Time-Division Energy Beamforming for Multiuser Wireless Power Transfer With Non-Linear Energy Harvesting

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Abstract—Energy beamforming has emerged as a promising technique for enhancing the energy transfer efficiency of radio-frequency (RF) enabled wireless power transfer (WPT). However, the performance of conventional energy beamforming may seriously degrade due to the non-linear RF to direct current (DC) conversion at energy receivers (ERs). To tackle this issue, this letter proposes a new time-division energy beamforming scheme, in which different energy beamforming matrices (of high ranks in general) are time shared to exploit the “convex-concave” shape of the RF-DC power relation at ERs. In particular, we maximize the minimum harvested DC energy among all ERs, by jointly optimizing the energy beamforming matrices and the corresponding time allocation subject to a given charging time duration (e.g., a second). To solve the formulated non-convex min-DC-energy maximization problem, we propose an efficient solution by using the techniques of alternating optimization and successive convex approximation (SCA). Numerical results show that the proposed time-division energy beamforming design indeed outperforms the conventional multi-beam and time-division-multiple-access (TDMA)-based energy transmissions.

Index Terms—Energy beamforming, wireless power transfer (WPT), non-linear energy harvesting, time division.

I. INTRODUCTION

MULTI-ANTENNA energy beamforming has been recognized as a promising technique to improve the end-to-end energy transfer efficiency for radio-signals-based wireless power transfer (WPT) [1], [2]. By deploying multiple antennas, energy transmitters (ETs) can properly adjust the transmit beamforming to steer wireless energy towards desirable directions, thus combating against the radio signal propagation loss, and charging intended energy receivers (ERs) more efficiently.

In the literature, there have been some prior works investigating the transmit energy beamforming design under various WPT applications such as simultaneous wireless information and power transfer (SWIPT) [3], [4], wireless powered communication networks (WPCN) [5], mobile edge computing (MEC) [6], and Internet of Things (IoT) [7]. These prior works generally considered linear energy harvesting (EH) models at ERs, i.e., the radio frequency (RF) to direct current (DC) conversion efficiency at each ER is assumed to be constant. In practice, however, such RF-to-DC conversion efficiency is non-linear. To characterize such non-linear behaviors, the authors in [8], [9] proposed a non-linear EH model based on the Taylor expansion of diode characteristics, which has been widely used to facilitate the transmit signal waveform design. By contrast, another non-linear model in [10]–[12] specifies the relation between the input RF and output DC power based on sigmoid functions, which is determined via curve fitting by using practical measurement results, and is normally used to facilitate the energy beamforming design under fixed signal waveforms. Based on the sigmoid function-based EH model, it is observed that the RF-DC power relation generally follows a “convex-concave” shape [2].

In multiuser WPT systems, how to fairly maximize the energy harvested at different ERs is an important issue, which has been studied in some prior works under linear [13] and non-linear EH models [14], [15]. It was shown in [13] that under the linear EH model, the multi-beam energy transmission is the optimal design for the multi-antenna ET to maximize the minimum energy harvested by all the ERs. The joint transmit beamforming and waveform design were studied in [14] to maximize the weighted-sum harvested power among ERs by considering the diode-characteristics-based non-linear EH models, and the max-min fair beamforming design was investigated in [15] for the SWIPT system under the sigmoid function-based EH model. However, in these prior works [13]–[15], the conventional multi-beam energy transmission is considered, in which the energy beams are fixed over the channel coherence time. Although optimal under the linear EH models [13], this design is generally not optimal under the non-linear EH models, as the received RF power at some ERs may fall into the convex regime with certain EH performance loss. Therefore, we are motivated to investigate new energy beamforming designs to address this issue.

In this letter, we study a multiuser multiple-input single-output (MISO) WPT system consisting of one ET with multiple transmit antennas and multiple ERs each with one single antenna, by considering the sigmoid function-based...
non-linear EH model. By considering a given charging time duration, we maximize the minimum harvested DC energy among all ERs by jointly optimizing the energy beamforming matrices over time. First, under the non-linear EH model, we use a simple example to show that the time-division multiple-access (TDMA)-based energy beamforming design can outperform the multi-beam energy transmission that was shown in [4] to be optimal under linear EH models. Motivated by this observation, we propose a more general beamforming design approach to exploit both benefits of multi-beam and TDMA-based energy transmissions, under which different energy beamforming matrices are time shared to exploit the “convex-concave” property of the RF-DC power relation at ERs. To solve the non-convex min-DC-energy maximization problem, we propose an efficient solution by using the techniques of alternating optimization and successive convex approximation (SCA). Numerical results show that the proposed time-division energy beamforming design outperforms the conventional multi-beam and TDMA-based energy transmission designs.

