Throughput Maximizing Games in the Two-Hop Relay Channel with Energy Cooperation

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***Abstract*—In this paper, we study a two-hop network where the source and the relay have data that the destination wishes to receive. The source node is not directly connected to the destination; it can send its data only via the relay. The relay node, on the other hand, does not have an external source of energy, and needs to perform RF energy harvesting from the source to send its and the source's data. Both nodes wish to send as much of their data to the destination as possible. For this setup, we first formulate a noncooperative game and improve upon its equilibrium by using a pricing scheme. Next, we model the communication setup as a Stackelberg game with the relay node as the leader and the source node as the follower of the game. We analyze the resulting equilibrium and interpret how the leader of the game chooses its strategy in order to influence the follower's decision. We provide numerical examples which compare the payoffs achieved by these equilibria. We investigate the impact of the model parameters on the decisions of the two players and the achieved payoffs. We observe that at the Stackelberg equilibrium, the leader of the game can manipulate the follower in order to achieve a higher payoff than it would at the social optimum.**

I. Introduction

Wireless networks powered by green energy have a wide range of applications including sensor networks powered by a variety of sources, e.g., solar radiation, biomass, and piezoelectric devices. A source of green energy is radio frequency (RF) energy where a wireless node can be powered by the energy harvested from another node's transmission [1]. RF energy transfer can be regarded as a form of energy cooperation between the nodes in a wireless network.

Energy cooperation has recently been proposed in a two-hop network where the source can one-way transfer energy to the relay for the relay to forward the source's information [2]. It has been shown that such an approach improves the end-to-end throughput significantly [2]. Reference [3] has explored two-way energy transfer between the nodes of an energy harvesting two-hop network to further improve the throughput. Reference [4] has studied the trade off between energy and information transfer over a point-to-point channel. Reference [5] has considered a two-hop network with multiple relays with energy transfer from the source to the relays. Other recent references that consider wireless power transfer/harvesting, including from RF signals, include [6]–[10].

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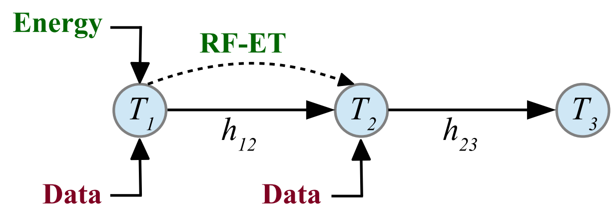

Fig. 1. The two-hop channel with radio frequency energy transfer (RF-ET).

From these recent studies, it is readily seen that energy cooperation is helpful in improving overall system performance, just like signal cooperation (relaying). While these setups foresee that the relay nodes receive energy for relaying the signals of the sources, one can ask the valid question as to what incentive a node has to participate in such a cooperative model. To address this question, in this paper, we consider game theoretic models to incentivize such a relay node. We consider that the relay node is powered solely by wireless energy transfer from the source node. We study a selfish setting where the source and the relay are interested in maximizing their own utilities. We propose a pricing scheme to have the nodes converge on a pair of strategies which together maximize the total utility of the network. In other words, we show that fully altruistic operation of the nodes can be facilitated by pricing. We next model the two-hop setup as a Stackelberg game [11] where the follower of the game, in this case, the source, chooses a strategy subject to the strategy chosen by the leader, in this case, the relay. We analyze how a Stackelberg competition between the nodes affects their decisions and the resulting utilities. We provide numerical results to assess the influence of the channel parameters such as the location of the nodes relative to each other and the harvesting efficiency at the relay on the nodes' decisions and the utilities. Our findings suggest that Stackelberg competition results in a suboptimal total utility for the network. However, the leader of the game can exploit its knowledge of the follower's decision to obtain a higher payoff at the cost of suboptimality for the entire network.

