LETTER

Wireless-Powered Relays Assisted Batteryless IoT Networks Empowered by Energy Beamforming*

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SUMMARY In this letter, we propose an energy beamforming empowered relaying scheme for a batteryless IoT network, where wireless-powered relays are deployed between the hybrid access point (HAP) and batteryless IoT devices to assist the uplink information transmission from the devices to the HAP. In particular, the HAP first exploits energy beamforming to efficiently transmit radio frequency (RF) signals to transfer energy to the relays and as the incident signals to enable the information backscattering of batteryless IoT devices. Then, each relay uses the harvested energy to forward the decoded signals from its corresponding batteryless IoT device to the HAP, where the maximum-ratio combing is used for further performance improvement. To maximize the network sum-rate, the joint optimization of energy beamforming vectors at the HAP, network time scheduling, power allocation at the relays, and relection coefficient at the users is investigated. As the formulated problem is non-convex, we propose an alternating optimization algorithm with the variable substitution and semi-definite relaxation (SDR) techniques to solve it efficiently. Specifically, we prove that the obtained energy beamforming matrices are always rank-one. Numerical results show that compared to the benchmark schemes, the proposed scheme can achieve a significant sum-rate gain.

key words: *relaying scheme, energy beamforming, batteryless IoT network, sum-rate maximization*

1. Introduction

With the development of Internet of Things (IoT), IoT devices are deployed throughout our daily life. However, IoT devices are usually energy-constrained as their battery capacities are limited, which seriously affects the lifetime of IoT devices. To address this issue, the way of replacing or recharging these batteries manually can be considered, but the cost of which is unacceptable especially when the number of IoT devices is numerous. Recently, wireless power transfer (WPT) has been considered as a promising way to extend the lifetime of IoT devices [1]. In particular, IoT devices can harvest energy from the ambient radio frequency (RF) signals and store the harvested energy in their batteries for future usage. However, the WPT efficiency is typically low due to the severe path-loss. Thus, a long duration of energy harvesting (EH) is required, which reduces the time for IoT devices' information transmission and limits the improvement of network performance.

Recently, batteryless IoT devices based on the backscatter communication (BackCom) technology has received a lot of attention from industry and academia. For batteryless IoT devices, the information transmission is achieved by reflecting the incident signals via adjusting their load impedance periodically [2]. Hence, the circuit power consumption of batteryless IoT devices is quite small and can be covered by instantaneously absorbing a portion of incident signal power. Hence, the duration of EH is not required for batteryless IoT devices, which thus have been widely applied in practice [3]. However, the main limitation of batteryless IoT devices is the short transmission range. Thus, how to address this drawback is a urgent need to promote the ubiquitous deployment of batteryless IoT devices in the near future.

Relaying transmission is an efficient way to extend the transmission range of batteryless IoT devices. In [4], a relay node enabled by BackCom was adopted to forward the information transmission in a batteryless IoT network. However, as the transmission distance of the relay node is also short, the extension of network coverage is still limited. Thus, relaying schemes with satisfying transmission range should be investigated. In [5], the active relays are employed to assist the information delivery in batteryless IoT networks. Specifically, the active relays first harvest energy from a hybrid access point (HAP) and then use the harvested energy to actively forward the information from batteryless IoT devices to the destination, which extends the network coverage significantly. However, as the HAP is only with single antenna, the efficiency of downlink energy transfer and uplink information forwarding is low especially if the distance between the HAP and relays/batteryless IoT devices is large, which severely degrades the network performance. To deal with this problem, solutions to enhance energy and communication efficiency of batteryless IoT networks should be proposed.