**Notation:** Boldface letters refer to vectors (lower case) or matrices (upper case). For a matrix $S$, $S^H$ and $S^T$ denote its conjugate transpose and transpose, respectively. $I$ denotes an identity matrix. $tr(\cdot)$ denotes the trace of a squared matrix. $\mathbb{E}(\cdot)$ denotes the statistical expectation. $\nabla f(x)$ denotes the first-derivative of $f(x)$ with respect to $x$. $\mathbb{C}^{x \times y}$ denotes the space of $x \times y$ complex matrices.

**II. SYSTEM MODEL**

As shown in Fig. 1, we consider a multiuser MISO WPT system, where an ET transmits RF signals to wirelessly charge $K \geq 1$ ERs. The ET is equipped with $M \geq 1$ antennas while each ER is equipped with one single antenna. Let $\mathcal{M} \triangleq \{1, \ldots, M\}$ and $\mathcal{K} \triangleq \{1, \ldots, K\}$ denote the set of transmit antennas at the ET and the set of ERs, respectively.

We consider a quasi-stationary channel model, in which the wireless channels remain unchanged within a particular time block. It is assumed that the ET perfectly knows the channel state information (CSI) to all ERs for quantifying the fundamental performance limits and gaining essential design insights. In practice, the CSI can be obtained by using different channel acquisition methods such as reverse-link training [16], forward-link training with limited feedback [17], and energy measurement and feedback [18]. Let $\mathcal{T} \triangleq \{0, T\}$ denote the given charging time block with duration $T$. At any time instant $t \in \mathcal{T}$, let $s(t) \in \mathbb{C}^{M \times 1}$ denote the energy-bearing signal transmitted from the ET, and $h_k \in \mathbb{C}^{M \times 1}$ denote the channel vector from the ET to ER $k$. Then, the received RF power at ER $k$ is

$$Q_{k}^{RF}(t) = \mathbb{E}[(h_k^H s(t))^2] = h_k^H S(t) h_k,$$

where $S(t) \triangleq \mathbb{E}[s(t)s(t)^H] \in \mathbb{C}^{M \times M}$ denotes the transmit covariance matrix, which is positive semi-definite, i.e., $S(t) \succeq 0$.\(^1\) Suppose that the maximum transmit power at the ET is $P_{\text{max}}$, and thus it follows $\text{tr}(S(t)) \leq P_{\text{max}}$.

As for the RF-to-DC energy conversion, we adopt the non-linear EH model introduced in [10], where the output DC power at the $k$-th ER is expressed as a sigmoid-like function with respect to the input RF power $Q_k^{RF}(t)$, i.e.,

$$Q_k^{DC}(Q_k^{RF}(t)) = \frac{Q_k^{\text{sig}}(Q_k^{RF}(t)) - Q_{\text{max}}}{1 - \Omega},$$

with $\Omega = \frac{1}{1 + e^{-a(\frac{Q_{\text{max}}}{b} - 1)}}$. Here, $\Omega$ is a constant to ensure the zero-input/zero-output response for EH, $Q_{\text{max}}$ denotes the maximum output DC power at the ERs when the rectifier is saturated, and $a$ and $b$ are two constants depending on the specific circuit. From (2), it follows the relationship between the harvested DC power $Q_k^{DC}(t)$ and the RF power $Q_k^{RF}(t)$ has a convex-concave shape [2], [10]. Accordingly, the average harvested DC energy over the charging block $\mathcal{T}$ at each ER $k$ is given by

$$\int_0^T Q_k^{DC}(h_k^H S(t) h_k) dt.$$

For the considered multiuser MISO WPT setup, our objective is to maximize the minimum average harvested DC energy among all the ERs over time block $\mathcal{T}$ by optimizing the transmit energy covariance matrices $S(t)$ over time. The optimization problem is formulated as