The remainder of this paper is organized as follows. In Section II, we describe the system model and the communication scenario. In Section III, we model this scenario as a noncooperative game and show that the unique Nash equilibrium

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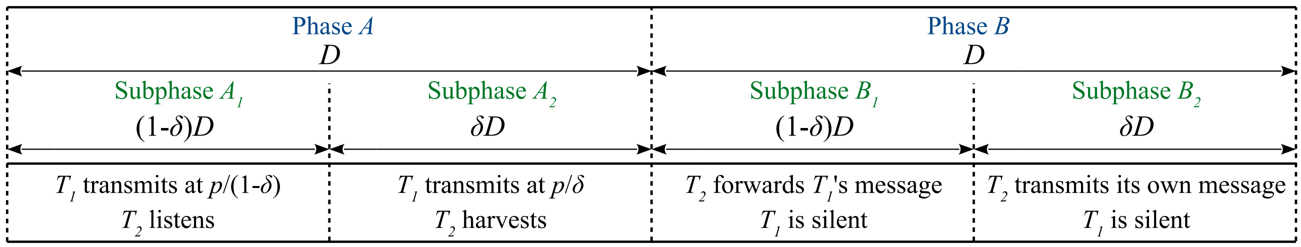

Fig. 2. The phases and subphases of the communication scenario.

of this game can be improved by pricing. In Section IV, we model a Stackelberg game for our communication setup. In Section V, we provide numerical results. In Section VI, we discuss our findings and conclude the paper.

II. System Model

We study a two-hop network shown in Fig. 1. Nodes T_1 and T_2 have data that they wish to transmit to node T_3. Node T_3 is interested in data from both nodes. Nodes T_1 and T_2 are selfish in the sense that their actions will be in favor of their respective utilities which are simply the amount of data they can deliver to node T_3, i.e., their individual throughputs.

Node T_1 is connected to node T_2 via a Gaussian link with power gain h_{12}, and node T_2 is connected to node T_3 via a Gaussian link with power gain h_{23}. Without loss of generality, the additive white Gaussian noise at any receiver is assumed to be zero mean and unit variance. Node T_1 does not have a direct link to its receiver, node T_3. Thus, node T_1 needs node T_2 to forward its data to node T_3. The nodes are assumed to be half duplex.

Node T_1 can buy energy from an external source at a price of σ per unit of energy. This source is assumed to be reliable in the sense that it can supply any amount of energy that node T_1 demands. Node T_2 does not have such a source of energy. It can, however, harvest the RF energy from node T_1's transmitted signal. This is done at harvesting efficiency $\eta \in [0, 1]$, i.e., node T_2 can harvest η fraction of the received energy [2]. Since this is the only source of energy for node T_2, it needs node T_1 to transmit at a positive power. That is, each node requires the other's signal or energy cooperation so that it can deliver its data to node T_3.

For simplicity, we employ amplify-and-forward relaying. Node T_1 can choose an average transmit power p as long as it is below a maximum power value, i.e., $0 \leq p \leq p_{max}$. Node T_2 can choose a fraction $\delta \in [0, 1]$ which denotes what portion of the RF energy in the signal received from T_1 will be harvested at efficiency η. In other words, δ signifies what portion of node T_2's operation is dedicated to node T_2's utility, and $1 - \delta$ signifies the remaining portion dedicated to node T_1's utility. Note, conversely, that node T_1's strategy p affects both nodes' operation in the positive direction.

We consider a communication scenario composed of two phases which we refer to as phase A and phase B, see Fig. 2. Without loss of generality, the two phases are considered to be of equal duration, which is denoted by D. Phase A (resp. B) is reserved for node T_1's transmission (resp. node T_2's transmission). The δ fraction chosen by T_2 divides each phase into two subphases. This directly follows from the definition of δ. That is, node T_2 will use δ fraction of phase A to harvest energy, and the remaining fraction to accommodate T_1's transmission. We model this by two subphases A_1 and A_2 of phase A of durations $(1 - \delta)D$ and δD, respectively.

- Subphase A_1: Node T_1 transmits at $p/(1 - \delta)$. Node T_2 listens to T_1's transmission and stores the received signal.
- Subphase A_2: Node T_1 transmits at p/δ. Node T_2 uses all of the received signal for energy harvesting. The receive power at T_2 is $h_{12}p/\delta$. Node T_2 harvests $\eta h_{12}pD$.

Note that the total energy spent by node T_1 is $2pD$ for which it incurs a cost of $2\sigma pD$.

Node T_2 spends phase B both forwarding node T_1's data and transmitting its own data. Since the relaying scheme is amplify-and-forward, the amount of time it allocates to forwarding T_1's data must be the same as the duration of subphase A_1 where it listened to T_1's transmission. Thus, we have subphases B_1 and B_2 of phase B of durations $(1 - \delta)D$ and δD, respectively.