In this letter, we propose an energy beamforming empowered relaying scheme for batteryless IoT networks, where wireless-powered relays are adopted to build the uplink transmission links from batteryless IoT devices to the HAP. In particular, the HAP with multi-antenna first exploits energy beamforming to transmit RF signals to enable the information backscattering of batteryless IoT devices and EH of wireless-powered relays. Then, the maximum-ratio combing (MRC) is used at the HAP to enhance the efficiency of information forwarding from the relays to the HAP by using

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the harvested energy. We aim to maximize the network sum-rate by jointly optimizing the energy beamforming vectors at the HAP, time scheduling for network, reflection coefficient of users, and transmit power at the relays. As the formulated problem is non-convex, we propose an alternating optimization (AO) algorithm to decompose the original problem into two sub-problems by introducing some auxiliary variables. For the first sub-problem, we first apply the semi-definite relaxation (SDR) technique to solve it efficiently. Then, we prove that the optimal energy beamforming matrices obtained by SDR are always rank-one. For the second sub-problem, the standard optimization method is applied. In addition, the computational complexity of the proposed algorithm is analyzed. Finally, numerical results verify the superiority of the proposed scheme over the benchmark schemes.

2. System Model

As shown in Fig. 1, we consider a wireless-powered relays assisted batteryless IoT network, in which there exists an HAP with sufficient energy supply, N users (i.e., batteryless IoT devices), and N wireless-powered relays. The HAP is equipped with M antennas and the other devices each has single antenna. Each user is equipped with a BackCom circuit and delivers its information to the HAP by backscattering the RF signals from the HAP. However, due to the limited backscattering range of users, the direct uplink transmission from the users to the HAP is unavailable[†]. Thus, the relays supporting the HTT protocol are deployed between the HAP and users. In particular, the i-th relay (denoted by G_i, $i = 1, \ldots, N$) first harvests energy from the HAP and then uses the harvested energy to forward the information of the i-th user (denote by U_i $i = 1, \ldots, N$) to the HAP via the decode-and-forward (DF) mode.

Denote the downlink channels from the HAP to G_i and from the HAP to U_i as $\boldsymbol{h}_{i,g}^H \in C^{1\times M}$ and $\boldsymbol{h}_{i,u}^H \in C^{1\times M}$, respectively. The uplink channels from U_i to G_i and from G_i to the HAP are denoted by $g_{i,u}$ and $\boldsymbol{g}_{i,g} \in C^{M\times 1}$, respectively.

[†] As the HAP transmits energy signals actively, its transmission range is much larger than that of the users. Thus, the downlink transmission links from the HAP to users are available.

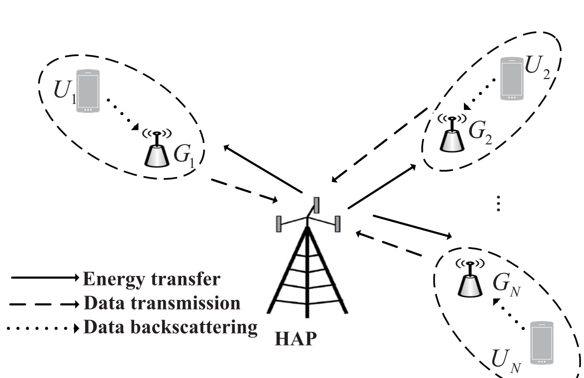

Fig. 1 Wireless-powered relays assisted batteryless IoT Network.

We divide the transmission block, normalized to be one, into two phases, i.e., data backscattering (DB) phase and data transmission (DT) phase. In the DB phase, the HAP transmits RF signals to enable both EH of relays and information backscattering of users. Specifically, U_i backscatters information by riding over the RF signals from the HAP to the G_i during b_i, while the other relays simultaneously harvest energy from the HAP. The total EH time of G_i is expressed as $\sum_{j=0}^{N} b_j - b_i$, where b_0 is a dedicated time slot for energy harvesting. In the DT phase, G_i forwards its decoded signal to the HAP during t_i. Thus, the time constraint for the network is given by $\sum_{i=0}^{N} b_i + \sum_{i=1}^{N} t_i \le 1$.