$$(P1): \max_{S(t)} \min_{k \in \mathcal{K}} \int_0^T Q_k^{DC}(h_k^H S(t) h_k) dt$$

s.t. $\text{tr}(S(t)) \leq P_{\text{max}}, \forall t \in \mathcal{T}$

$s(t) \succeq 0, \forall t \in \mathcal{T}.$

Note that without loss of generality, in problem (P1) the transmit energy covariance matrices $\{S(t)\}$ are adjustable over time. Due to the non-convexity of the objective function in (3a), (P1) is generally difficult to be solved optimally. In the following, we introduce two conventional energy beamforming designs and show the effect of the nonlinear EH model in (2) on the performance of the harvested DC energy.

**A. Multi-Beam Energy Transmission**

In this design, the energy covariance matrix $S(t)$ remains unchanged over the entire charging time block, i.e., $S(t) = S, \forall t \in \mathcal{T}$. In this case, the min-DC-energy maximization problem in (P1) is simplified as

$$(P2): \max_{S} \min_{k \in \mathcal{K}} Q_k^{DC}(h_k^H S h_k)$$

s.t. $\text{tr}(S) \leq P_{\text{max}}$

$S \succeq 0.$

It is observed that function $Q_k^{DC}(h_k^H S h_k)$ in (4a) is non-decreasing with respect to $h_k^H S h_k$. Therefore, maximizing $Q_k^{DC}(h_k^H S h_k)$ is equivalent to maximizing $h_k^H S h_k$. By using this fact and introducing an auxiliary variable $E$, the
optimization of $S$ in problem (P2) is equivalent to solving

\[(P2.1) \quad \max_{S,E} E \quad \text{s.t.} \quad h_k^H S h_k \geq E, \quad \forall k \in \mathcal{K} \quad \text{(5a)}\]
\[\quad \text{and} \quad (4b)\text{ and } (4c) \quad \text{(5c)}\]

Problem (P2.1) is a semi-definite program (SDP) [19], which can be efficiently solved using standard convex optimization tools such as CVX [20]. Let $S^*$ denote the optimal solution to (P2), then the corresponding minimum harvested DC energy among the ERs is $T \min\{Q_k^{DC}(S^*), \ldots, Q_K^{DC}(S^*)\}$.

It is worth emphasizing that in general, the optimal energy covariance matrix $S^*$ may be of high rank, that is, more than one energy beams are required to balance the harvested DC energy among all the ERs for fairness. This is the case, especially when the number of ERs $K$ becomes sufficiently large [13]. Furthermore, it can be verified that under the special case with the linear EH model, the multi-beam energy transmission is optimal for maximizing the minimum harvested DC energy among all ERs [4].

B. TDMA-Based Energy Transmission

In the TDMA-based design, the charging time block $T$ is divided into $N = K$ time slots with optimizable durations denoted as $\{\tau_n\}$, where $\tau_n \geq 0, \forall n \in \mathcal{N} \triangleq \{1, \ldots, N\}$, and $\sum_{n \in \mathcal{N}} \tau_n = T$. In time slot $n = k$, the ET designs the energy beamforming matrices for maximizing the harvested DC energy at ER $k$ with $S_n^* = P_{\max}^{-1} h_k^H h_k$. Accordingly, the harvested DC energy for ER $k$ over the entire charging time block is given as $\sum_{n \in \mathcal{N}} \tau_n Q_k^{DC}(h_k^H S_n^* h_k)$. In this case, we only need to optimize the time allocation $\{\tau_n\}$ to maximize the minimum harvest DC energy among all the ERs, for which the optimization problem is expressed as

\[(P4): \quad \max_{\{\tau_n \geq 0\}} \min_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} \tau_n Q_k^{DC}(h_k^H S_n^* h_k) \quad \text{(6a)}\]
\[\text{s.t.} \quad \sum_{n \in \mathcal{N}} \tau_n = T. \quad \text{(6b)}\]

By introducing an auxiliary variable $E$, problem (P4) is re-expressed as the following linear program (LP) [19]:

\[(P4.1): \quad \max_{\{\tau_n \geq 0\}} E \quad \text{s.t.} \quad \sum_{n \in \mathcal{N}} \tau_n Q_k^{DC}(S_n^*) \geq E, \quad \forall k \in \mathcal{K} \quad \text{(7b)}\]
\[\text{and} \quad (6b) \quad \text{(7c)}\]

which can be optimally solved by CVX.