- Subphase B_1: Node T_2 forwards node T_1's data that it received in subphase A_1. Node T_1 is silent since it is not directly connected to T_3, and T_2 is a half duplex node.
- Subphase B_2: Node T_2 transmits its own data using the $\eta h_{12}pD$ units of energy it harvested in subphase A_2. Node T_1 is silent.

Notice that the subphases are indexed in a way that events that happen in A_i and B_i are in favor of only node T_i's utility, $i = 1, 2$.

Given that the strategies chosen by T_1 and T_2 are p and δ, respectively, their utilities u_1 and u_2 are defined as

$$u_1(p, \delta) = D(1 - \delta)C\left(\frac{h_{12}h_{23}}{1 + h_{23}}\frac{p}{1 - \delta}\right) - 2\sigma pD, \quad (1)$$

$$u_2(p, \delta) = D\delta C\left(\eta h_{12}h_{23}\frac{p}{\delta}\right) \quad (2)$$

where $C(x) = \frac{1}{2}\log(1 + x)$. Both utilities are jointly concave in p and δ [12, §3.2.6]. In the sequel, we refer to $u_1(p, \delta) + u_2(p, \delta)$ as the total utility.

Next, we formulate a noncooperative game for this setup and analyze its equilibria. We then employ a pricing scheme which gives nodes T_1 and T_2 incentive to agree upon an equilibrium that achieves the maximum total utility.

III. Noncooperative Game

A. Noncooperative Game without Pricing

Define the following noncooperative game.

$$G_{NC} = (\mathcal{M}, \{\mathcal{S}_i\}, \{u_i\}) \tag{3}$$

Here, $\mathcal{M} = \{T_1, T_2\}$ is the set of players, $\mathcal{S}_1 = [0, p_{max}] \ni p$ and $\mathcal{S}_2 = [0, 1] \ni \delta$ are the strategy sets, and u_1 and u_2 are the utilities as given in (1) and (2). The best response is defined as the strategy that maximizes a player's utility given the other player's strategy, i.e., it is the best way a player can react to the other player's decision. The best responses for both players are given as

$$\mathcal{B}_1(\delta; u_1) = \arg\max_{p \in \mathcal{S}_1} u_1(p, \delta), \tag{4}$$

$$\mathcal{B}_2(p; u_2) = \arg\max_{\delta \in \mathcal{S}_2} u_2(p, \delta). \tag{5}$$

A strategy pair (p^*, δ^*) is a Nash equilibrium of G_{NC} if

$$u_1(p^*, \delta^*) \geq u_1(p, \delta^*), \qquad \forall p \in \mathcal{S}_1, \tag{6}$$

$$u_2(p^*, \delta^*) \geq u_2(p^*, \delta), \qquad \forall \delta \in \mathcal{S}_2. \tag{7}$$

The observation that $u_2(p, \delta)$ is strictly increasing in δ for $p > 0$ yields

$$\mathcal{B}_2(p; u_2) = 1 \tag{8}$$

for any $p \in \mathcal{S}_1 \setminus \{0\}$. For $\delta = 1$, u_1 is nonpositive and has maximum value 0. Thus,

$$\mathcal{B}_1(\delta; u_1) = 0 \tag{9}$$

for $\delta = 1$. Note that no $(p, \delta) \in \{0\} \times [0, 1)$ can be a Nash equilibrium since solving the maximization in (4) for any $\delta \in [0, 1)$ will yield $\mathcal{B}_1(\delta; u_1) > 0$ which achieves a higher utility for player 1. Therefore, the unique equilibrium of G_{NC} is $(p^*, \delta^*) = (0, 1)$ which achieves $u_1(0, 1) = u_2(0, 1) = 0$, and thus zero total utility.

This result can be interpreted as follows. Although there exists $(p, \delta) \in \mathcal{S}_1 \times \mathcal{S}_2 \setminus \{(0, 1)\}$ which achieves a positive total utility, the players cannot agree upon this strategy pair. Due to the noncooperative nature of G_{NC}, both players have incentive for unilateral deviation at all strategy pairs in $(p, \delta) \in \mathcal{S}_1 \times \mathcal{S}_2 \setminus \{(0, 1)\}$. We can, however, achieve a positive total utility at a noncooperative equilibrium by modifying the payoffs (utilities) as explained next.

