Time Allocation And Optimization Of Wireless Powered Communication Networks

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***Abstract* -This paper investigates multi-antenna beamforming and time allocation to maximise the network energy efficiency (EE) in a very wireless hopped-up communication network (WPCN). Since the applied science improvement downside has associate inherent fractional kind, it's tough to get the optimum worth directly due to the dearth of convexity within the objective operate. To overcome this challenge, we tend to initial convert the initial downside into an additional tractable one by the incomplete programming. Then, 2 schemes are projected to search out the optimum worth. The first theme, the repetitious worth is updated in line with the EE supported energy beamforming and time allocation derived in the current iteration. Within the other, the optimum worth is obtained by consecutively shrinking the region within which it's located. Simulation results show that the projected 2 schemes can improve the network applied science considerably compared with the algorithm that solely pursues high output. Additionally, it is shown that the 2 schemes have similar performance in the network ee. However, the computation complexness of the first one is below that of the other.**

Keywords—energy efficiency, beamforming, time allocation, fractional programming, iterate.

1.INTRODUCTION

The proliferation of wireless data traffic has posed significant challenge to device power supply for maintaining steady and durable communication. This issue becomes more severe in energy constrained networks such as wireless sensor networks. Fortunately, with the development of energy harvesting techniques [1], it is possible to charge wireless nodes by wireless energy transfer (WET) that provides actually perpetual and stable energy transmission to wireless device over the air. On account of its great promising application values, recently, WET has attracted significant attention and has been widely studied. There are generally two directions regarding WET related communications. The first one is based on the fact that information and energy can be simultaneously carried over the radio frequency (RF), which leads to simultaneous wireless information and power transfer (SWIPT) systems.Note that SWIPT pays attention to downlink information transmission. However, many practical systems need uplink information transmission, which gives rise to a new type of wireless powered communication networks (WPCNs). In a WPCN, wireless nodes are at first charged by downlink WET and then transmit uplink information to the access point.

The harvest-then-transmit protocol and time division multiple access (TDMA) in WPCN with one hybrid access point (HAP) were first proposed by Ju and Zhang [2]. In order to achieve a more balanced throughput, they studied user cooperation with optimal resource allocation in a twouser WPCN [3]. However, co-locating the energy station (ES) with the information station (IS) as one HAP in [2] and [3], which would lead to 'doubly near-far' phenomenon that users far from HAP harvest less energy than nearer users but need more energy to transmit information. To tackle this problem, the network that separately located energy and information access points was considered in [4]. A WPCN
consisting of a single-antenna ES and IS was described in [5], where the authors studied the optimization of subchannels and power allocation to achieve the maximum data transmission rate. As for the multi-antenna WPCN systems, the work [6] investigated beamforming design and time allocation for WPCNs with ES equipped with multiple antennas. Besides, in multi-cell WPCNs [7], intra-cell time allocation and inter-cell load balancing are jointly optimized to maximize the system throughput.

It is worth noting that all the aforementioned works make effort to maximize the network sum-throughput. However, in practical systems, the enhancement of energy efficiency (EE) also deserves investigation, since users can only harvest quite limited energy which should be efficiently spent. The authors in [8] designed a high-efficiency energy harvesting circuit to save the hardware energy-consumption, and the work in [9] minimized the WET power consumption to improve the energy utilization efficiency. However, both of them enhanced the EE by reducing power consumption in WET stage. Besides, system performance is often evaluated by an EE measured in bits per joule, which has been accepted as a critical criterion of next generation communication system design due to the rising energy costs and the tremendous carbon footprints. The works [10] and [11] studied the EE maximization problem for WPCN in two simplified networks, respectively, purely WPCNs and initial energy limited communication networks. Considering fairness among users, the work [12] presented time allocation scheme to maximize the minimum EE of all users. In WPCN under the protocol of time division mode switching scheme, the EE optimization was investigated in [13]. Notice that [11]-[13] are proposed for WPCN with a single antenna beamforming to perform energy control the amount of equipped at the ES, which cannot energy transferred to different users. As a result, there is a need to investigate EE optimization problem in the case of multi-antenna ES.

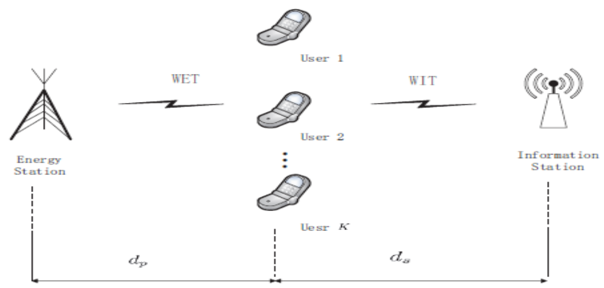

Fig. 1: The system model of WPCN where ES and IS are separately located.