Note that under the special case of linear EH models, the TDMA-based design is a suboptimal solution to the min-DC-energy maximization problem for multiuser WPT, and thus performs inferior to the optimal multi-beam energy transmission in Section II-A. Nevertheless, this may not hold in general under the practical non-linear EH model, as shown in the following example.

Example 1: Let $K = 2, M = 4$, and $P_{\max} = 15$ W. Suppose that the channel vectors from the ET to the two ERs are orthogonal, given by $h_1 = [10^{-4}, 10^{-4}, 0, 0]^T$ and $h_2 = [0, 0, 10^{-4}, 10^{-4}]^T$, respectively. As for the non-linear EH model, we set $Q_{\max} = 10.73$ mW, $a = 0.2308$, and $b = 5.365$ [2]. Under this setup and by considering $T = 1$, it can be shown that for the multi-beam energy transmission, the achieved RF power at each ER is 1.5 mW and the corresponding average DC power at each ER is 0.9127 mW. By contrast, for the TDMA-based energy transmission, the achieved RF power by ET 1 at the two slots is 3 mW and 0 mW, and the corresponding DC power is 1.9666 mW and 0 mW, respectively; while the achieved RF power by ET 2 at the two slots is 0 mW and 3 mW, and the corresponding DC power is 0 mW and 1.9666 mW, respectively. Accordingly, with the optimal equal time allocation between the two slots, the average DC power at each ER is 0.9833 mW, which is higher than that achieved by the multi-beam transmission. This example clearly shows that the TDMA-based design outperforms the multi-beam design.

III. TIME-DIVISION ENERGY BEAMFORMING

In this section, we propose a new time-division energy beamforming approach. Similar to the TDMA-based design, we consider $N = K$ time slots with optimizable durations $\{\tau_n\}$. In each time slot $n$, the transmit energy covariance is $S_n$, which is to be optimized as a decision variable. In this design, we jointly optimize the beamforming matrices $\{S_n\}$ and time durations $\{\tau_n\}$, and thus, the min-energy maximization problem is formulated as

\[(P5): \quad \max_{\{\tau_n \geq 0\}, \{S_n\}} \min_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} \tau_n Q_k^{DC}(h_k^H S_n h_k) \quad \text{(8a)}\]
\[\text{s.t.} \quad \text{tr}(S_n) \leq P_{\max}, \quad \forall n \in \mathcal{N} \quad \text{(8b)}\]
\[S_n \succeq 0, \quad \forall n \in \mathcal{N} \quad \text{(6c)}\]
\[\text{(6d)} \quad \text{(8d)}\]

Note that for the special case of $S_n = S, \forall n \in \mathcal{N}$, our proposed design reduces to the conventional multi-beam energy transmission; while if $S_n = P_{\max}^{-1} h_k^H h_k$, it becomes the TDMA-based design. Therefore, our proposed design can exploit the benefits of both conventional designs of multi beam and TDMA at the same time.

Problem (P5) is non-convex due to the coupling between the time durations $\{\tau_n\}$ and covariance matrices $\{S_n\}$, and thus is challenging to be optimally solved. To overcome this issue, we propose an efficient alternating-optimization-based algorithm to solve (P5) by optimizing $\{\tau_n\}$ and $\{S_n\}$ in an alternating manner [21].

1) Optimization of $\{S_n\}$ Under Given $\{\tau_n\}$: Under given time durations $\{\tau_n\}$, the optimization of $\{S_n\}$ is expressed as

\[(P5.1): \quad \max_{\{S_n\}} \min_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} \tau_n Q_k^{DC}(h_k^H S_n h_k) \quad \text{(9a)}\]
\[\text{s.t.} \quad \text{(8b)} \quad \text{and} \quad \text{(8c)} \quad \text{(9b)}\]