B. Noncooperative Game with Pricing

We employ a pricing scheme on the payoffs for both players to facilitate an equilibrium with a positive total utility. The pricing scheme is similar to the interference compensation scheme in [13], except here, the prices are not determined by the players. Instead, node T_3 announces the prices since it has complete control over how much to pay T_1 and T_2 for their data. Define the following noncooperative game.

$$\tilde{G}_{NC} = (\mathcal{M}, \{\mathcal{S}_i\}, \{\tilde{u}_i\}) \tag{10}$$

Here, the modified payoffs are given as

$$\tilde{u}_1(p, \delta; \pi_2) = u_1(p, \delta) - p\pi_2, \tag{11}$$

$$\tilde{u}_2(p, \delta; \pi_1) = u_2(p, \delta) - \delta\pi_1, \tag{12}$$

where price π_i models a penalty charged to player j as a result of the negative effect of its strategy on the utility of player i, $i, j = 1, 2$, $j \neq i$. Prices π_1 and π_2 are announced by node T_3 and can be used by node T_3 to maximize the total amount of data it receives. Node T_3 wishes nodes T_1 and T_2 to agree upon an equilibrium that optimally solves the social problem which can be stated as

$$\max_{(p,\delta) \in \mathcal{S}_1 \times \mathcal{S}_2} u_1(p, \delta) + u_2(p, \delta). \tag{13}$$

The objective in (13) is jointly strictly concave in (p, δ) and $\mathcal{S}_1 \times \mathcal{S}_2$ is a convex set. Thus, problem (13) admits a unique optimizer, say $(p^\dagger, \delta^\dagger)$. This strategy pair can be made the unique Nash equilibrium of $\tilde{G}_{NC}$ if node T_3 calculates prices using

$$\pi_1(p, \delta) = -\frac{\partial u_1(p, \delta)}{\partial \delta}, \tag{14}$$

$$\pi_2(p, \delta) = -\frac{\partial u_2(p, \delta)}{\partial p}. \tag{15}$$

We employ a modified version of the asynchronous distributed pricing (ADP) algorithm in [13]. p and δ are asynchronously updated by T_1 and T_2 using $\mathcal{B}_1(\delta, \pi_2; \tilde{u}_1)$ and $\mathcal{B}_2(p, \pi_1; \tilde{u}_2)$, respectively. Since both players are using best response updates, any limit point of the modified ADP algorithm is a Nash equilibrium of $\tilde{G}_{NC}$. After each update of p or δ, node T_3 calculates π_1 and π_2 using (14) and (15), and announces them. This selection of the prices guarantees that any limit point of the algorithm will satisfy the Karush-Kuhn-Tucker (KKT) conditions of (13). Since (13) is a convex problem with a strictly concave objective, the KKT conditions are necessary and sufficient for optimality. Thus, the modified ADP algorithm can have at most one limit point, $(p^\dagger, \delta^\dagger)$, which is the unique maximizer of the total utility.

The convergence of the modified ADP algorithm follows from supermodular game theory and can be shown by defining an equivalent game with strategies p and $-\delta$ as was done in [13] for an interference channel setup. Therefore, $\tilde{G}_{NC}$ has a unique Nash equilibrium $(p^\dagger, \delta^\dagger)$ which solves the social problem in (13) optimally.

In order to identify $p^\dagger$ and $\delta^\dagger$ analytically, we restate (13) in the following equivalent form.

$$\max_{p \in \mathcal{S}_1} \left[\max_{\delta \in \mathcal{S}_2} u(p, \delta) \right] D - 2\sigma p D \tag{16}$$

where

$$u(p, \delta) = (1 - \delta) C \left(g_1 \frac{p}{1 - \delta} \right) + \delta C \left(g_2 \frac{p}{\delta} \right) \tag{17}$$

where $g_1 \triangleq \frac{h_{12} h_{23}}{1 + h_{23}}$ and $g_2 \triangleq \eta h_{12} h_{23}$. Since $C(x)$ is concave in x, we have

$$u(p, \delta) \leq C((g_1 + g_2)p). \tag{18}$$

This upperbound can be achieved for any p as

$$C((g_1+g_2)p) = u\left(p, \frac{g_2}{g_1+g_2}\right). \quad (19)$$

Thus, $\delta^\dagger = \frac{g_2}{g_1+g_2}$ optimally solves the inner maximization problem in (16), which then becomes

$$\max_{p\in\mathcal{S}_1}(C((g_1+g_2)p) - 2\sigma p)D. \quad (20)$$

The unique optimal solution of (20) is

$$p^\dagger = \min\left\{\max\left\{\frac{1}{4\sigma\ln 2} - \frac{1}{g_1+g_2}, 0\right\}, p_{max}\right\}. \quad (21)$$

This completes the description of $(p^\dagger, \delta^\dagger)$, the unique Nash equilibrium of $\tilde{G}_{NC}$. As a concluding remark, we note that the optimal solution of the inner problem does not depend on p. $\delta^\dagger$ is chosen as the optimal balance between the total amounts of data delivered by the two players, and depends only on the channel conditions and η. With the optimal solution for the inner problem available for any p, the outer problem is a convex problem with the optimal close form given by (21).