The HAP's transmit signal in b_i is denoted by $\boldsymbol{x}_i(t) = \sqrt{P_H}\boldsymbol{w}_i s(t)$, where P_H is the maximum transmit power at the HAP, $\boldsymbol{w}_i \in C^{M\times 1}$ satisfying $||\boldsymbol{w}_i||^2 \le 1$ is the energy beamforming vector in b_i, and $s(t)$ is previously generated sequence with unit power. In the DB phase, the received signal at U_i is expressed as $y_{i,u} = \sqrt{P_H}\boldsymbol{h}_{i,u}^H \boldsymbol{w}_i s(t)$. It is worth noting that U_i should absorb a part of received signal to enable the BackCom circuit for the DB [6]. Denote ρ as the reflection coefficient of U_i, where $0 \le \rho \le 1$. Thus, the instantaneous absorbed power by U_i, denoted by $P_{u,i}$, is given by $P_{i,u} = (1-\rho)P_H|\boldsymbol{h}_{i,u}^H\boldsymbol{w}_i|^2$. We then have the power causality constraint at U_i, i.e., $P_{c,u} \le P_{i,u}$, where $P_{c,u}$ is the circuit power consumption at U_i. The reflected signal at U_i is expressed as $u_i = \sqrt{\rho}\sqrt{P_H}\boldsymbol{h}_{i,u}^H\boldsymbol{w}_i s(t)c_i(t)$, where $c_i(t)$ satisfying $\mathbb{E}[|c_i(t)|^2] = 1$ denotes the intended signal needed to be delivered by U_i. The received signal at G_i during b_i is expressed as $y_{i,g} = \sqrt{P_H}\boldsymbol{h}_{i,g}^H\boldsymbol{w}_i s(t) + \sqrt{\rho}\sqrt{P_H} g_{i,u}\boldsymbol{h}_{i,u}^H\boldsymbol{w}_i s(t)c_i(t) + n_{i,g}$, where $n_{i,g} \sim \mathcal{CN}(0, \sigma_{i,g}^2)$ is the noise at G_i. As $s(t)$ can be previously known and the power of $\sqrt{P_H}\boldsymbol{h}_{i,g}^H\boldsymbol{w}_i s(t)$ is much larger than that of $\sqrt{\rho}\sqrt{P_H} g_{i,u}\boldsymbol{h}_{i,u}^H\boldsymbol{w}_i s(t)c_i(t)$, we employ the self-interference cancellation technique to cancel the interference from $y_{i,g}$, i.e., $\sqrt{P_H}\boldsymbol{h}_{i,g}^H\boldsymbol{w}_i s(t)$. Thus, the signal-to-noise ratio (SNR) at G_i can be formulated as $\gamma_{i,g} = \rho P_H|g_{i,u}|^2|\boldsymbol{h}_{i,u}^H\boldsymbol{w}_i|^2/\sigma_{i,g}^2$. Then, the achievable rate from U_i to G_i for $i = 1, \ldots, N$ is expressed as $R_{i,1} = b_i \log_2(1+\gamma_{i,g})$. As the backscattering range of U_i is limited and the distance between U_i and G_j ($j \ne i$) can be large, we consider that the reflected signal by U_i can only be received by G_i. Thus, G_i in b_j ($j \ne i$) can only harvest energy from the HAP. The received signal by G_i in b_j, denoted by $\hat{y}_{i,g}$, is expressed as $\hat{y}_{i,g} = \sqrt{P_H}\boldsymbol{h}_{i,g}^H\boldsymbol{w}_j s(t) + n_{i,g}$. Thus, the received power by G_i in b_j is $P_{i,j,g} = P_H|\boldsymbol{h}_{i,g}^H\boldsymbol{w}_j|^2$. The total harvested energy by G_i is then formulated as $E_i = \eta\sum_{j=0, j\ne i}^{N} P_{i,j,g} b_j = \eta P_H(\sum_{j=0}^{N} b_j|\boldsymbol{h}_{i,g}^H\boldsymbol{w}_j|^2 - b_i|\boldsymbol{h}_{i,g}^H\boldsymbol{w}_i|^2)$, where η is the EH efficiency of U_i.

We consider that G_i decodes its received signal successfully and then forwards the decoded signal, i.e., $c_i(t)$, to the HAP during t_i by using its harvested energy. Denote the transmit power of G_i as $P_{i,g}$, which satisfies $P_{i,g}t_i \le E_i$. Thus, the received signal by the HAP from G_i during t_i is given by $\boldsymbol{y}_{i,h} = \sqrt{P_{i,g}}\boldsymbol{g}_{i,g}c_i(t) + n_h(t)$, where $n_h(t) \sim \mathcal{CN}(0, \sigma_h^2)$ is the noise at the HAP. Denote the SNR at the HAP as $\gamma_{i,h}$. By exploiting the MRC technique at the

HAP, $\gamma_{i,h}$ can be expressed as $\gamma_{i,h} = P_{i,g}||\boldsymbol{g}_{i,g}||^2/\sigma_h^2$. Then, the achievable rate from G_i to the HAP during t_i is given by $R_{i,2} = t_i \log_2(1+\gamma_{i,h})$. In summary, the achievable rate from U_i to the HAP in the assistance of G_i is formulated as $R_i = \min\{R_{i,1}, R_{i,2}\}$.

