazine*, vol. 27, pp. 20–34, May 2010.

[10] H. Fawzi, J. Saunderson, and P. A. Parrilo, "Semidefinite approximations of the matrix logarithm," *Foundations of Computational Mathematics*, vol. 19, pp. 259–296, Apr 2019.

[11] M. Grant and S. Boyd, "CVX: Matlab software for disciplined convex programming, version 2.1," Mar. 2014.

[12] R. Tutuncu, K. Toh, and M. Todd, "Solving semidefinite-quadratic-linear programs using sdpt3," *Mathematical Programming Ser. B*, vol. 95, pp. 189–217, 2003.

[13] S. Deng, M. K. Samimi, and T. S. Rappaport, "28 ghz and 73 ghz millimeter-wave indoor propagation measurements and path loss models," in *2015 IEEE International Conference on Communication Workshop (ICCW)*, pp. 1244–1250, June 2015.