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Matching Games for Ad Hoc Networks with Wireless Energy Transfer

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***Abstract*—A wireless network of N transmitting and M receiving nodes is considered, where the goal is to communicate data from transmitters to the receiving side of the network. Nodes have energy suppliers that provide energy at a price for transmission or reception. Nodes wish to optimize their individual utilities rather than a network-wide utility. We consider one-to-one and one-to-many matching games where each transmitter can be matched with one or multiple receivers. In both cases, transmitters find the best rate for them and propose it to the receivers. We modify the well-known Deferred Acceptance Algorithm to solve this game and improve network sum utility. We next consider wireless energy cooperation for the transmitters to make their proposals more desirable and compete with each other. Energy transfer introduces an additional energy cost at the transmitter and reduces the cost of the receiver and influences its decision. For the one-to-many matching games, we demonstrate that the available proposals at each transmitter can be reduced without loss of optimality. The results point to the observation that populating the network with additional nodes along with the possibility of energy transfer improves the rates for the entire network despite the selfish nature of the nodes.**

***Index Terms*—Energy transfer, matching games, ad hoc networks, Vickrey auction, max-min fairness.**

I. Introduction

PRACTICAL wireless networking scenarios often call for cooperation between pairs of nodes. Cloud radio access networks are one example where a base station can send its data to a cloud for computing [2] . Among others are sensor networks [3] where the sensors can pair up with relays for the delivery of their measurements, and vehicular networks [4] where the transmitter-receiver pairs may change during the communication session due to the dynamic network topology. Previous work on pair-wise cooperation in wireless networks has mostly assumed altruistic behavior for all nodes in the network, where the nodes are assumed to obey the instructions of a network operator to improve a network wide utility. It remains interesting to study how to network selfish wireless nodes that would rather improve their individual utilities than work together for the sake of the entire network, as they would be willing to cooperate with each other only if said cooperation improves both parties' utilities. The framework of matching games is an appropriate tool to study such scenarios and its application on wireless ad hoc networks with one-to-one and one-to-many matchings will be the focus of this paper.

Matching games are a suitable model for communities of individuals with conflicting interests that may be willing to cooperate in pairs for mutual benefit [5], [6]. The seminal work in matching theory [5] addresses the problem of matching an equal number of men and women. Each individual in one group has different preferences for the members of the other group. The authors in [5] propose the now well-known Deferred Acceptance Algorithm (DAA) where the men propose to the women in the order determined by their preferences. In this algorithm, each woman chooses the best proposal she has received at each stage, but *defers the acceptance* of this proposal until she has seen all of her available options. The matches found by the algorithm are stable and optimal for the proposers. The algorithm is also extended to college admission games which are games between colleges and students where each college can be matched to several students in [5]. The stability and optimality results are shown to extend as well.

Matching games have previously been employed for resource allocation in wireless networks [7]–[17]. Reference [7] studies one-to-one and many-to-one matchings for resource allocation in wireless networks and shows that the throughput maximizing matchings are not always stable. Reference [8] considers matching games between primary and secondary users in a cognitive radio network for spectrum allocation, and proposes a distributed algorithm that can identify a stable matching. Reference [9] also considers matching games for cognitive radio networks. Reference [10] studies a many-to-many matching game between the base stations and service providers in a small cell network, and proposes an algorithm that finds a matching that is pairwise stable. Reference [11] investigates the advantages of matching based modeling for networking problems over optimization and game theory. Reference [12] studies a matching game between the users and base stations in a small cell network and finds a matching which balances the traffic among cells and satisfies the quality of service requirements of the users. For an overview on the application of matching theory on future wireless networks, see [13].