3. Sum-Rate Maximization

In this section, we study the network sum-rate maximization problem by jointly optimizing the network's time allocation, energy beamforming vectors at the HAP, transmit power at the relays, and relection coefficient at the users. The optimization problem is formulated as

$$\begin{aligned}
&\max_{\boldsymbol{b},\boldsymbol{t},\boldsymbol{R},\boldsymbol{w}_i,\boldsymbol{P},\rho} \sum_{i=1}^{N} R_i,\\
&\text{s.t. C1: } R_i \le R_{i,1}, \forall i,\\
&\quad \text{C2: } R_i \le R_{i,2}, \forall i\\
&\quad \text{C3: } \sum_{i=0}^{N} b_i + \sum_{i=1}^{N} t_i \le 1,\\
&\quad \text{C4: } 0 \le b_i, t_i \le 1,\ \forall i,\\
&\quad \text{C5: } ||\boldsymbol{w}_i||^2 \le 1,\ \forall i,\\
&\quad \text{C6: } P_{i,g} t_i \le E_i,\ \forall i,\\
&\quad \text{C7: } P_{c,u} \le P_{i,u},\ \forall i,\\
&\quad \text{C8: } 0 \le \rho \le 1,
\end{aligned} \qquad (\mathbf{P1})$$

where $\boldsymbol{b} = [b_0, b_1, \ldots, b_N]$, $\boldsymbol{t} = [t_1, \ldots, t_N]$, $\boldsymbol{R} = [R_1, \ldots, R_N]$, and $\boldsymbol{P} = [P_{1,g}, \ldots, P_{N,g}]$. It can be found **P1** is a non-convex optimization problem since the variables are coupled in both the objective function and constraints. To address this issue, we first introduce some auxiliary variables to transform **P1**. We first introduce $\hat{\boldsymbol{w}}_i = \sqrt{b_i}\boldsymbol{w}_i$ and set $\boldsymbol{W}_i = \hat{\boldsymbol{w}}_i \hat{\boldsymbol{w}}_i^H$, where $\text{Rank}(\boldsymbol{W}_i) = 1$, $\boldsymbol{W}_i \succeq 0$, and $\text{Tr}(\boldsymbol{W}_i) \le b_i$. Then, we introduce e_i and x_i, which satisfy $e_i = P_{i,g} t_i$ and $x_i \le \rho P_H |g_{i,u}|^2 \text{Tr}(\boldsymbol{h}_{i,u}\boldsymbol{h}_{i,u}^H \boldsymbol{W}_i)/\sigma_{i,g}^2$, respectively. With these new variables, the constraints C1, C2, C6 and C7 can be recast as C9: $R_i \le b_i \log_2(1+\frac{x_i}{b_i}), \forall i$, C10: $R_i \le t_i \log_2(1+\frac{e_i||\boldsymbol{g}_{i,g}||^2}{\sigma_h^2 t_i}), \forall i$, C11: $e_i \le \eta P_H[\sum_{j=0}^{N} \text{Tr}(\boldsymbol{h}_{i,g}\boldsymbol{h}_{i,g}^H \boldsymbol{W}_j) - \text{Tr}(\boldsymbol{h}_{i,g}\boldsymbol{h}_{i,g}^H \boldsymbol{W}_i)]$, $\forall i$, and C12: $(1-\rho)P_H \text{Tr}(\boldsymbol{h}_{i,u}\boldsymbol{h}_{i,u}^H \boldsymbol{W}_i) \ge P_{c,u}$, $\forall i$, respectively. Then, **P1** can be transformed into the following problem, which is given by