IV. Stackelberg Game

In this section, we take an alternative approach to model the competition between nodes T_1 and T_2 and analyze the resulting equilibria. We define a Stackelberg game for our two-hop setup, which is a sequential leader-follower game [14]. The follower wishes to maximize its payoff and chooses its strategy accordingly subject to the strategy chosen by the leader. The leader is assumed to be capable of calculating the follower's best response to any leader strategy. The leader chooses its strategy that maximizes its own payoff knowing how the follower will react to the leader's strategy.

Define the following Stackelberg game.

$$G_{ST} = (\tilde{\mathcal{M}}, \{\mathcal{S}_i\}, \{u_i\}) \quad (22)$$

Here, $\tilde{\mathcal{M}} = \{T_2, T_1\}$ is the set of players where we designate node T_2 as the leader and node T_1 as the follower of the game. The strategy spaces and the payoffs are the same as the noncooperative game in Section III-A.

For any leader strategy $\delta \in \mathcal{S}_2$, node T_1, the follower, solves

$$p^\ddagger(\delta) = \arg\max_{p\in\mathcal{S}_1} u_1(p,\delta). \quad (23)$$

The unique optimal solution of (23) can be identified as

$$p^\ddagger(\delta) = \min\left\{\max\left\{\left(\frac{1}{4\sigma\ln 2} - \frac{1}{g_1}\right)(1-\delta), 0\right\}, p_{max}\right\}. \quad (24)$$

As can be seen, $p^\ddagger(\delta)$ is nonincreasing in δ. Node T_1 reacts to a high δ chosen by node T_2 by lowering its transmit power. This is because a higher δ implies less time dedicated to improving T_1's utility, and the throughput it can achieve can no longer compensate for its energy cost, $2\sigma pD$. The leader, node T_2, knows this, i.e., T_2 can calculate $p^\ddagger(\delta)$ for all $\delta \in \mathcal{S}_2$. The leader takes this information into account while choosing a δ, and solves

$$\delta^\ddagger = \arg\max_{\delta\in\mathcal{S}_2} u_2(p^\ddagger(\delta), \delta), \quad (25a)$$

$$= \arg\max_{\delta\in\mathcal{S}_2} \delta C\left(g_2 \frac{\min\{\max\{\phi(1-\delta), 0\}, p_{max}\}}{\delta}\right) \quad (25b)$$

where $\phi \triangleq \frac{1}{4\sigma\ln 2} - \frac{1}{g_1}$.

Before solving (25), let us analyze $p^\ddagger(\delta)$ in (24). If $\phi \le 0$, then $p^\ddagger(\delta) = 0$ for all $\delta \in \mathcal{S}_2$. In this case, the objective of (25) is zero, and regardless of the choice of δ, the total utility achieved is zero. This results from the power cost σ of node T_1 being too high, or the overall power gain g_1 for node T_1 being too low, i.e., node T_1 could not achieve a positive payoff even if it were given the entire transmission session with $\delta = 0$.

Let us now investigate the more interesting case of $\phi > 0$ where node T_1 has incentive to transmit. In this case, we can restate $p^\ddagger(\delta)$ as

$$p^\ddagger(\delta) = \begin{cases} p_{max} & \text{if } \delta \in \mathcal{S}_{2,1} \\ \phi(1-\delta) & \text{if } \delta \in \mathcal{S}_{2,2} \end{cases} \quad (26)$$

where $\mathcal{S}_{2,1} \triangleq [0, 1-\min\{\max\{p_{max}/\phi, 0\}, 1\})$ and $\mathcal{S}_{2,2} \triangleq [1-\min\{\max\{p_{max}/\phi, 0\}, 1\}, 1]$. Using the piecewise description of $p^\ddagger(\delta)$ in (26), we separate the feasible region of (25) into two regions $\mathcal{S}_{2,1}$ and $\mathcal{S}_{2,2}$, solve the problem in each region, and finally identify $\delta^\ddagger$.