Energy cooperation has been proposed as a way of improving energy efficiency of wireless networks by means of transfer of energy from energy rich nodes to energy deficient nodes [18]–[27]. References [18], [19] have studied the sum through-

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put maximization problem for energy harvesting multi terminal networks with energy transfer. Reference [20] has proposed energy transfer over radio frequencies (RF) performed simultaneously with the transfer of data. RF energy harvesting has been considered in a number of models including the work in cognitive radio networks [21] which has studied cognitive radio networks with primary users whose radio transmission can be used as a source of energy by the secondary users, and in non-cooperative or leader-follower game theoretic settings [22] where we have modeled cooperation between selfish nodes as noncooperative games and Stackelberg games.

While majority of work on energy management in wireless networks has been for transmission energy, the receivers' processing costs have recently gained attention [28]–[33]. Reference [28] has studied an energy harvesting network with sampling and decoding costs at the receiver and shown that when the battery at the receiver is the bottleneck of the system, it is optimal for the receiver to sample data packets at every opportunity and decode them only to avoid battery overflows. Reference [29] has proposed a framework for utility maximization in wireless networks with energy harvesting transmitters and receivers. Reference [30] has studied decoding costs at the receivers in energy harvesting networks with energy harvesting receivers. Reference [30] has considered a decoding cost that is convex in the rate and in particular, an exponential cost model as we will in the sequel.

Different from these aforementioned references which consider optimum energy allocation, in given *static* network topologies, this paper introduces a methodology for network formation. In particular, we consider ad hoc network formation where the nodes are (i) capable of energy cooperation, (ii) selfish in the sense that they wish to maximize their individual utilities, and (iii) willing to cooperate in pairs as long as it improves their utilities.

We utilize the framework of matching games [5] with both one-to-one and one-to-many matchings. In particular, we consider a wireless ad hoc network of N transmitters and M receivers. We consider that the expenditure of energy at each node, whether it is a transmitter or a receiver, comes at a price and results in a decrease in the node's utility. We formulate a matching game between the transmitters and receivers where the transmitters propose to the receivers with the optimal communication rate for the transmitters' utilities. The receivers choose one among all proposals they have received to maximize their own utilities. We find the optimal decisions for all nodes and derive the resulting utilities. We next provide the transmitters with the knowledge of the utility functions of the receivers so that they can take into account the needs of the receivers when they determine their proposals. In addition, we let the transmitters offer to *transfer energy to their favorite receiver*, i.e., energy cooperation. This allows the transmitters to assist the receivers with their processing costs to increase their chances of forming a beneficial cooperation pair. We model this layer of competition between the transmitters as a Vickrey auction [34]. We modify the DAA [5] to solve these games.

We next consider the case where one transmitter can be matched to multiple receivers. The transmitter multi-casts its data to these receivers at the same rate and collects a reward that is proportional to the number of receivers. We model this communication scenario as a one-to-many matching game where each transmitter proposes to several receivers for multicasting. We solve this game by using the DAA [5] and find a stable matching that is optimal for the transmitters. We show that we can limit the proposals that each transmitter can make without changing the outcome of the algorithm, which leads to finding a stable and optimal matching with polynomial number of proposals in the number of receivers. We next extend this game to include *energy cooperation* as well where each transmitter offers an energy transfer to every receiver that it is interested in. We consider max-min fairness in calculating these energy offers so that every targeted receiver is satisfied with the energy transfer. We observe that the competition between the nodes facilitated by the matching framework becomes more intense with the addition of energy cooperation and results in improved rates for the whole network. In addition, we observe that our modified approach yields larger rates and requires a smaller number of proposals before it can identify the solution as compared to the DAA.

The main contributions of this paper are summarized as follows:

- A matching-game formulation leading to a stable one-to-one matching of transmitters to receivers is provided, when energy expenditures of both the transmitters and the receivers are explicitly taken into account.
- Energy transfer from transmitters to receivers is introduced into the matching game to instigate competition between the proposing transmitters. Accordingly a Vickrey auction is employed between competing transmitters.
- These settings are extended to one-to-many matching games where a transmitter can be matched to multiple receivers, and a reduced complexity optimal matching algorithm is provided.