$$\begin{aligned}
&\max_{\boldsymbol{b},\boldsymbol{t},\boldsymbol{R},\boldsymbol{W}_i,\boldsymbol{e},\boldsymbol{x},\rho} \sum_{i=1}^{N} R_i,\\
&\text{s.t. C3, C4, C8} - \text{C12},\\
&\quad \text{C13}: x_i \le \rho P_H |g_{i,u}|^2 \text{Tr}(\boldsymbol{h}_{i,u}\boldsymbol{h}_{i,u}^H \boldsymbol{W}_i)/\sigma_{i,g}^2, \forall i,\\
&\quad \text{C14: } \text{Tr}(\boldsymbol{W}_i) \le b_i, \forall i,\\
&\quad \text{C15: } \boldsymbol{W}_i \succeq 0, \forall i,\\
&\quad \text{C16: } \text{Rank}(\boldsymbol{W}_i) = 1, \forall i,\\
&\quad \text{C17:} e_i \ge 0,\ \forall i.
\end{aligned} \qquad (\mathbf{P2})$$

where $\boldsymbol{e} = [e_1, \ldots, e_N]$, and $\boldsymbol{x} = [x_1, \ldots, x_N]$. It can be found that **P2** is still non-convex due to the constraints C12 and C13, which cannot be solved by standard convex optimization methods. To solve **P2**, we propose an AO algorithm. First, we optimize $\{\boldsymbol{b}, \boldsymbol{t}, \boldsymbol{R}, \boldsymbol{W}_i, \boldsymbol{e}, \boldsymbol{x}\}$ with ρ fixed. Second, we optimize $\{\boldsymbol{R}, \boldsymbol{x}, \rho\}$ with $\{\boldsymbol{b}, \boldsymbol{t}, \boldsymbol{W}_i, \boldsymbol{e}\}$ fixed. By iteratively implementing the above two steps, we can finally obtain a sub-optimal solution to **P2** with satisfying accuracy.

3.1 Optimizing $\{\boldsymbol{b}, \boldsymbol{t}, \boldsymbol{R}, \boldsymbol{W}_i, \boldsymbol{e}, \boldsymbol{x}\}$ with ρ Fixed

Given ρ, we first optimize $\{\boldsymbol{b}, \boldsymbol{t}, \boldsymbol{R}, \boldsymbol{W}_i, \boldsymbol{e}, \boldsymbol{x}\}$ in the following problem

$$\begin{aligned}
&\max_{\boldsymbol{b},\boldsymbol{t},\boldsymbol{R},\boldsymbol{W}_i,\boldsymbol{e},\boldsymbol{x}} \sum_{i=1}^{N} R_i,\\
&\text{s.t. C3, C4, C9} - \text{C17}.
\end{aligned} \qquad (\mathbf{P3})$$

Proposition 1: After relaxing the constraint C16 by the SDR technique [7], **P3** is a convex optimization problem.

Proof 1: We first define a concave function with respect to x_i as $f_i(x_i) = \log_2(1+x_i)$. Due to the fact that the concavity can be kept by the perspective operation [8], we can obtain that $b_i \log_2(1+\frac{x_i}{b_i})$ is concave with respect to x_i and b_i. Thus, the constraint C9 is convex. Similarly, we can prove that the constraint C10 is convex. It is obvious the other constraints are affine. In addition, the objective function is linear. Thus, we can obtain that **P3** is a convex optimization problem.

According to Proposition 1, we can use the CVX tool [9] to solve **P3** directly. However, the obtained energy beamforming matrices by applying the SDR technique may not satisfy the rank-one constraint shown in C16. In the following proposition, we will verify the tightness of the SDR technique.

Proposition 2: The optimal solution to **P3**, denoted by $\boldsymbol{W}_i^*$, is a rank-one matrix, where $i = 1, \ldots, N$.