The above problem (P5.1) is still non-convex due to the non-convex objective function. Thus, we propose to update the beamforming matrices $\{S_n\}$ by applying the SCA technique [22]. Consider the (inner) iteration $l \geq 1$, in which the current point of $\{S_n\}$ is $\{S_n^{(l-1)}\}$. At the current point $\{S_n^{(l-1)}\}$, we approximate the non-convex objective function...
of (9a) by its first-order Taylor expansion, given by
\[
Q_k^{DC}(h_k^H S_n h_k) \approx Q_k^{DC}(h_k^H S_n^{(l-1)} h_k) + \nabla Q_k^{DC}(h_k^H S_n^{(l-1)} h_k) h_k^H S_n h_k, \quad (10)
\]
where
\[
\nabla Q_k^{DC}(h_k^H S_n^{(l-1)} h_k) = \frac{Q_{\text{max}}}{1 + e^{-a(h_k^H S_n^{(l-1)} h_k - b)}}. \quad (11)
\]
Since \(Q_k^{DC}(h_k^H S_n h_k)\) is not convex nor concave, we need to define a trust region to ensure the approximation accuracy. The following trust region constraints are imposed:
\[
|h_k^H S_n h_k - h_k^H S_n^{(l-1)} h_k| \leq \Gamma_l, \forall k \in K, \forall n \in N', (11)
\]
in which \(\Gamma_l > 0\) denotes the radius of the trust region.

By replacing \(Q_k^{DC}(h_k^H S_n h_k)\) as the approximation in (10), introducing an auxiliary variable \(E\), and after some manipulations, the approximated solution to problem (P5.1) at iteration \(l\) is derived by solving the following problem:
\[
(P5.2): \quad \max_{\{S_n\}_n} E \quad \text{s.t.} \quad \sum_{n \in N} \tau_n \nabla Q_k^{DC}(h_k^H S_n^{(l-1)} h_k) h_k^H S_n h_k \geq E, \quad (12a)
\]
\[
\quad \forall k \in K \quad \forall n \in N' \quad (8b), \quad (8c), \quad \text{and} \quad (11). \quad (12c)
\]
Problem (P5.2) is convex and thus can be solved by, e.g., CVX. Let \(\{S_n^{(l)}\}\) denote the optimal solution to (P5.2) at iteration \(l\). By taking \(\{S_n^{(l)}\}\) into (9a), if the objective value increases, then we replace the current point by \(\{S_n^{(l)}\}\) and go to the next iteration; otherwise, we reduce \(\Gamma_l\) and go back to solve problem (P5.2) until \(\Gamma_l\) is less than the tolerance \(\epsilon\), i.e., \(\Gamma_l \leq \epsilon\).

2) Optimization of \(\{\tau_n\}\) Under Given \(\{S_n\}\): We optimize the time duration \(\{\tau_n\}\) under given beamforming matrices \(\{S_n\}\). In this case, problem (P4) can be expressed as
\[
(P5.3): \quad \max_{\{\tau_n \geq 0\}} \min_{k \in K} \sum_{n \in N} \tau_n Q_k^{DC}(h_k^H S_n h_k) \quad (13a)
\]
\[
\quad \text{s.t.} \quad (6b). \quad (13b)
\]
Problem (P5.3) is similar to problem (P4), and thus can be transformed into an LP and solved by, e.g., CVX.

By solving problem (P5.1) and (P5.3) in an alternating manner, problem (P5) can be finally solved. The detailed algorithm is summarized as Algorithm 1. By properly choosing the initial covariance matrices, the proposed design will converge to a stationary point [23]. The complexity for solving problem (P5) generally depends on that for solving the SDR problem (P5.2) in the inner loop and the LP problem (P5.3) in the outer loop together with the tolerances \(\epsilon > 0\) and \(\epsilon > 0\). Based on [24], the complexity of solving problems (5.2) and (5.3) is \(O((M + K)^{0.5} M^4 (M^2 + K))\) and \(O(K^{3.5})\), respectively.

IV. NUMERICAL RESULTS

In this section, we provide numerical results to validate the performance of our proposed time-division energy beamforming design, as compared to the conventional multi-beam and TDMA-based energy transmission designs. Furthermore, we also consider the isotropic beamforming design as another benchmark scheme, in which the transmit energy covariance matrix is set as \(S_{\text{ist}} = \frac{P_{\text{max}}}{\gamma_0} I\) over the entire time block, such that the wireless energy is broadcast isotropically over space.

