

Relay-Centric Two-Hop Networks with Asymmetric Wireless Energy Transfer: A Multi-Leader-Follower Stackelberg Game

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Abstract—This paper studies a two-hop network with wireless energy transfer consisting of one source, multiple relays, and multiple destinations. The relays' main objective is to communicate their own messages to their own destinations. The message of each relay is transmitted to its associated destination along with the source's information that is intended for the same destination. As an incentive for relaying, the source offers wireless energy transfer to the relays via radio frequency signals. The relays harvest energy and receive information one by one. The relays that are further down in the order in which they are powered incur delay, but are able to harvest from previous time slots and thus are able to accumulate more energy until it is their turn to transmit, thus establishing an energy-delay trade-off. We formulate a multi-leader-follower Stackelberg game to capture the self-interest and hierarchically competing nature of the nodes. The relay-destination pairs play as leaders and the source-destination pairs as followers. We incorporate data rate, energy cost and delay in the utility functions. The existence and the uniqueness of the Stackelberg equilibrium (SE) are proved, and two algorithms that achieve SE in centralized and distributed fashion are provided. Numerical results verify analytical findings.

I. INTRODUCTION

Wireless energy transfer (WET) is a recently proposed paradigm for improving energy efficiency and network lifetime [1]. Wireless energy transfer can be accomplished by sending radio frequency (RF) signals [1], [2]. As a counterpart of wireless information transmission (WIT), WET can be viewed as a new dimension for cooperation among wireless nodes [3]. Significant research effort has already studied WET from different perspectives, for instance, the trade-off between WIT and WET in various systems, practical issues in the implementation of WET, and so on [1].

One such direction focuses on wireless information and power transfer (WIPT) in relay networks. A relay network with WIPT has been studied in [4], where the relay harvests energy from the received RF signals of the source in either power splitting or time switching protocol and forwards the source's information by the harvested energy. Based on this model, various extensions have been investigated on systems of multiple-input-multiple-output (MIMO), full duplex relaying (FD), relay selection, and other setups [5]–[7]. Another line of research considers wireless powered communication networks (WPCN), which was proposed in [8]. WPCN refers to the

system that a set of users without energy access harvest energy from an access point (AP) in downlink and transmit information to the AP in uplink using the harvested energy. This model has been extended to the setup with full duplex AP in [9], and to the setup the AP working as both power beacon and destination in a relaying cooperative communication network in [10].

This paper builds on the WIPT model with the primary consideration of relays' objective of transmitting information to destinations. It is also an extension of WPCN model since the source performing as a power beacon aims at sending signals to the destinations with the help of relays. In addition to having relay's message transmissions as a main objective, a distinctive feature of our proposed model is that, we provide opportunities for relay nodes to harvest additional energy from signals intended for other relay nodes *at the expense of delay*, which we term *asymmetric WET*. We study this system with a game theory perspective. As related work, several papers have investigated energy harvesting relay networks by the framework of game theory [11]–[13]. For example, the amount of harvested energy at the relay has been considered as an optimizing objective in a Nash bargaining game in [12]. In [13], a WIPT relaying system with a single destination is studied. Vickery auction is employed for relay selection and a single-leader Stackelberg game is formulated and solved taking into account the objectives of both the source and the relay. The present paper builds upon our previous work [13], but by contrast, considers multi-leader-follower games, and asymmetric WET, which lead to improved competitive performance.

We study a general two-hop model with multiple relays and multiple destinations. A time division multiple access (TDMA) transmission protocol is adopted in the first hop between the source and the relays, where each relay harvests energy from the RF signals of the source in a time switching manner. In particular, while waiting for source's data transmission, each relay harvests energy from the signals for *previous* relays who have earlier access to source's information. Thus, an asymmetric wireless energy transfer scenario arises, where relays with longer waiting time have opportunities to harvest more energy but suffer from a larger delay. Different from existing work, the relays' objective of transmitting information

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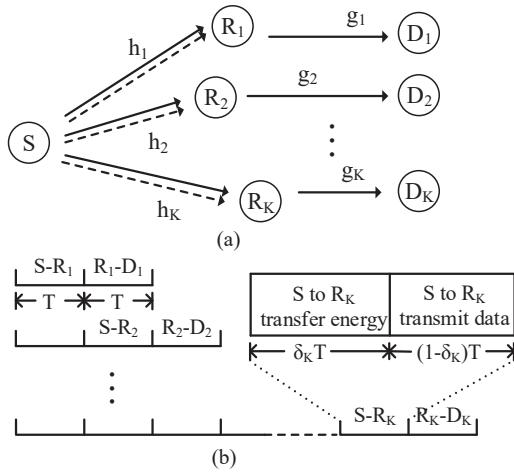