Proof 2: The Lagrangian of **P3** is expressed as

$$\begin{aligned}
\mathcal{L} =& \sum_{i=1}^{N} \nu_i \eta P_H [\sum_{j=0}^{N} \text{Tr}(\boldsymbol{h}_{i,g}\boldsymbol{h}_{i,g}^H \boldsymbol{W}_j) - \text{Tr}(\boldsymbol{h}_{i,g}\boldsymbol{h}_{i,g}^H \boldsymbol{W}_i)]\\
&+ \sum_{i=1}^{N} [\mu_i \rho |g_{i,u}|^2/\sigma_{i,g}^2 + \varphi(1-\rho)] P_H \text{Tr}(\boldsymbol{h}_{i,u}\boldsymbol{h}_{i,u}^H \boldsymbol{W}_i)\\
&- \sum_{i=0}^{N} \lambda_i \text{Tr}(\boldsymbol{W}_i) + \sum_{i=0}^{N} \text{Tr}(\boldsymbol{\Omega}_i \boldsymbol{W}_i) + \xi
\end{aligned} \qquad (1)$$

where $\nu_i \ge 0$, $\varphi \ge 0$, $\mu_i \ge 0$, $\lambda_i \ge 0$, and $\boldsymbol{\Omega}_i \succeq 0$ are the multipliers associated with the constraints C11- C15, respectively, ξ represents the term unrelated with $\boldsymbol{W}_i$. The Karush–Kuhn–Tucker (KKT) conditions of **P3** are given by

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{W}_0} = \boldsymbol{\Omega}_0^* - \lambda_0^* \boldsymbol{I}_M + \sum_{j=1}^{N} \nu_j^* \eta P_H \boldsymbol{h}_{j,g}\boldsymbol{h}_{j,g}^H = 0, \qquad (2)$$

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{W}_i} = \boldsymbol{\Omega}_i^* - \boldsymbol{A}_i + \boldsymbol{B}_i = 0,\ i = 1, \ldots, N, \tag{3}$$

$$\mathrm{Tr}(\boldsymbol{\Omega}_i^* \boldsymbol{W}_i^*) = 0,\ i = 0, 1, \ldots, N, \tag{4}$$

where $\boldsymbol{B}_i = [\mu_i \rho |g_{i,u}|^2/\sigma_{i,g}^2 + \varphi(1-\rho)] P_H \boldsymbol{h}_{i,u} \boldsymbol{h}_{i,u}^H \boldsymbol{W}_i$, $\boldsymbol{A}_i = \lambda_i^* \boldsymbol{I}_M + \nu_i^* \eta P_H \boldsymbol{h}_{i,g} \boldsymbol{h}_{i,g}^H - \sum_{j=1}^N \nu_j^* \eta P_H \boldsymbol{h}_{j,g} \boldsymbol{h}_{j,g}^H$, ν_i^*, μ_i^*, λ_i^*, and $\boldsymbol{\Omega}_i^*$ are the optimal multipliers.

We first prove $\boldsymbol{W}_i$ for $i = 1, \ldots, N$ are rank-one. It is obvious in the optimal condition, the constraints C11 and C14 hold as equalities. Thus, we can obtain that λ_i^* and ν_i^* are all positive. In addition, the channels, i.e., $\boldsymbol{h}_{i,g}^H$ for $i = 1, \ldots, N$, are independently distributed. Thus, $\boldsymbol{A}_i$ is a full-rank matrix, i.e., $\mathrm{Rank}(\boldsymbol{A}_i) = M$. From (3), we can obtain $\mathrm{Rank}(\boldsymbol{\Omega}_i^*) = \mathrm{Rank}(\boldsymbol{A}_i - \boldsymbol{B}_i) \geq M - 1$ because the rank of $\boldsymbol{B}_i$ is one. If $\mathrm{Rank}(\boldsymbol{\Omega}_i^*) = M$, $\boldsymbol{W}_i^* = \boldsymbol{0}$ according to (4). It is obvious $\boldsymbol{W}_i^* = \boldsymbol{0}$ is not the optimal solution. If $\mathrm{Rank}(\boldsymbol{\Omega}_i^*) = M - 1$, we can find a vector spanning the null space of $\boldsymbol{\Omega}_i$. Thus, according to (4), we can conclude that $\boldsymbol{W}_i^*$ is a rank-one matrix. Similarly, we can prove $\boldsymbol{W}_0$ is also rank-one.

This thus proves Proposition 2.