The remainder of this paper is organized as follows. In Section II, we describe the system model. In Section III, we cover the basics of one-to-one matching games and consider two such games without and with energy cooperation. In Section IV, we introduce one-to-many matching games and consider two such games without and with energy cooperation. In Section V, we provide simulation results. In Section VI, we conclude the paper.

II. System Model

Consider an ad hoc network with transmitters T_n, $n \in \mathcal{N} \triangleq \{1, 2, \ldots, N\}$, and receivers R_m, $m \in \mathcal{M} \triangleq \{1, 2, \ldots, M\}$ with block fading as shown in Fig. 1.

Each transmitter can communicate with any receiver. For clarity of exposition, we consider a time slotted scenario with slots of equal duration. The fading coefficient between transmitter T_n to receiver R_m is denoted by $h_{n,m}$ indicating the channel quality. The available channels are orthogonal to one another. Without loss of generality, the noise at each receiver is modeled as zero-mean and unit-variance additive white Gaussian noise.

Each node has access to an energy supplier that can provide any desired amount of energy at a price. T_n can purchase

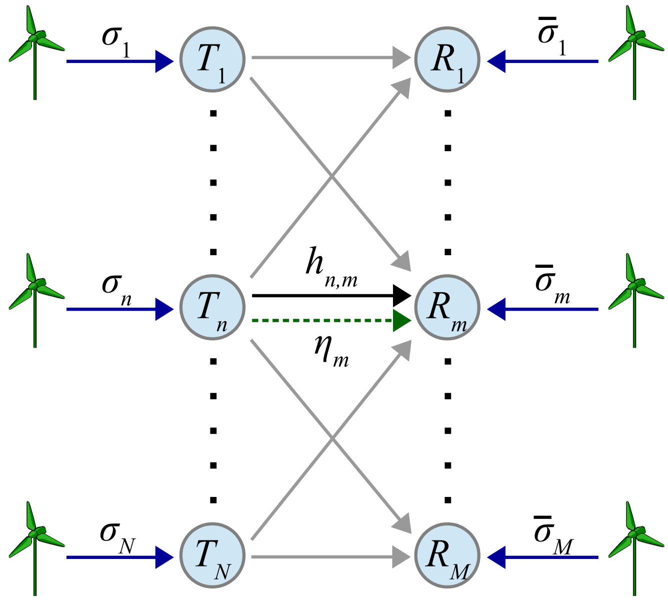

Fig. 1. The N-by-M ad hoc network with energy transfer. For clarity of exposition, only one energy transfer is shown as a dotted line with the harvesting efficiency of the corresponding receiver.

energy from its supplier at a price of σ_n, and likewise, R_m can purchase energy at a price of $\bar{\sigma}_m$. The prices lead to a reduction of the total reward that is due to the expended energy. The unit for the price is bits/Joule, leading to the total reward in bits as the total bits transmitted or received minus the energy cost.

The models considered in this work include those that allow the transmitters to transfer energy to the receivers by RF energy transfer. For such settings, we consider that receiver R_m has a harvesting efficiency of $\eta_m \in [0, 1]$, $m \in \mathcal{M}$. Note that η_m accounts for the losses associated with the harvesting of the energy after it reaches the receiver R_m. The energy sent by the transmitter is reduced by the channel coefficient while making its way to the receiver. In other words, if T_n sends E units of energy to R_m, R_m will receive $Eh_{n,m}$ units, and be able to harvest $Eh_{n,m}\eta_m$ units to expend for decoding. The nodes do not have access to any other source of energy for transmission or decoding, i.e., they must either acquire energy from the supplier or harvest energy from an energy cooperating node's transmission.

During a given time slot, each receiver is interested in receiving data from one transmitter only. In the one-to-one case, each transmitter wishes to send data to one receiver only. We also study the one-to-many case where a transmitter can send data to several receivers at the same time. At the beginning of each slot, transmitter-receiver pairs are formed which will communicate over the orthogonal link reserved for the transmitter for the duration of the time slot.