Fig. 1. (a) The two-hop network model. Solid lines and dash lines indicate information transmission and energy transfer, respectively. (b) TDMA transmission protocol in the first hop with asymmetric wireless energy transfer.

to the associated destinations is the principal goal of the system. Furthermore, the trade-off between energy harvesting and data transmission delay is captured in relays' payoff functions. We investigate the resource allocation of power and time in a game theory setup, where a multi-leader-follower Stackelberg game is proposed with relay-destination pairs as leaders and the source-destination pairs as followers. The proposed algorithms are shown to achieve the unique Stackelberg equilibrium (SE) in a centralized and a distributed manner. Simulation results confirm that the system performance significantly improves as compared to previous approaches adopting this generalized hierarchical competitive framework.

II. SYSTEM MODEL

We consider the two hop network shown in Fig. 1(a). The source (S) transmits information to K destinations through relays. Each destination (D) has one subscribed relay (R) to help forward signals interference free, i.e., each relay has an orthogonal channel to its destination provided by time, frequency or code division. Decode-and-forward (DF) relaying is adopted. Let $\mathcal{K} = \{1, 2, \dots, K\}$ denote the set of destinations and the associated relays. We consider the setup where direct channels are too weak to be useful and thus only include the channels of S-R and R-D pairs within the two-hop model. The channel gains of S-R and R-D are denoted respectively by h_k and g_k , $\forall k \in \mathcal{K}$, which are normalized by noise power. The channel state information (CSI) of the first and second hop is known at the respective transmitters and receivers¹.

The source transmits to R-D pairs in a predefined order by time division multiple access (TDMA) shown in Fig. 1(b). Assume that a slot of T units of transmission time is assigned for each pair. For the k th S-R-D link, the source transmits to relay k in the k th slot, and then the relay transmits to

¹We consider quasi-static channels where a proper transmitting period enables CSI acquisition at the receivers and feedback to the transmitters.

destination k subsequently in the next slot. In particular, the relays have no access to energy except that harvested from the RF signals of the source. Time switching protocol is adopted at each relay, where the S-R transmission is divided into the energy transfer subplot of length $\delta_k T$ and the information transmission subplot of length $(1 - \delta_k)T$ with $\delta_k \in [0, 1]$ for all $k \in \mathcal{K}$. The transmit power from the source to relay k for energy transfer and for information transmission is $\frac{p_k}{\delta_k}$ and $\frac{p_k}{1 - \delta_k}$, respectively. The source determines the average transmit power $2p_k$ over T such that p_k conforms to the maximum power constraint P_k . The relays are always in listening mode throughout the first hop session, meaning each relay harvests energy constantly while waiting for their turn for source access, then allocates the harvested energy on transmitting its own information and forwarding the source's signals to the associated destination. Throughout the transmission, orthogonal channels are used to avoid interference.

In the first phase, the amount of data received at relay k from the source is

$$R_{S_k} = (1 - \delta_k)T \log \left(1 + h_k \frac{p_k}{1 - \delta_k} \right). \quad (1)$$

Relay k harvests energy not only from its dedicated energy beam radiated by the source in its WET subplot, but also from the signals intended for relays $1, 2, \dots, k-1$ in sequence at slots $1, 2, \dots, k-1$. Thus, the available energy harvested from WET for relay k transmitting to destination k is

$$E_{R_k} = \eta_k h_k \left(\sum_{j=1}^{k-1} 2p_j + p_k \right) T, \quad (2)$$

where $\eta_k \in (0, 1)$ represents the fraction of energy that is available for transmission. The loss of $1 - \eta_k$ fraction of the energy captures the energy transfer efficiency and processing energy [13]. Then, with the transmit power $\frac{E_{R_k}}{T}$, the amount of data received at destination k from relay k is given by

$$R_{R_k} = T \log \left(1 + g_k \eta_k h_k \left(\sum_{j=1}^{k-1} 2p_j + p_k \right) \right). \quad (3)$$

We take into account the energy cost of the source and the delay of information delivery due to the relays. To be more specific, the energy cost is given by

$$E_{S_k} = 2\mu_k p_k T, \quad \forall k, \quad (4)$$

where μ_k denotes the cost per energy unit, which is fixed for each relay. In order to incorporate the delay impact, we consider the average payoff over the time duration in which the S-R-D link completes information transmission. Then, the utility of S-D pair is expressed as

$$U_{S-D_k} = \frac{1}{kT} (R_{S_k} - E_{S_k}), \quad \forall k. \quad (5)$$

The principle purpose of the relay is to convey its own message to the corresponding destination, thus, the utility of relay is

$$U_{R-D_k} = \frac{1}{kT} (R_{R_k} - E_{R_k}), \quad \forall k. \quad (6)$$

Next, we formulate the multi-leader-follower Stackelberg game and investigate the Stackelberg equilibrium (SE).