From Proposition 2, the optimal energy beamforming vectors, denoted by $\boldsymbol{w}_i^*$, can be achieved by applying Cholesky decomposition of $\boldsymbol{W}_i^*$.

3.2 Optimization of $\{\boldsymbol{R}, \boldsymbol{x}, \rho\}$ with $\{\boldsymbol{b}, \boldsymbol{t}, \boldsymbol{W}_i, \boldsymbol{e}\}$ Fixed

Given $\{\boldsymbol{b}, \boldsymbol{t}, \boldsymbol{W}_i, \boldsymbol{e}\}$, we then optimize $\{\boldsymbol{R}, \boldsymbol{x}, \rho\}$ in the following problem

$$\max_{\boldsymbol{R}, \boldsymbol{x}, \rho} \sum_{i=1}^N R_i, \tag{\textbf{P4}}$$
$$\text{s.t. C8, C9, C10, C12, C13.}$$

where $\boldsymbol{x} = [x_1, \ldots, x_N]$. It can be proved that **P4** is a convex optimization problem and can be solved by the CVX tool.

The algorithm to solve the optimization problem is shown in Algorithm 1. It can be found that the objective function's value of **P1** is a non-decreasing function after each iteration. Hence, the convergence of Algorithm 1 can be guaranteed. We then analyze the computational complexity of Algorithm 1. The computational complexities for solving **P3** and **P4** are $O\left((NM^2 + 5N + 1)^2 \ \ (M^2N^2 + NM^2 + 11N + 3)\right)$ $O(\sqrt{2N+1})$, respectively. Thus, the total computational complexity of Algorithm 1 is $O((NM^2 + 5N + 1)^2\ (M^2N^2 + NM^2 + 11N + 3)L + \sqrt{2N+1}L)$, where L is the required number of iterations to achieve convergence.

Algorithm 1 The Algorithm for Solving **P1**.

1: Initialize ρ^i, where $i = 0$ is the iteration index for the proposed AO algorithm.
2: **repeat**
3: Solve **P3** to obtain $\boldsymbol{b}^{i+1}$, $\boldsymbol{t}^{i+1}$, $\boldsymbol{W}_i^{i+1}$, and $\boldsymbol{e}^{i+1}$.
4: Solve **P4** to obtain ρ^{i+1}.
5: Update $i = i + 1$.
6: **until** the convergence is achieved.

4. Numerical Results

In this section, numerical results are provided to show the superiority of the proposed scheme. The channels are modeled following the setting in [10], which are composed of the large-scale path-loss and small-scale fading. The large-scale path-loss model is expressed as $C_0 \left(d_{m,n}/d_0\right)^{-\alpha}$, where $C_0 = (\zeta/(4\pi))^2$ is the path-loss at the reference distance d_0 = 1 m, ζ is the wavelength with the carrier frequency of 750 MHz, $d_{m,n}$ denotes the distance between two nodes m and n, α is the path loss exponent and set at 2. The small-scale fading model is considered to be Rayleigh fading with circularly symmetric complex Gaussian random variables with zero mean and unit variance. Denote the distances between the HAP and U_i, between the HAP and G_i, and between U_i and G_i as d_{HAP,U_i}, d_{HAP,G_i}, and d_{U_i,G_i}, respectively. Unless other stated, the parameters are set as follows: $d_{HAP,U_i} = 10$ m, $d_{HAP,G_i} = 9$ m, $d_{U_i,G_i} = 2$ m, $N = 5$, $\eta = 0.7$, $M = 5$, $\sigma_{i,g}^2 = \sigma_h^2 = -70$ dBm, and $P_{c,u} = 0.25$ μW. The following schemes are considered for performance comparisons.

- Random energy beamforming scheme: The energy beamforming vector $\boldsymbol{w}_i$ in b_i is generated randomly, while the network time allocation, transmit power at the relays and reflection coefficient are jointly optimized.
- Equal time allocation scheme: The duration of each time slot is the same, i.e., $b_i = t_i = 1/(2N+1)$. In addition, the energy beamforming vectors, transmit power at the relays and reflection coefficient are jointly optimized.