1) $\mathcal{S}_{2,1}$ as the feasible region of (25): In this case, $p^\ddagger(\delta) = p_{max}$ for all δ, and the objective of (25) is strictly increasing in δ. Therefore, no $\delta \in \mathcal{S}_{2,1}$ can outperform $\delta_1^\ddagger = 1-\min\{\max\{p_{max}/\phi, 0\}, 1\} \in \mathcal{S}_{2,2}$.
2) $\mathcal{S}_{2,2}$ as the feasible region of (25): In this case, $p^\ddagger(\delta) = \phi(1-\delta)$ for all $\delta \in \mathcal{S}_{2,2}$, and the objective of (25) becomes $\delta C(g_2\phi(1/\delta - 1))$ which is concave in $\delta \in \mathcal{S}_{2,2}$. In order to find the optimal solution for this case, one needs to solve

$$\ln\left(1 + g_2\phi\left(\frac{1}{\tilde{\delta}} - 1\right)\right) = \frac{1}{1 + \tilde{\delta}\left(\frac{1}{g_2\phi} - 1\right)}. \quad (27)$$

Equation (27) has a unique solution which can be found numerically. Then we have the optimal solution found as $\delta_2^\ddagger = \min\{\max\{\tilde{\delta}, \delta_1^\ddagger\}, 1\}$.

The optimal solution of (25) is $\delta_1^\ddagger$ or $\delta_2^\ddagger$, whichever achieves a larger objective for (25). We know that no strategy in $\mathcal{S}_{2,1}$ can outperform $\delta_1^\ddagger$, and also that $\delta_1^\ddagger \in \mathcal{S}_{2,2}$. Hence, it follows that $\delta^\ddagger \in \mathcal{S}_{2,2}$, and thus $\delta^\ddagger = \delta_2^\ddagger$.

We can observe from (27) that as σ increases or g_1 decreases, T_2 tends to choose a lower δ. This follows from the fact that T_2 knows that, such changes in σ and g_1 will urge node T_1 to lower its power. As a result, node T_2 proactively lowers δ so as to counteract the influence of σ and g_1 on node T_1's decision. An increase in g_2, however, is directly exploited by T_2 with the choice of a larger δ. T_1 cannot react to a change in g_2, but T_2 can take advantage of an increase in g_2 with a higher δ which, together with the higher g_2, results

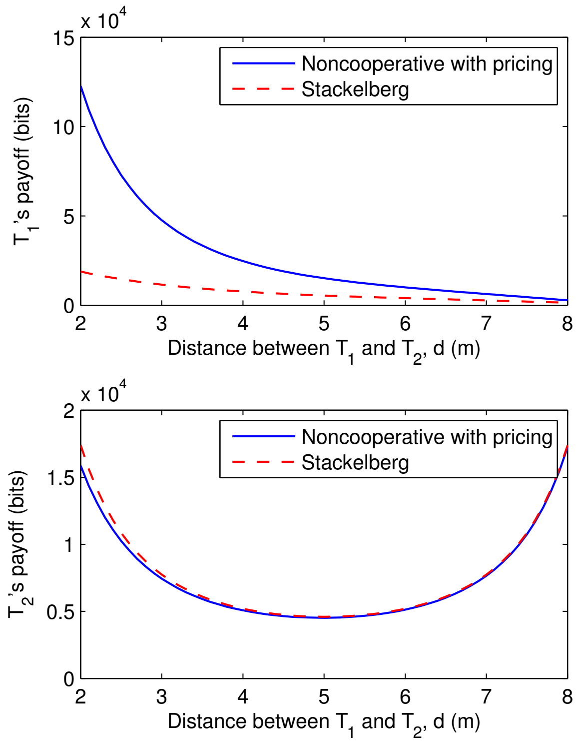

Fig. 3. The two players' payoffs versus the location of T_2 with $d' = 10$ m, $\sigma = 0.05$ bps/W, $\eta = 0.1$, and $p_{max} = 100$ mW.