III. MULTI-LEADER-FOLLOWER STACKELBERG GAME

We adopt the framework of Stackelberg games to model the selfish nature of each node and the hierarchical competition between S-D pairs and R-D pairs. In general, a multi-leader Stackelberg game consists of multiple leaders, each of which anticipates the followers' strategies and competes with other leaders by optimizing its own strategy, and multiple followers, that compete with each other and choose their strategies in response to the leaders' strategies. Thus, an outer game among the leaders and an inner game [14] among the followers are formed. In our relay-centric system, we have the R-D pairs as leaders and the S-D pairs as followers. For simplicity, we denote $\delta \triangleq (\delta_1, \dots, \delta_K)$ the strategies of leaders, $\delta_{-k} \triangleq (\delta_1, \dots, \delta_{k-1}, \delta_{k+1}, \dots, \delta_K)$ the strategies of leaders except leader k , $\mathbf{p} \triangleq (p_1, \dots, p_K)$ the strategies of followers, and $\mathbf{p}_{-k} \triangleq (p_1, \dots, p_{k-1}, p_{k+1}, \dots, p_K)$ the strategies of followers except follower k . Leader k chooses its strategy δ_k by solving the following optimization problem.

$$\max_{\delta_k} U_{R-D_k}(\delta_k, \delta_{-k}, \mathbf{p}) \quad (7a)$$

$$\text{s.t. } 0 \leq \delta_k \leq 1. \quad (7b)$$

The optimization problem for the follower k is given by

$$\max_{p_k} U_{S-D_k}(p_k, \mathbf{p}_{-k}, \delta) \quad (8a)$$

$$\text{s.t. } 0 \leq p_k \leq P_k. \quad (8b)$$

The Stackelberg equilibrium (SE) is defined as follows.

Definition 1: Let δ_k^* and p_k^* be the optimal solutions for the leader's and the follower's problems in (7) and (8), respectively. Then, (δ^*, \mathbf{p}^*) is a SE for the proposed multi-leader-follower Stackelberg game if for any feasible (δ, \mathbf{p})

$$U_{R-D_k}(\delta_k^*, \delta_{-k}^*, \mathbf{p}^*) \geq U_{R-D_k}(\delta_k, \delta_{-k}^*, \mathbf{p}^*), \quad \forall k \in \mathcal{K}, \quad (9)$$

$$U_{S-D_k}(p_k^*, \mathbf{p}_{-k}^*, \delta^*) \geq U_{S-D_k}(p_k, \mathbf{p}_{-k}^*, \delta^*), \quad \forall k \in \mathcal{K}. \quad (10)$$

We analyze the game by backward induction. In the followers' game, problem (8) is convex with respect to p_k for given δ . Applying the first-order optimality condition on the unconstrained objective function (8a) yields

$$\frac{\partial U_{S-D_k}}{\partial p_k} = \frac{1 - \delta_k}{k} \frac{h_k}{1 - \delta_k + h_k p_k} - \frac{2\mu_k}{k} = 0. \quad (11)$$

Solving p_k in (11) and projecting to constraint (8b), we have

$$p_k = \begin{cases} (1 - \delta_k)\phi_k, & \text{if } \delta_k \in [\bar{\delta}_k, 1], \\ P_k, & \text{if } \delta_k \in [0, \bar{\delta}_k], \end{cases} \quad (12)$$

where $\phi_k \triangleq \max \{0, \frac{1}{2\mu_k} - \frac{1}{h_k}\}$ and $\bar{\delta}_k \triangleq 1 - \min \{\frac{P_k}{\phi_k}, 1\}$.