Suppose for a given time slot, nodes T_n and R_m, for some $n \in \mathcal{N}$ and $m \in \mathcal{M}$, are matched with each other and agree on a data rate of $r_{n,m}$. We begin with the one-to-one case and a general definition of utilities for all transmitters and receivers which are given as

$$u_{n|m}(r_{n,m}) = \rho_n(r_{n,m}) - \sigma_n \kappa_n(r_{n,m}) \tag{1}$$

for T_n given it is matched to R_m, and

$$\bar{u}_{m|n}(r_{n,m}) = \bar{\rho}_m(r_{n,m}) - \bar{\sigma}_m \bar{\kappa}_m(r_{n,m}) \tag{2}$$

for R_m given it is matched to T_n. Here, $\rho_n(r_{n,m})$ and $\bar{\rho}_m(r_{n,m})$ are concave and non-decreasing in $r_{n,m}$, and represent the reward that nodes T_n and R_m obtain for transmitting or receiving data at rate $r_{n,m}$, respectively. Conversely, $\kappa_n(r_{n,m})$ and $\bar{\kappa}_m(r_{n,m})$ are convex and non-decreasing in $r_{n,m}$, and represent the energy cost of nodes T_n and R_m for transmitting or receiving data at rate $r_{n,m}$, respectively. Note that the reward and cost functions are averaged over the duration of the time slot. The utility definitions will be extended to the case of one-to-many matchings in Section IV.

For clarity of exposition, we focus on the following selection of reward and cost functions, recalling that our results are valid for any concave reward and convex cost selection:

$$\rho_n(r_{n,m}) = \lambda_n r_{n,m}, \tag{3}$$

$$\bar{\rho}_m(r_{n,m}) = \bar{\lambda}_m r_{n,m}, \tag{4}$$

$$\kappa_n(r_{n,m}) = \frac{1}{h_{n,m}}\left(2^{2r_{n,m}} - 1\right), \tag{5}$$

$$\bar{\kappa}_m(r_{n,m}) = c_m 2^{\alpha_m r_{n,m}} + \beta_m r_{n,m} + \gamma_m, \tag{6}$$

for some $\lambda_n, \bar{\lambda}_m, c_m, \alpha_m, \beta_m \geq 0$ and $\gamma_m \in \mathbb{R}$. In other words, we consider linear rewards (3) and (4) for both nodes, additive white Gaussian noise at the receivers leading to the energy cost for T_n given in (5), and a general processing cost for R_m given in (6) which addresses exponential and linear processing costs and activation costs [30], [35], [36]. The resulting utilities for nodes T_n and R_m are expressed as

$$u_{n|m}(r_{n,m}) = \lambda_n r_{n,m} - \frac{\sigma_n}{h_{n,m}}\left(2^{2r_{n,m}} - 1\right), \tag{7}$$

$$\bar{u}_{m|n}(r_{n,m}) = \bar{\lambda}_m r_{n,m} - \bar{\sigma}_m\left(c_m 2^{\alpha_m r_{n,m}} + \beta_m r_{n,m} + \gamma_m\right). \tag{8}$$

Lastly, we define $\mathcal{T} \triangleq \{T_n, n \in \mathcal{N}\}$ and $\mathcal{R} \triangleq \{R_m, m \in \mathcal{M}\}$ as the set of all transmitters and the set of all receivers, respectively. Sets $\mathcal{N}$ and $\mathcal{M}$ index sets $\mathcal{T}$ and $\mathcal{R}$, respectively. In the sequel, we consider two matching game formulations for our model where each transmitter proposes to the receivers. Each transmitter aims to maximize its utility that results from a rate value which the transmitter and the matched receiver can agree upon.

In the sequel, we will consider one-to-one and one-to-many matching games for the ad hoc network in consideration. That is, we will let the transmitters and receivers form cooperation pairs in the one-to-one case for every time slot. For the one-to-many case, we will let the transmitters change the receivers to which they broadcast, to maximize the total data sent to the receivers.