Time allocation scheme to maximize the minimum EE of all users. In WPCN under the protocol of time division mode switching scheme, the EE optimization was investigated in [13]. Notice that [11]-[13] are proposed for WPCN with a single antenna equipped at the ES, which cannot perform energy beamforming to control the amount of energy transferred to different users. As a result, there is a need to investigate EE optimization problem in the case of multi-antenna ES.

In this paper, we consider a WPCN system, where a multi-antenna ES and a single-antenna IS were separately located. Taking into consideration the circuit power consumption of ES and user terminals, we jointly optimize the energy beamforming and time allocation to maximize EE. Since the EE optimization problem is nonlinear and nonconvex, it is hard to address it. To overcome this challenge, we first transform the original issue to an equivalent parameterized problem in a subtractive-form by exploiting the properties of fractional programming. Then, two efficient iterative methods are proposed to find the optimal solution.

The rest of the paper is organized as follows. Section II Presents the system model of WPCN for EE maximization. The problem formulation and two algorithms to solve the problem are proposed in Section III. The simulation result is described in section IV. Finally, Section V concludes the whole paper.

II. SYSTEM MODEL

We consider a WPCN system consisting of one Nt-Antenna ES, one single-antenna IS and K single-antenna users. Note that we separately deploy the ES and IS to alleviate the 'doubly near-far' problem [2]. The system operates in the harvest-then-transmit protocol as in [2].In particular, all users are first powered by WET in the downlink (DL), and then use harvested energy to transmit information to the IS in the uplink (UL). One time frame with unit length is divided into two successive stages, namely, WET stage and wireless information transfer (WIT) stage.During the WET stage, the broadcasting signal from ES.The total energy consumption in the system denoted as E_{ps} is given by,

$$E_{ps}(\tau_0, \mathbf{X}) = \tau_0\left(\mathrm{Tr}(\mathbf{X}) + b_0\right),$$

where Tr X is the average transmitted signal power, and b_0 is the constant power consumption of ES accounting for antenna circuits, transmit filter, ect.. Assume that both DL channels and UL channels are quasi-static flat-fading. Particularly, all channels remain constant during one frame but may vary from frame to frame.

The amount of energy that each user node can harvest from RF signal during the WET stage can be modeled as,

$$\begin{aligned} E_k &= \xi_k \tau_0 \mathbb{E}\{|\mathrm{h}_k^H \mathrm{x}|^2\} \\ &= \xi_k \tau_0 \mathbb{E}\left(\mathrm{h}_k^H \mathrm{x}\mathrm{x}^H \mathrm{h}_k\right) \\ &= \xi_k \tau_0 \mathrm{h}_k^H \mathrm{X} \mathrm{h}_k, \end{aligned} \tag{2}$$

where _k 2 0; 1 is the energy harvesting efficiency at user node k.

During the WIT stage, suppose that users do not have initial energy and use up all the harvested energy. The transmit power Pk of user k can be figured out as,

$$P_k = \frac{E_k}{\tau_k} - a_k = \frac{\tau_0 \xi_k \mathbf{h}_k \mathbf{X} \mathbf{h}_k^H}{\tau_k} - a_k \geq 0 \qquad \forall k, \tag{3}$$

III. ENERGY-EFFICIENCY MAXIMIZATION

In this section, we address the optimization problem to maximize the EE through time allocation and beamforming design jointly. The system EE is formulated as a fraction of the sum-throughput and the total energy consumption, and the EE optimization problem can be formulated as,

$$\max_{\tau, \mathbf{X}} \frac{\sum_{k=1}^{K} \tau_k \log_2\left(1 + \gamma_k\left(\frac{\tau_0 \mathbf{h}_k \mathbf{X} \mathbf{h}_k^H}{\tau_k} - \frac{a_k}{\xi_k}\right)\right)}{\tau_0\left(\mathrm{Tr}(\mathbf{X}) + b_0\right)} \tag{4}$$

$$\begin{aligned} \text{s.t.}\quad & \tau_k \geq 0, k = 0, \ldots, K, && \text{(6a)} \\ & \sum_{k=0}^{K} \tau_k \leq 1, && \text{(6b)} \\ & \mathbf{X} \succeq \mathbf{0}, && \text{(6c)} \\ & \mathrm{Tr}(\mathbf{X}) \leq P_{\max}, && \text{(6d)} \\ & \tau_0 \mathbf{h}_k^H \mathbf{X} \mathbf{h}_k \geq \tau_k \frac{a_k}{\xi_k}, k = 1, \ldots, K, && \text{(6e)} \end{aligned}$$

where _ and X are the optimization variables. The constraint (6b) indicates that the total time allocated to all users in WET stage and WIT stage is no more than time length of one frame. The constraint (6c) shows that X should be positive semi-definite. The average transmit power of the ES is assumed to be less than or equal to its power budget Pmax, as shown in (6d). The constraint (6e) ensures that the information transmission power of each user during the WIT should be no less than its circuit power consumption. It is evident that problem (6) is a highly non-convex problem due to the fractional form and coupled variables. However, we can convert the problem into a more tractable one by exploiting the fractional programming.