Next, we consider the leaders' game by substituting p_k into (7). For $\delta_k \in [0, \bar{\delta}_k]$, we have

$$U_{R-D_k}(\delta_k, \delta_{-k}) = \frac{1}{k} \left[\log \left(1 + g_k \eta_k h_k \left(\sum_{j=1}^{k-1} 2p_j + P_k \right) \right) \right. \\ \left. - (1 - \delta_k) \log \left(1 + h_k \frac{P_k}{1 - \delta_k} \right) \right]. \quad (13)$$

Observe that $U_{R-D_k}(\delta_k, \delta_{-k})$ increases on δ_k given δ_{-k} . This implies that the optimal δ_k that maximizes the objective

function falls into the range $[\bar{\delta}_k, 1]$. Thus, it suffices to focus on $\delta_k \in [\bar{\delta}_k, 1]$. We can rewrite the leaders' optimization problem by substituting $p_k = (1 - \delta_k)\phi_k$ into (7) as follows.

$$\max_{\delta_k} U_{R-D_k}(\delta_k, \delta_{-k}) = \frac{1}{k} \left[-(1 - \delta_k)\beta_k + \log \left(1 + \alpha_k \left(\sum_{j=1}^{k-1} 2\phi_j(1 - \delta_j) + \phi_k(1 - \delta_k) \right) \right) \right] \quad (14a)$$

$$\text{s.t. } \bar{\delta}_k \leq \delta_k \leq 1, \quad (14b)$$

where $\alpha_k \triangleq g_k \eta_k h_k$ and $\beta_k \triangleq \log(1 + h_k \phi_k)$. It can be observed that by optimizing δ_k , U_{R-D_k} is nonnegative, which guarantees the relaying of the source's data. Note that when $\phi_k = 0$, the source has zero utility on R-D pair k , and the relay k becomes a free rider that can transmit its own information by the harvested energy without forwarding any signal from the source. To avoid this case, we only consider $\phi_k > 0, \forall k$, in the sequel.

Let $\mathbf{U} \triangleq (U_{R-D_1}, \dots, U_{R-D_K})$. And denote the strategy set of the leaders' game by $\mathcal{Q} \triangleq Q_1 \times \dots \times Q_K$, where $Q_k \triangleq \{\delta_k \in \mathbb{R} : \bar{\delta}_k \leq \delta_k \leq 1\}$ and \times denotes the Cartesian product. Then, the leaders' game \mathcal{G} is given by the triple $(\mathcal{K}, \delta, \mathbf{U})$, which is a noncooperative game. The SE of the multi-leader-follower Stackelberg game can be obtained by solving the Nash equilibrium (NE) of the noncooperative game \mathcal{G} . The existence of NE can be guaranteed since U_{R-D_k} is continuous and concave with respect to δ_k and the strategy set Q_k is nonempty, convex, and compact. Next, we discuss the uniqueness of the NE of \mathcal{G} .

Theorem 1: The game \mathcal{G} has an unique NE, thus, the SE of the proposed multi-leader-follower Stackelberg game is unique.

Proof: Define

$$\mathbf{G} \triangleq \begin{pmatrix} \frac{\partial U_{R-D_1}}{\partial \delta_1 \partial \delta_1} & \frac{\partial U_{R-D_1}}{\partial \delta_1 \partial \delta_2} & \dots & \frac{\partial U_{R-D_1}}{\partial \delta_1 \partial \delta_K} \\ \frac{\partial U_{R-D_2}}{\partial \delta_2 \partial \delta_1} & \frac{\partial U_{R-D_2}}{\partial \delta_2 \partial \delta_2} & \dots & \frac{\partial U_{R-D_2}}{\partial \delta_2 \partial \delta_K} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial U_{R-D_K}}{\partial \delta_K \partial \delta_1} & \frac{\partial U_{R-D_K}}{\partial \delta_K \partial \delta_2} & \dots & \frac{\partial U_{R-D_K}}{\partial \delta_K \partial \delta_K} \end{pmatrix}. \quad (15)$$

Then, for the game \mathcal{G} with Q_k convex and compact and U_{R-D_k} continuous and concave with respect to δ_k , a sufficient condition of the uniqueness of NE is that $\mathbf{G} + \mathbf{G}^T$ is negative definite [15]. Note that \mathbf{G} is a lower triangular matrix since the k - j th element $[\mathbf{G}]_{kj} = 0$ for $j > k$. The diagonal element $[\mathbf{G}]_{kk}$ is calculated as

$$[\mathbf{G}]_{kk} = \frac{-(\alpha_k \phi_k)^2}{k \left[1 + \alpha_k \left(\sum_{j=1}^{k-1} 2\phi_j(1 - \delta_j) + \phi_k(1 - \delta_k) \right) \right]^2}. \quad (16)$$

Since $[\mathbf{G}]_{kk} < 0$, the eigenvalues of \mathbf{G} , which are those diagonal elements, are negative. This implies that \mathbf{G} is negative definite. So is \mathbf{G}^T . Hence, $\mathbf{G} + \mathbf{G}^T$ is indeed negative definite. This completes the proof of the uniqueness of the NE. ■

Based on the existence and uniqueness of SE, we propose a centralized algorithm, which achieves the SE analytically, and

also a distributed iterative algorithm.