Figure 2 investigates the achievable sum-rate versus the HAP's transmit power. It can be observed that as the transmit power increases, the sum-rates of all schemes improve. This is because a higher transmit power can make the relays harvest more energy from the HAP and the users reflect information with a larger power, which thus enhances the performance of both DB and DT phases. We can also observe that the proposed scheme can always achieve the best performance, which confirms the necessity of optimizing the

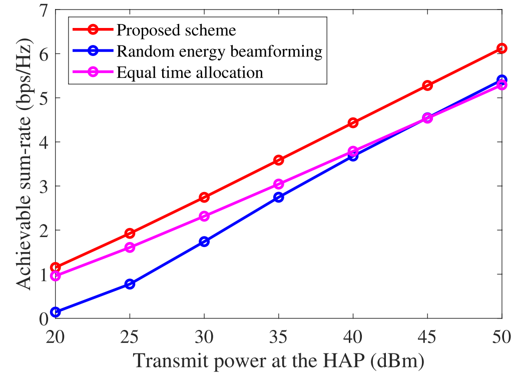

Fig. 2 Sum-rate versus transmit power at the HAP.

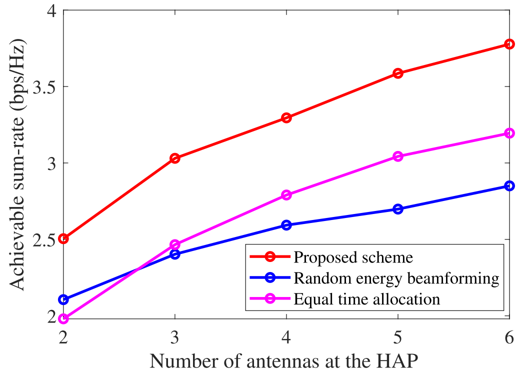

Fig. 3 Sum-rate versus number of antennas at the HAP.

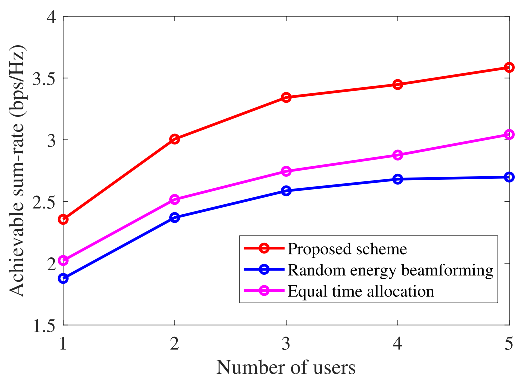

Fig. 4 Sum-rate versus number of users.

energy beamforming and time allocation.

Figure 3 shows the effect of the number of antennas at the HAP on the achievable sum-rate. As the number of antennas at the HAP increases, the sum-rates of all schemes improve. The reason is that more diversity can be achieved for a larger number of antennas. In addition, the number of the sum-rate gap between the proposed scheme and the scheme with random energy beamforming is also an increasing function with respect to the number of antennas, which indicates the importance of energy beamforming optimization. When the number of antennas at the HAP is small, e.g., $M = 2$, the sum-rate of the scheme with equal time allocation is smaller than that of the scheme with random energy beamforming. However, the sum-rate of the scheme with equal time allocation is better when the number of antennas at the HAP become large.

In Fig. 4, we evaluate the achievable sum-rate versus the number of users (relays). The sum-rates of all schemes are increasing functions with respect to the number of users. Again, we find that the proposed scheme can achieve the best performance compared to the benchmark schemes, which confirms the superiority of the proposed scheme.

5. Conclusions

In this letter, we have proposed an efficient relaying scheme for batteryless IoT networks empowered by energy beamforming at the HAP, where the information delivery from the batteryless IoT devices to the HAP is assisted by the wireless-powered relays. The energy beamforming has been exploited at the HAP for enhancing the efficiency of energy transfer to the relays, information backscattering from the batteryless IoT devices to the relays, and information forwarding from the relays to the HAP. We have formulated a problem to maximize the network sum-rate and proposed an AO algorithm with the variable substitution and SDR techniques to solve it efficiently. In addition, we can proved the tightness of the SDR technique, i.e., the obtained energy beamforming matrices are rank-one. Numerical results have been provided to verify the performance of the proposed scheme.

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