Algorithm 2

Initialization:

Set $\eta_{min} < e^*, \eta_{max} > e^*$.
Set tolerance ϵ.

```
repeat
  e = (η_min + η_max)/2.
  Solve the convex feasibility problem in (14).
  if The problem is feasible, then
    η_min = e.
  else
    η_max = e.
  end if
until η_max − η_min ≤ ε.
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iteration. As shown in line 4, the iterative value is updated by the formula (13) to converge to the maximum EE.

B. Algorithm 2

As mentioned above, the problem (12) is convex. It can be transformed as a feasibility problem as follows.

$$
\begin{aligned}
\text{Find} \quad & \tau, \mathbf{V} \\
\text{s.t.} \quad & \sum_{k=1}^{K} \tau_k \log_2\left(1 + \gamma_k\left(\frac{\mathrm{Tr}\left(\mathbf{h}_k \mathbf{h}_k^H \mathbf{V}\right)}{\tau_k} - \frac{a_k}{\xi_k}\right)\right) \\
& \geq e\left(\mathrm{Tr}(\mathbf{V}) + \tau_0 b_0\right), && (14) \\
& \tau_k \geq 0, k = 0, \ldots, K, && (14a) \\
& \sum_{k=0}^{K} \tau_k \leq 1, && (14b) \\
& \mathbf{V} \succeq 0, && (14c) \\
& \mathrm{Tr}(\mathbf{V}) \leq \tau_0 P_{max}, && (14d) \\
& \mathrm{Tr}(\mathbf{h}_k^H \mathbf{h}_k \mathbf{V}) \geq \tau_k \frac{a_k}{\xi_k}, k = 1, \ldots, K. && (14e)
\end{aligned}
$$

If the convex feasibility problem is feasible then we have $e^* > e$. Otherwise, we have $e^* < e$. This observation can be accepted as the basis of Algorithm 2 for solving the EE optimization problem using bisection [17].

In Algorithm 2, we initialize the interval $e \in [\eta_{min}, \eta_{max}{}^1]$, which is known to contain the maximum EE e^*. We then take the half the width of the initial interval to produce a new interval, which also contains the optimal value. In order to guarantee that the new interval contains e^*, we update the interval according to the solution of the convex feasibility problem at its midpoint $e = \frac{\eta_{min} + \eta_{max}}{2}$, to determine whether the optimal value is in the lower or upper half of the interval. This is repeated until the tolerance of the interval is small enough as the Algorithm 2 described.

In each iteration, the length of the interval after n iterations is $2^{-n}(y)$, where y is the length of the initial interval. It required that exactly $log(y/\epsilon)$ iterations before the algorithm terminates, which implies that we can obtain the maximum EE e^* with less frequent iterations.

This iterative method shrinks a region with a small enough width to obtain the optimal parameter e, which is different from algorithm 1 via converging to the optimal value.

[1] The upper bound of the interval is obtained by assuming that the channel gain of all users are the same with the best one.

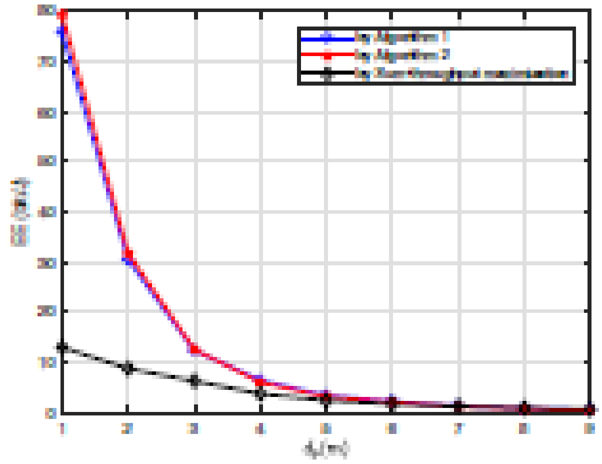


Fig. 2: EE versus the distance d_p in different methods, where the number of user K set as 4.

IV. Simulation Result

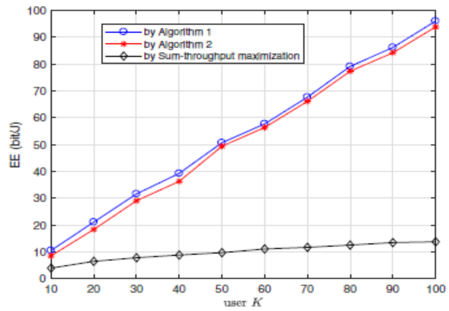
Consider a WPCN as shown in Fig. 1, where all users are located in a length of 10 meters line with uniform distribution as in [6]. The ES and IS are perpendicular to the user array, and the vertical distances from ES and IS to the bisector of the user array are denoted by d_p and d_s respectively. ES is equipped with $N_t = 4$ antennas. Our DL channel is modelled as

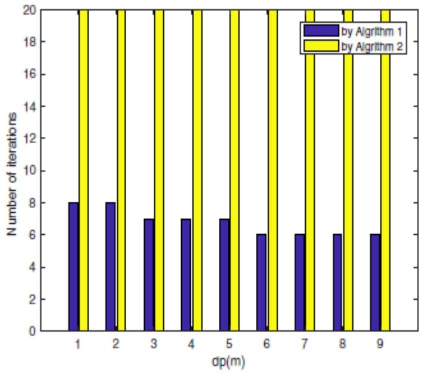
$$
\mathbf{h}_k = \sqrt{\frac{K_R}{1 + K_R}} \mathbf{h}_k^{LOS} + \sqrt{\frac{1}{1 + K_R}} \mathbf{h}_k^{NLOS} \qquad (15)
$$