A. Centralized Algorithm

We first define a set of auxiliary variables as follows.

$$\tilde{\phi}_k = \sum_{j=1}^{k-1} 2\phi_j + \phi_k, \quad \tilde{\delta}_k = \frac{1}{\tilde{\phi}_k} \left(\sum_{j=1}^{k-1} 2\phi_j \delta_j + \phi_k \delta_k \right). \quad (17)$$

Then, note that $\sum_{j=1}^{k-1} 2\phi_j(1 - \delta_j) + \phi_k(1 - \delta_k) = \tilde{\phi}_k(1 - \tilde{\delta}_k)$. In particular, we apply a linear transformation of variables such that $\tilde{\delta} = \Phi\delta$, where $\tilde{\delta} \triangleq (\tilde{\delta}_1, \dots, \tilde{\delta}_K)$ and matrix Φ is lower triangular with the diagonal elements $[\Phi]_{kk} = \phi_k/\tilde{\phi}_k$ and off diagonal elements $[\Phi]_{kj} = 2\phi_j/\tilde{\phi}_k$ for $j < k$, and $[\Phi]_{kj} = 0$ for $j > k$, $\forall k$. We see that Φ is invertible as $\phi_k > 0$, $\forall k$. Denote the inverse matrix of Φ by Φ^{-1} . Note that the diagonal elements of Φ^{-1} is the reciprocal of the diagonal elements of Φ since Φ is lower triangular, i.e., $[\Phi^{-1}]_{kk} = [\Phi]_{kk}^{-1}$, $\forall k$. The leader problem (14) can be transformed into an equivalent form expressed in terms of $\tilde{\delta}$.

$$\max_{\tilde{\delta}_k} U_{R-D_k}(\tilde{\delta}_k, \tilde{\delta}_{-k}) = \frac{1}{k} \left[\log(1 + \alpha_k \tilde{\phi}_k(1 - \tilde{\delta}_k)) - \beta_k \sum_{j=1}^K (1 - \tilde{\delta}_j) [\Phi^{-1}]_{kj} \right] \quad (18a)$$

$$\text{s.t. } \bar{\tilde{\delta}}_k \leq \tilde{\delta}_k \leq 1, \quad (18b)$$

where $\bar{\tilde{\delta}}_k = \frac{1}{\tilde{\phi}_k} (\sum_{j=1}^{k-1} 2\phi_j \bar{\delta}_j + \phi_k \bar{\delta}_k)$. Due to the concavity of the objective function (18a) on $\tilde{\delta}_k$, the optimal $\tilde{\delta}_k$ can be analytically solved by applying the first-order optimality condition on the unconstrained objective function (18a) and projecting to the feasible set in (18b). We obtain that

$$\tilde{\delta}_k = \min \left\{ 1, \max \left\{ \bar{\tilde{\delta}}_k, 1 - \frac{[\Phi]_{kk}}{\beta_k} + \frac{1}{\alpha_k \tilde{\phi}_k} \right\} \right\}. \quad (19)$$

As a result, original variable δ_k can be solved by forward substitution involving (17) and (19), and then mapping to the original feasible range in (14b), which gives

$$\delta_k^* = \min \left\{ 1, \max \left\{ \bar{\delta}_k, \frac{1}{\phi_k} \left(\tilde{\delta}_k \tilde{\phi}_k - \sum_{j=1}^{k-1} 2\phi_j \delta_j^* \right) \right\} \right\}. \quad (20)$$

Notice that ϕ_k , for all k , has to be known to calculate the leaders' strategy δ . Specifically, the centralized algorithm can be executed at a node that is aware of the global CSI of the system, for instance, the base station where all nodes are connecting with. We summarize the centralized algorithm in Algorithm 1.