Remark 1: We assume channel state information (CSI) availability at the transmitters. The acquisition of the CSI on the transmit side can be accomplished with receiver side channel measurements with a pilot and fed back to the transmitters. The ad hoc network to be formed is effectively one-hop, with non-interfering links.

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Remark 2: We assume that a small portion of each time slot is used for the coordination of energy transfer. This assumption results in the utilities being multiplied by a constant factor since only a portion of each time slot can contribute to the utilities, which are averaged over the entire duration of the time slots. Since this factor is the same for all time slots and all utilities, it does not affect our analysis or results, and is omitted.

III. One-to-One Matching Games

A. Preliminaries

We begin by providing a few fundamental definitions from matching theory from [5], [6].

Definition 1: A (one-to-one) matching is a function $\mu\colon \mathcal{T} \cup \mathcal{R} \to \mathcal{T} \cup \mathcal{R}$ satisfying

1) $\mu(T_n) = R_m$ if and only if $\mu(R_m) = T_n$ for all $n \in \mathcal{N}$, $m \in \mathcal{M}$,
2) $\mu(T_n) \in \mathcal{R}$ or $\mu(T_n) = T_n$ for all $n \in \mathcal{N}$,
3) $\mu(R_m) \in \mathcal{T}$ or $\mu(R_m) = R_m$ for all $m \in \mathcal{M}$.

The definition of matchings requires that μ be a bijection, i.e., each node in the network can be matched to either one other node or to itself, and it must be equal to its inverse, i.e., $\mu(\mu(K)) = K$ for any node $K \in \mathcal{T} \cup \mathcal{R}$.

Definition 2: Preference relations $\succ_n$ on $\mathcal{R}$ and $\bar{\succ}_m$ on $\mathcal{T}$ for all $n \in \mathcal{N}$, $m \in \mathcal{M}$ are strict and complete partial orders.

Here, the preference relations symbolize each node's preference over all nodes on the other side of the network. That is, $R_m \succ_n R_{m'}$ means that T_n prefers R_m over $R_{m'}$, and likewise, $T_n \,\bar{\succ}_m\, T_{n'}$ means that R_m prefers T_n over $T_{n'}$. We assume that there are no ties, i.e., the preference relations are strict. This is in line with our selection of block fading coefficients which are drawn from continuous distributions, resulting in strict preferences with probability 1. The completeness of the preference relations means that each node has a favorite among any collection of nodes from the other side of the network, i.e., for all $n \in \mathcal{N}$ and $\mathcal{M}' \subset \mathcal{M}$, there exists $m \in \mathcal{M}'$ such that $R_m \succ_n R_{m'}$ for all $m' \in \mathcal{M}' \setminus \{m\}$. Likewise, for all $m \in \mathcal{M}$ and $\mathcal{N}' \subset \mathcal{N}$, there exists $n \in \mathcal{N}'$ such that $T_n \,\bar{\succ}_m\, T_{n'}$ for all $n' \in \mathcal{N}' \setminus \{n\}$.

Definition 3: Matching μ is stable if there exists no $(T_n, R_m) \in \mathcal{T} \times \mathcal{R}$ such that $\mu(T_n) \neq R_m$, but $R_m \succ_n \mu(T_n)$ and $T_n \,\bar{\succ}_m\, \mu(R_m)$. That is, there does not exist a transmitter-receiver pair that prefer each other and are not matched to each other, i.e., all nodes are satisfied by μ.

Definition 4: Stable matching μ is optimal for the transmitters (resp. the receivers) if the utility of T_n (resp. R_m) under μ is no less than its utility under any other stable matching μ' for all $n \in \mathcal{N}$ (resp. all $m \in \mathcal{M}$).

Although there may exist multiple stable matchings, the optimal matching must be unique, provided that it exists, due to the fact that all preference relations are strict. We next study the matching game given by $(\{\mathcal{T}, \mathcal{R}\}, \{\succ_n, \bar{\succ}_m\})$ and how energy cooperation impacts the resulting matchings. We consider the case where the transmitters propose to the receivers and note that our results can readily be extended to the case where the receivers propose. We consider that the one-shot matching game given by $(\{\mathcal{T}, \mathcal{R}\}, \{\succ_n, \bar{\succ}_m\})$ is played at the beginning of each time slot and confine our analysis to one time slot.