where $\mathbf{h}_k^{LOS}$ denotes the line of sight (LOS) with the form $\mathbf{h}_k = [1, e^{-j\pi \sin(\beta_k)}, \ldots, e^{j(1-N_t)\pi \sin(\beta_k)}]^T$, and β_k is the direction of user k to ES. $\mathbf{h}_k^{NLOS}$ follows the standard Rayleigh fading $\mathbf{h}_k^{NLOS} \sim \mathcal{CN}(0, 1)$, where $\mathcal{CN}(\mu, \sigma_k^2)$ stands for a circularly symmetric complex Gaussian random variable with mean μ and variance σ_k^2. K_R is the Rician factor. The average power of $\mathbf{h}_k$ is normalized by the path loss $10^{-3}(d_k^{DL})^{-\alpha}$, where d_k^{DL} is the distance between the ES and U_k, and α is the path loss exponent. The UL channel g_k is modeled as $g_k = 10^{-3}\rho_k^2(d_k^{UL})^{-\alpha}$, where d_k^{UL} is the distance between IS and U_k, and $\rho_k \sim \mathcal{CN}(0, 1)$ follows the standard Rayleigh fading. Set $K_R = 3, \alpha = 2, \sigma^2 = -110$dBm, $P_{max} = 30$dBm, $\xi_k = 0.5$ for all k, and the SNR gap $\Gamma = 9.8$dB. The distance d_s is fixed at 5 meters. The tolerance ϵ is set at 10^{-4} and the simulation results are averaged over 1000 channel realizations.

Fig. 2 plots the EE versus d_p by the proposed two algorithms and the algorithm of only maximizing the sum-throughput in WPCN system, where d_p varies in 1 to 9 meters and the number of users fixed at $K = 4$. The result shows that Algorithm 1 and Algorithm 2 have the same performance in terms of EE optimization, and EE decreases as d_p increases. What's more, comparing the EE value obtained by maximizing the sum-throughput only, it's obvious that the EE value obtained by the proposed method is much larger, which demonstrates that our solution could improve the system EE greatly.

The system EE versus the amount of users in system is showed in Fig. 3, where d_p is fixed at 5 meters. The common point of the three curves is that EE value increases





this paper. Simulation results demonstrate that the EE curves from two different algorithms are basically coincident and the network efficiency is enhanced obviously. Fig. 4: This figure shows the number of iterations of

Algorithm 1 and Algorithm 2 versus the distance dp. with the number of users rising, which indicates that the more users in system the larger EE can be achieved. The proposed two algorithms lead to much larger EE than the strategy of pursuing the maximum sum-throughput only. In general, whatever dp or K fluctuates, both algorithms in this paper have better performance than the maximization of sum-throughput only in terms of EE value. This is owing to the fact that the EE optimization problem takes into account the energy consuming in whole system, while the maximization of sum-throughput did not, which highlights the performance impact of EE optimization.

Fig. 4 depicts the number of iterations versus the distance between ES and users array dp.It is shown that the number of iterations in Algorithm 2 is fixed at 20 times and much higher.

V. CONCLUSION

In this paper, we investigate the maximum EE based on energy beamforming and time distribution in a WPCN. Wefirst construct an equivalent parameterized subtractive form, then introduce variables to transform the parameterized problem into a convex problem. The maximum EE can be obtained by two iterative algorithms that involve solving the convex problem in each iteration. Algorithm 1 has the lower computation complexity in comparison with Algorithm 2 in this paper. Simulation results demonstrate that the EE curves from two different algorithms are basically coincident and
the network efficiency is enhanced obviously.

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