B. Distributed Iterative Algorithm

To reduce system overhead, we propose a distributed algorithm which can be executed iteratively at each relay, i.e., with parameters available at each node (including CSI). We notice that (14) is a convex optimization problem with respect to δ_k for given δ_{-k} . Thus, δ_k can be solved similarly as for $\tilde{\delta}_k$ in Sec. III-A. By taking the derivative of (14a) with respect to δ_k and equating to zero, we obtain

$$\delta_k = 1 - \frac{1}{\beta_k} + \frac{1 + \alpha_k \sum_{j=1}^{k-1} 2\phi_j(1 - \delta_j)}{\alpha_k \phi_k}. \quad (21)$$

Algorithm 1 Centralized algorithm

- 1: Let $\tilde{\mathcal{K}} = \mathcal{K} \setminus \mathcal{I}$, $\mathcal{I} \triangleq \{i : \phi_i = 0, i \in \mathcal{K}\}$.
- 2: **for** $k \in \tilde{\mathcal{K}}$ **do**
- 3: calculate the strategy of R-D pair δ_k as in (19) and (20).
- 4: **end for**
- 5: Compute the strategies of S-D pairs \mathbf{p} as in (12).

Algorithm 2 Distributed iterative algorithm

- 1: Let $\tilde{\mathcal{K}} = \mathcal{K} \setminus \mathcal{I}$, $\mathcal{I} \triangleq \{i : \phi_i = 0, i \in \mathcal{K}\}$.
- 2: Choose an initial strategy $\delta^{(0)} = (\delta_k^{(0)})_{k \in \tilde{\mathcal{K}}}$, set $n = 0$.
- 3: **repeat**
- 4: **for** $k \in \tilde{\mathcal{K}}$ **do**
- 5: compute $\delta_k^{(n+1)}$ as in (21) and (22) for given $\delta_{-k}^{(n)}$.
- 6: **end for**
- 7: set $\delta^{(n+1)} = (\delta_k^{(n+1)})_{k \in \tilde{\mathcal{K}}}$ and $n \leftarrow n + 1$.
- 8: **until** $\delta^{(n+1)}$ satisfies a suitable termination criterion.
- 9: Compute the strategies of S-D pairs \mathbf{p} as in (12).

Then, mapping δ_k to constraint (14b) results in

$$\delta_k^* = \min \left\{ 1, \max \left\{ \bar{\delta}_k, \delta_k \right\} \right\}, \quad (22)$$

where δ_k is given in (21). The SE of the game can be achieved by iteratively solving the strategy δ_k at relay k , $\forall k$, with the knowledge of local CSI and the CSI of previous relays, which can be obtained from the source. Due to the uniqueness of the SE, the convergence of iterations is guaranteed. The distributed iterative algorithm is summarized in Algorithm 2.

IV. SIMULATION RESULTS

We present simulation results of the proposed algorithms in this section. We set the carrier frequency to be 900 MHz and the bandwidth is 1 MHz. The noise power spectrum density is 10^{-19} W/Hz. We simulate a Rayleigh fading channel with average power -3 dB for multi-path fading. For large-scale fading, the free space path loss model is used with path loss exponent 2 and reference distance 1 meter. The antenna gain is given as 6 dBi. The destinations are 100 meters away from the source and the relays are uniformly located in between with average 50 meters from the source. Set $T = 1$ second and $\eta_k = 0.8$ for all k . For simplicity, we set $\mu_k = \mu$ (bits/Hz/J) and $P_k = P$ (W) for all k . In the following figures, we use 'Cen' and 'Dis' to notate the proposed centralized and distributed algorithms, respectively. For comparison, we consider the protocol proposed in [13], where the relay with best channel state is selected by Vickery auction (VA) and a single-leader Stackelberg game considering the source as leader and the selected relay as follower is solved. We provide extensive comparisons with [13] since it provides a valid benchmark, meaning more naive protocols that do not fully address the competitive nature perform worse. We vary the values of μ and P to investigate the impact of parameters.

In Figs. 2-6, the simulation results confirm that the centralized and the distributed iterative algorithms are consistent, both of which achieve the SE. In particular, we illustrate system performance in terms of sum utility of

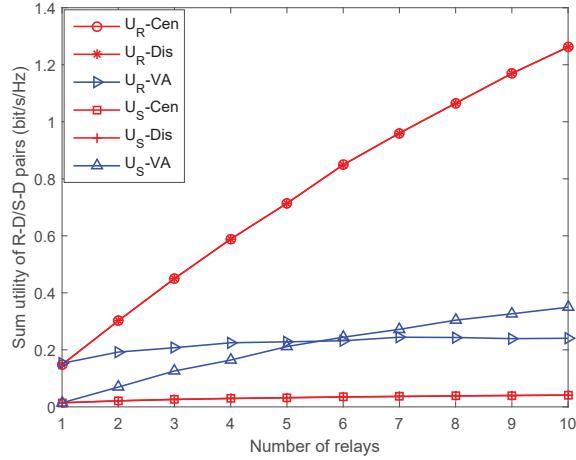


Fig. 2. Sum utility of R-D/S-D pairs versus the number of relays for $\mu = 0.01$ bit/Hz/J and $P = 0.05$ W.