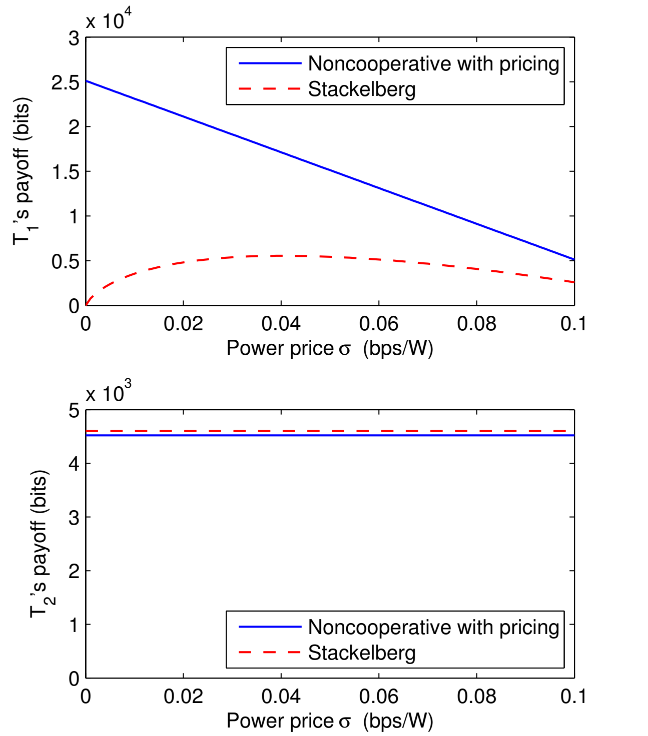

Fig. 4. The two players' payoffs versus the power price with $d = 5$ m, $d' = 10$ m, $\eta = 0.1$, and $p_{max} = 100$ mW.

in an increased throughput for node T_2 even though node T_1 chooses a lower p.

Next, we will see how the resulting utilities by the Nash equilibria for the two cases compare.

V. Numerical Results

In this section, we evaluate the payoffs (throughput) of the two players at the Nash equilibria found in Sections III-B and IV. We omit the Nash equilibrium found in Section III-A since it yields zero payoffs for both players. For all simulations, we denote by d the distance between T_1 and T_2, and by d' the distance between T_1 and T_3. The available bandwidth is 1 MHz, the noise density at any receiver is 10^{-19} W/Hz, and thus the noise variance at any receiver is 10^{-13} W. The normalized power gains are computed using a path loss model as $h_{12} = -110$ dB$/(10^{-13}d^3) = 100/d^3$ and $h_{23} = 100/(d' - d)^3$ where we assume the path loss exponent to be 3. The duration of phases A and B is chosen as unity. We vary the remaining parameters d, σ, η, and p_{max} in order to assess their impact on the payoffs. See the captions of Fig. 3–6 for a detailed description.

Fig. 3 shows payoffs achieved by the noncooperative Nash equilibrium with pricing, and the Stackelberg equilibrium. Recall that the first equilibrium is socially optimal, thus it maximizes the total utility in all settings considered here. In this figure, node T_2 moves along the line between T_1 and T_3. As can be seen, node T_2 achieves a high payoff when it is near T_1 or T_3. This is because it harvests more energy when near T_1, and has a better link to its destination when near T_3. When T_2 moves away from T_1, T_1 has to transmit its data over a link with a lower channel gain to T_2, and thus achieves a smaller payoff.

Fig. 4 shows payoffs achieved for varying power price σ. The power price does not affect node T_2's operations, but it causes node T_1 to be more conservative with its power usage. Thus, at the social optimum, node T_1's payoff is decreasing in σ. At the Stackelberg equilibrium, node T_2 chooses a lower δ as ϕ decreases in order to give node T_1 incentive to transmit even though σ is increasing.

Fig. 5 shows the resulting payoffs versus the harvesting efficiency $0 \leq \eta \leq 1$. Node T_2's payoff is increasing in η as it can harvest a larger amount of energy with a larger harvesting efficiency. As the amount of energy harvested by node T_2 increases, its contribution in the total utility becomes more powerful. As a result, node T_1 loses some of its payoff due to a larger δ. Lastly, it is confirmed that g_2 which is a function of η does not impact node T_1's decision at the Stackelberg equilibrium.

Fig. 6 shows resulting payoffs for varying maximum power constraints. We observe that all payoffs are increasing in p_{max}. However, the payoffs for the socially optimal case are concave, which means the gain from a high p_{max} diminishes as p_{max} is further increased. This is due to the energy cost of node T_1 being a part of the total utility. At the Stackelberg equilibrium, node T_2 uses its knowledge of $p^\ddagger(\delta)$ to entice node T_1 not to lower its transmit power.