B. A One-to-One Matching Game

Initially, we assume that the transmitters have no knowledge of the other nodes' utility functions or the strategies available to them. However, T_n knows $h_{n,m}$ for all $m \in \mathcal{M}$. T_n's best strategy is therefore to maximize its own utility, i.e.,

$$r^*_{n,m} = \arg\max_{r_{n,m} \geq 0} u_{n|m}(r_{n,m}) \tag{9}$$

$$= \arg\max_{r_{n,m} \geq 0} \lambda_n r_{n,m} - \frac{\sigma_n}{h_{n,m}} \left(2^{2 r_{n,m}} - 1\right) \tag{10}$$

$$= \left[\frac{1}{2} \log\left(\frac{\lambda_n h_{n,m}}{2\sigma_n \ln 2}\right)\right]^+ \tag{11}$$

where we obtain (11) by simply finding the stationary point and projecting to non-negative values due to concavity of the objective.

At rate $r^*_{n,m}$, T_n's utility is given as

$$u_{n|m}(r^*_{n,m}) = \frac{\lambda_n}{2} \log\left(\frac{\lambda_n h_{n,m}}{2e\sigma_n \ln 2}\right) + \frac{\sigma_n}{h_{n,m}}. \tag{12}$$

T_n can use (12) to find its favorite receiver among any collection of receivers $\mathcal{R}' \subset \mathcal{R}$, and subsequently characterize its preference relation $\succ_n$. Note that (12) depends on receiver index m only through $h_{n,m}$ and it is convex in $\frac{\sigma_n}{h_{n,m}}$. Therefore, T_n's favorite receiver in $\mathcal{R}'$ is either R_{m_1} or R_{m_2}, whichever results in a larger utility for T_n where indices m_1 and m_2 are found as

$$m_1 = \arg\max_{m\colon R_m \in \mathcal{R}'} h_{n,m}, \tag{13}$$

$$m_2 = \arg\min_{m\colon R_m \in \mathcal{R}'} h_{n,m}. \tag{14}$$

Starting with $\mathcal{R}' = \mathcal{R}$, T_n finds $R_m \succ_n R_{m'}$ for all $m' \in \mathcal{R}' \setminus \{R_m\}$, and next finds the second favorite receiver by setting $\mathcal{R}' = \mathcal{R} \setminus \{R_m\}$. Continuing in this fashion, preference relation $\succ_n$ is identified for all $n \in \mathcal{N}$ (see Algorithm 1, lines 2–8 for a detailed description).

For the receivers' preference relations, suppose R_m receives a proposal from all $T_n \in \mathcal{T}_m \subset \mathcal{T}$ where we define $\mathcal{T}_m$ to be the set of all transmitters which have proposed to R_m with a rate offer. The ideal proposal for R_m would maximize its utility, i.e.,

$$r^\dagger_{n,m} = \arg\max_{r_{n,m} \geq 0} \bar{u}_{m|n}(r_{n,m}) \tag{15}$$

$$= \arg\max_{r_{n,m} \geq 0} \bar{\lambda}_m r_{n,m} - \bar{\sigma}_m \left(c_m 2^{\alpha_m r_{n,m}} + \beta_m r_{n,m} + \gamma_m\right) \tag{16}$$

$$= \left[\frac{1}{\alpha_m} \log\left(\frac{\bar{\lambda}_m / \bar{\sigma}_m - \beta_m}{c_m \alpha_m \ln 2}\right)\right]^+ \tag{17}$$

where (17) is again obtained by identifying the stationary point of (16).