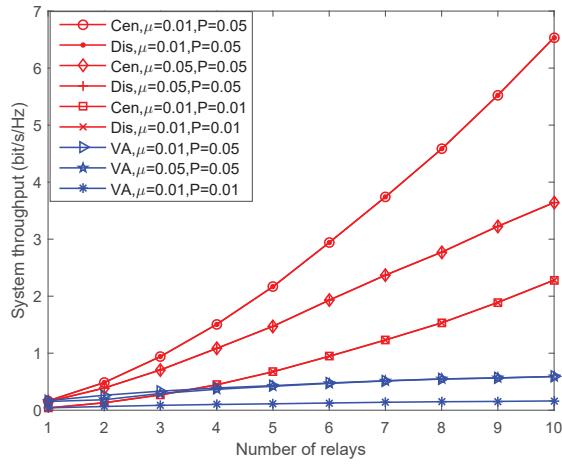


Fig. 3. System Throughput versus the number of relays.

R-D pairs, sum utility of S-D pairs, system utility, and system throughput in Figs. 2-4. System utility is defined as $\sum_{k \in \mathcal{K}} \frac{1}{kT} (R_{R-D_k} - E_{S_k})$. And system throughput is given by $\sum_{k \in \mathcal{K}} R_{R-D_k}$. We see that the overall system performance is improved as the number of relays increases.

Fig. 2 shows that the proposed algorithms improve the utility of R-D pairs significantly as compared to [13], while the utility of S-D pairs is lower than that achieved by [13]. This is because in the proposed relay-centric algorithms, the R-D pairs as leaders have the priority to determine their strategies in the first place and the S-D pairs respond secondly. Relays benefit from anticipating source's strategy and obtain higher utilities. In [13], the source is at an advantage and thus obtains higher utility. Fig. 3 and Fig. 4 demonstrate system throughput and system utility, respectively. Our proposed algorithms achieve a significant enhancement on both performance metrics compared to the baseline in [13]. It is also notable that the superiority of the proposed algorithms becomes more significant when there are a large number of relays. This is again in contrast to the baseline in [13], where both system

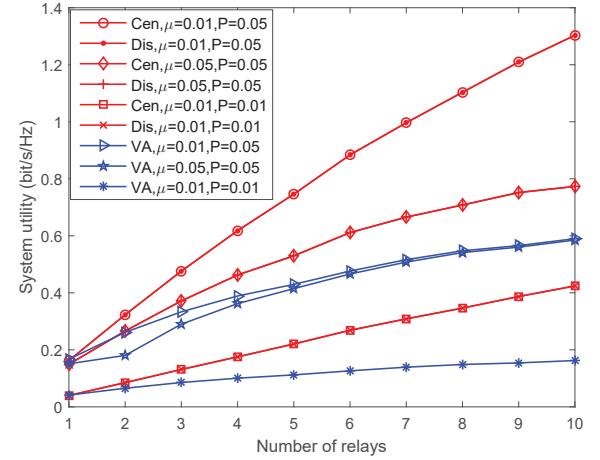


Fig. 4. System utility versus the number of relays.

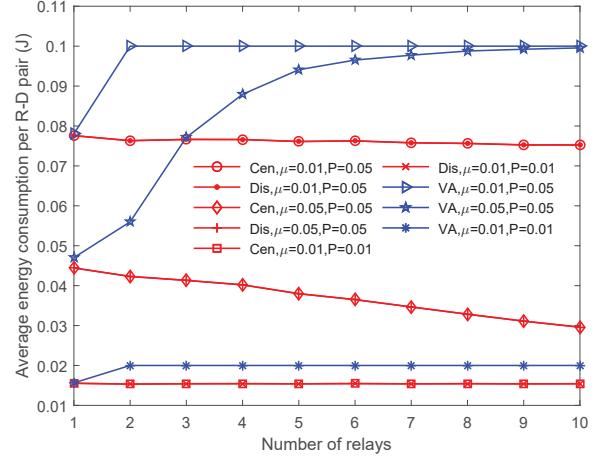


Fig. 5. Average energy consumption per R-D pair versus the number of relays.

throughput and utility have diminishing returns as the number of relays grows since only one relay is selected from the VA. We can also observe from the experiments that higher maximum transmit power P provides larger throughput and utility by comparing the curves of $\mu = 0.01, P = 0.01$ and $\mu = 0.01, P = 0.05$. On contrast, from curves of $\mu = 0.01, P = 0.05$ and $\mu = 0.05, P = 0.05$, we see that higher μ causes a decrease on the performance due to the higher energy cost.