In the simulation, we consider the Rician fading channel from the ET to ER, given by
\[
h_k = \sqrt{\frac{K_R}{1 + K_R}} h_k^{\text{LOS}} + \sqrt{\frac{1}{1 + K_R}} h_k^{\text{NLOS}}. \quad (14)
\]
Here, the Rician factor is set to be \(K_R = 5\) dB, \(h_k^{\text{LOS}}\) denotes the LOS component, and \(h_k^{\text{NLOS}}\) denotes the non-LOS Rayleigh fading component. We consider the uniform linear antenna array model at the ET, i.e., \(h_k^{\text{LOS}} = \sqrt{\gamma T}[1, e^{j\theta_1}, \ldots, e^{j(M-1)\theta_T}]^T\) with \(\theta_k = \frac{-2\pi\pi\sin(\phi_k)}{\lambda}\), in which \(\kappa = \frac{\lambda}{d}\) denotes the spacing between two successive antenna elements at the ET, \(\lambda\) is the carrier wavelength, and \(\phi_k = \frac{2\pi}{d} + 2\pi + (k-1)\) is the direction of ER \(k\) from the ET. Then, \(\gamma = \frac{\Phi}{d^2}\) denotes the average channel power gain, in which \(d = 4\) meters (m) is the distance between the ET and each ER, and \(\Phi = -30\) dB denotes the channel power gain at a reference distance of \(d_0 = 1\) m. Furthermore, we set the transmit antenna gain at the ET as 10 dBi and the receive antenna gain at each ER as 2.8 dBi. The number of ERs is set to be \(K = 30\). As for the non-linear EH model, the parameters are same as those in Example 1.

Fig. 2 shows the average minimum harvested DC power among the ERs versus the transmit power at the ET \(P_{\text{max}}\), where the transmit antenna is \(M = 4\). It is observed that our proposed time-division energy beamforming design achieves the best performance. More specifically, when the transmit power is \(P_{\text{max}} = 38\) dBm, our proposed design achieves around 7% higher harvested DC energy than the multi-beam energy transmission, as the received RF power falls in the convex region for RF-to-DC power conversion, which validates the effectiveness of the proposed design. When the transmit power becomes large (e.g., \(P_{\text{max}} \geq 42\) dBm), our proposed design and multi-beam energy transmission have the same performance. This is due to the fact that the received RF power is in the concave region in this case, and thus the proposed time-division energy beamforming reduces to the conventional multi-beam energy transmission that is optimal.

Fig. 3 shows the minimum harvested DC power among ERs versus the number of antennas at the ET \(M\) with the transmit power being \(P_{\text{max}} = 40\) dBm. It is observed that when
Fig. 2. The minimum harvested DC power among the ERs versus the transmit power at the ET $P_{\text{max}}$ with $M = 4$.

Fig. 3. The minimum harvested DC power among all ERs versus the number of transmit antennas $M$ with $P_{\text{max}} = 40$ dBm.

$2 \leq M \leq 6$, our proposed design outperforms the multi-beam energy transmission. When the number of antennas becomes large, these two designs have the same performance. This is because with more transmit antennas, higher array gains can be exploited to increase the received RF power, such that the RF-to-DC conversion may work in the concave regime. Therefore, the proposed design achieves the same performance as the multi-beam energy transmission. Note that for the isotropic beamforming design, the resultant harvested DC energy is observed to almost keep unchanged. This is due to that in the isotropic beamforming design, the energy is broadcasted isotropically no matter how many antennas are employed.

V. CONCLUSION

This letter investigated the multiuser MISO WPT system under the non-linear EH model. Under this setup, we found that the conventional multi-beam energy transmission, which is optimal for min-DC-energy maximization under the linear EH models, are not optimal any longer under the practical non-linear EH models. To overcome this drawback, we proposed a novel time-division energy beamforming, in which different energy beamforming matrices are time shared to exploit the non-linear nature of RF-to-DC energy conversion. We jointly optimized the beamforming matrices and the corresponding time division to maximize the minimum harvested DC energy among all the ERs. Numerical results showed that our proposed design indeed improved the performance especially when the received RF power falls in the convex region for RF-to-DC conversion. Our proposed time-division energy beamforming can be extended to SWIPT systems by exploiting the time-division protocol for both energy and information beamforming designs. How to jointly optimize the energy and information beamformers together with time allocations to meet both information and energy requirements is an interesting problem, which will be investigated in the future.

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