We observe that $\bar{u}_{m|n}(r_{n,m})$ is concave in $r_{n,m}$. Therefore, R_m finds its favorite among all proposals it has received from the transmitters in $\mathcal{T}_m$ as the proposal of T_{n_1} or T_{n_2}, whichever results in a larger utility for R_m where indices n_1 and n_2 are identified as

$$n_1 = \underset{\substack{n:\, T_n \in \mathcal{T}_m, \\ r^*_{n,m} \leq r^\dagger_{n,m}}}{\arg\max}\ r^*_{n,m}, \tag{18}$$

$$n_2 = \underset{\substack{n:\, T_n \in \mathcal{T}_m, \\ r^*_{n,m} > r^\dagger_{n,m}}}{\arg\min}\ r^*_{n,m}. \tag{19}$$

Note that R_m can identify its preference relation $\bar{\succ}_m$ over $\mathcal{T}_m$ using a similar procedure to the one described above for the transmitters, i.e., R_m starts with $\mathcal{T}_m$, finds its favorite transmitter in $\mathcal{T}_m$, removes this transmitter from $\mathcal{T}_m$, finds the second favorite transmitter and so on. However, as will be seen in Algorithm 1, our solution requires only the favorite proposal.

Now that matching game $(\{\mathcal{T}, \mathcal{R}\}, \{\succ_n, \bar{\succ}_m\})$ is fully characterized, we can identify the optimal matching for our setting. In order to accomplish this, we adopt the DAA proposed in [5] to our setting. It is shown in [5, Theorem 2] that DAA finds the unique stable matching that is optimal for the proposing nodes, in our case, the transmitters. In this algorithm, the transmitters first propose to their favorite receivers. Each receiver finds the one proposal that yields the largest receiver utility and rejects all others. In the next iteration, the rejected transmitters propose to their second favorite receivers and the receivers find the best proposal among all new proposals and the best proposal from the previous iteration. In this fashion, the receivers identify the best proposal for themselves, rejecting all others, but *defer* the acceptance of said proposal until they have seen all of their options.

In our implementation of this algorithm, we improve upon the resulting utilities by imposing that the transmitters refrain from proposing to receivers which yield negative utilities for them. Likewise, we require that receivers prefer being matched to themselves if the best proposal they receive results in a negative utility for them. This modification eliminates all matches which result in negative utilities while retaining those with positive utilities, and necessarily results in improved utilities for the whole network. In addition, this modification is in line with the selfish nature of the nodes in our model since they cannot be expected to tolerate negative utilities which they can easily improve by solitude. We provide the complete optimal solution of $(\{\mathcal{T}, \mathcal{R}\}, \{\succ_n, \bar{\succ}_m\})$, including the computation of preference relations and the Modified DAA, in Algorithm 1.

Here, we denote by $\mathcal{R}_n$ the set of receivers that can be matched to T_n with a positive utility. $\mathcal{R}_n$ is updated throughout the algorithm and gives a collection of possible matches for T_n at any point in the algorithm. The worst case complexity is $O(N^2)$ which is the same as the original DAA in [5].

In the next section, we consider the game under a different setting where each transmitter is provided with additional knowledge, i.e., the utility functions of the receivers, in order to facilitate competition among the transmitters.

Algorithm 1 Optimal solution μ of $(\{\mathcal{T}, \mathcal{R}\}, \{\succ_n, \bar{\succ}_m\})$.