Fig. 5 shows the average energy consumption per R-D pair versus the number of relays. As the number of relays increases, the average energy consumed per R-D pair decreases in the proposed algorithms. This implies that the system is more energy efficient for larger K . While, in the baseline [13], only one relay is selected, thus, the energy consumption per relay converges to $2P$. In particular, when μ is large, the energy consumption decreases which is consistent with the solution of the source's strategy in Sec. III. Fig. 6 presents the sum utility of R-D pairs versus the distance between the source and the relays for different number of relays. When relays are located either close to the source or close to the destinations, higher

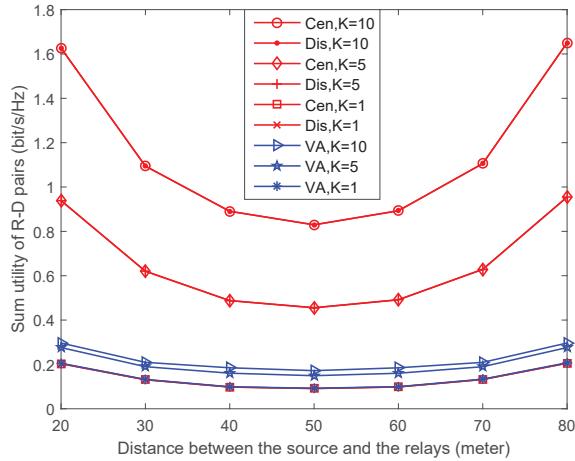


Fig. 6. Sum utility of R-D pairs versus the distance between the source and the relays for $\mu = 0.01$ bit/Hz/J and $P = 0.05$ W.

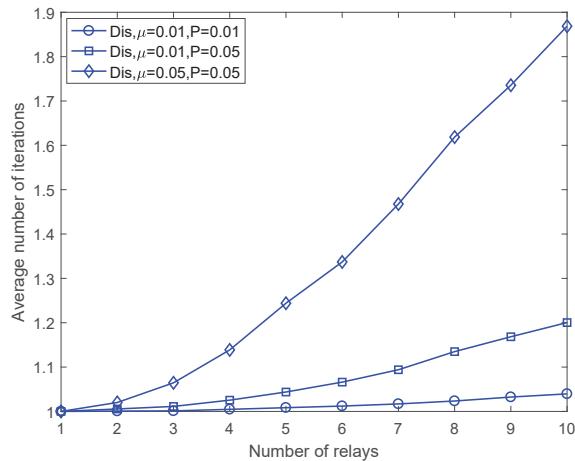


Fig. 7. Average number of iterations versus the number of relays for the distributed iterative algorithm.

utility is achieved, because the relays have either good channels for energy harvesting from the source or for data transmission to the destinations. Therefore, the lowest utility appears when the relays are in the middle point. Furthermore, for $K = 1$, the proposed algorithms give consistent results as the baseline [13] since the only relay is selected. As K becomes large, the advantage of the proposed algorithms gets more remarkable compared to the baseline. Fig. 7 shows the number of iterations until convergence for the distributed algorithm averaged over channel variations. We observe that the convergence is fast.

V. CONCLUSION

In this paper, we have studied a relay-centric two-hop network with signal and energy cooperation. Considering the primary objective of transmitting relays' data to destinations, we have adopted the framework of multi-leader-follower Stackelberg game to model the competition between the R-D pairs, the leaders, and the S-D pairs, the followers. We have adopted the model where the source transmits information and

provides WET to the relays via RF signals one by one. We have further allowed the relays to harvest energy from the signals intended for previous relays while waiting their turn and thus considered an asymmetric energy harvesting scenario. We have modeled the data rate, energy cost, and delay in the utility functions. The existence and uniqueness of the equilibrium of the game have been proved. We have provided a centralized algorithm that can be easily executed with global CSI. We have also considered a distributed iterative algorithm. The simulation results have confirmed both algorithms achieve the SE and outperform the baseline protocol significantly. Future work includes considering joint optimization of resources; relay powering durations and order; powering groups of relays for systems with wireless energy transfer; and the impact of imperfect energy and channel state information.

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