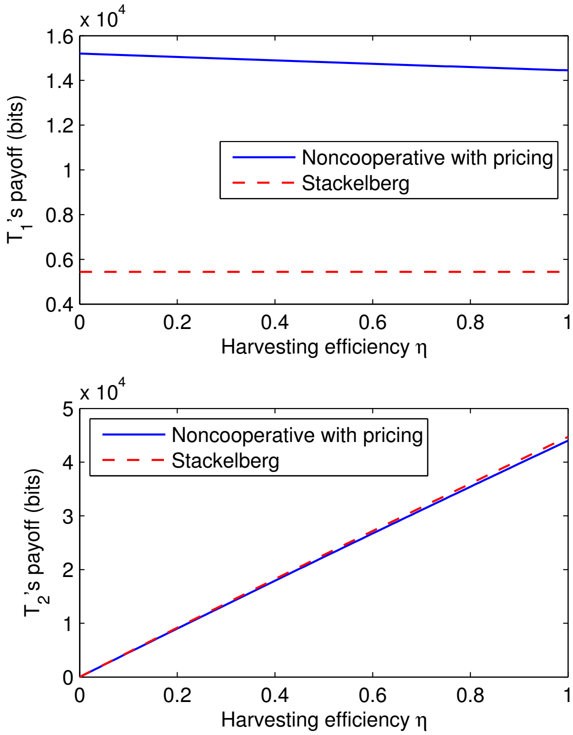

Fig. 5. The two players' payoffs versus the harvesting efficiency with $d = 5$ m, $d' = 10$ m, $\sigma = 0.05$ bps/W, and $p_{max} = 100$ mW.

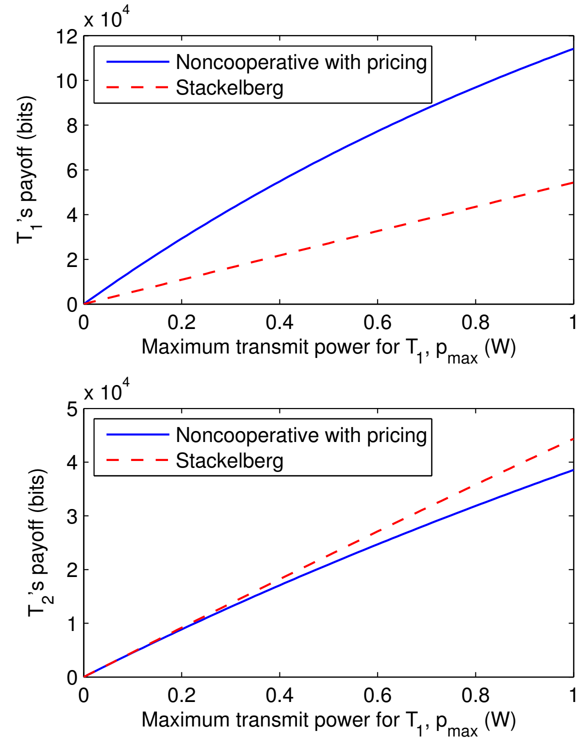

Fig. 6. The two players' payoffs versus the maximum transmit power for T_1 with $d = 5$ m, $d' = 10$ m, $\sigma = 0.05$ bps/W, and $\eta = 0.1$.

VI. Conclusion

We have studied a two-hop network in a game theoretic setup, with the goal of properly incentivizing the source and the relay in energy and signal cooperation. The two players of the game need each other to achieve positive throughput, but are selfish by nature, i.e, they do not agree to cooperate when they are left to their own devices. We have investigated two methods to incentivize them so that better payoffs can be achieved. In the first noncooperative game, the social optimum can be achieved using pricing. The second game, the Stackelberg game, does not result in a socially optimal equilibrium. However, the leader of the game can achieve a higher individual utility by influencing the follower's decision accordingly as observed by numerical results. In addition, the Stackelberg game has a lower signaling overhead since node T_3 does not have to announce any prices. We have also observed via numerical results the impact of model parameters on the resulting utilities and the interaction between the two players in the two settings. Future work includes studying a two-hop network with multiple relay nodes and the inter-relay competition over the transmission opportunities provided by the energy harvested from T_1's transmission.

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