// The transmitters identify their preference relations $\succ_n$.
for $n = 1, 2, \ldots, N$ **do**
  Initialize $\mathcal{R}' = \mathcal{R}$.
  while $\mathcal{R}' \neq \emptyset$ **do**
    Find R_{m_1} and R_{m_2} using (13) and (14).
    Identify the favorite receiver as $R_m = R_{m_1}$ or R_{m_2}.
    Update $\mathcal{R}' := \mathcal{R}' \setminus \{R_m\}$.
    Update $\succ_n$ such that $R_m \succ_n R_{m'}$, $\forall R_{m'} \in \mathcal{R}'$.
  end while
end for
// The Modified Deferred Acceptance Algorithm.
Initialize $\mathcal{R}_n = \mathcal{R}$, $\forall n \in \mathcal{N}$; $\mu(K) = K$, $\forall K \in \mathcal{T} \cup \mathcal{R}$.
Remove all R_m yielding $u_{n|m}(r^*_{n,m}) < 0$ from $\mathcal{R}_n$, $\forall n$.
while $\exists n \in \mathcal{N}$: $\mu(T_n) = T_n$ and $\mathcal{R}_n \neq \emptyset$ **do**
  for $n = 1, 2, \ldots, N$ **do**
    if $\mu(T_n) = T_n$ and $\mathcal{R}_n \neq \emptyset$ **then**
      T_n finds its favorite $R_m \in \mathcal{R}_n$ and proposes (11).
      Update $\mathcal{R}_n := \mathcal{R}_n \setminus \{R_m\}$.
    end if
  end for
  for $m = 1, 2, \ldots, M$ **do**
    if $\mathcal{T}_m \neq \emptyset$ **then**
      R_m finds its favorite $T_n \in \mathcal{T}_m \cup \{\mu(R_m)\}$ using (18) and (19).
      if $\bar{u}_{m|n}(r^*_{n,m}) \geq 0$ **then**
        Set $T'_n = \mu(R_m)$, and update $\mu(T'_n) = T'_n$.
        Update $\mu(R_m) = T_n$, $\mu(T_n) = R_m$.
      end if
    end if
  end for
end while

C. A One-to-One Matching Game with Energy Cooperation

Consider now that the transmitters are aware of the utility functions of the receivers. This additional knowledge allows them to tailor their proposals better to the needs of the receivers. In this setup, we consider the additional incentive of *energy transfer* from the transmitters to their favorite receiver in order to promote their proposals over others. Note that this was not possible for the setting in Section III-B since the transmitters could not compute the ideal proposal for their favorite receiver, and therefore could not compete with one another directly. We incorporate energy cooperation into our model by modifying the utilities as

$$u_{n|m}(r_{n,m}, p_{n,m}) = \lambda_n r_{n,m} - \frac{\sigma_n}{h_{n,m}}(2^{2r_{n,m}} - 1) - \sigma_n p_{n,m} \tag{20}$$

$$\bar{u}_{m|n}(r_{n,m}, p_{n,m}) = \bar{\lambda}_m r_{n,m} - \bar{\sigma}_m(c_m 2^{\alpha_m r_{n,m}} + \beta_m r_{n,m} + \gamma_m - p_{n,m} h_{n,m} \eta_m) \tag{21}$$

where $p_{n,m}$ is the amount of energy offered to R_m by T_n averaged over the duration of the time slot for consistency with other average quantities in our model. Observe that energy transfer improves the utility in (21).

For the receivers that receive multiple proposals, we employ a Vickrey auction [34] between the proposing transmitters to

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determine which one should be matched to the receiver. A Vickrey auction is a second price sealed bid auction where the bidder with the highest bid wins the auction, but pays the second highest bid only. In other words, upon receiving the bids, the receiver determines the transmitter with the highest bid, but the winning transmitter has to provide the receiver with the utility promised only by the runner-up which is lower than the winner's original bid [37]. Thanks to this second price property of Vickrey auctions, each transmitter can *go all out* and bid the highest receiver utility they can provide. However, as the transmitters' bids increase, their own utility decreases and they increase their bids until their own utilities reach zero. In other words, each transmitter calculates its bid by setting its own utility to zero and finding the corresponding receiver utility that it can provide. Since in the end the winning transmitter delivers the bid of the runner up only, its final utility is positive. Therefore, the Vickrey auction yields improved utilities for the auctioneers without resulting in vanishing utilities for the bidders.

T_n first uses (12) to find its favorite receiver among collection of receivers $\mathcal{R}' \subset \mathcal{R}$, and similarly generates its preference relation $\succ_n$. Note that transmitter utilities at this point are the same as those in Section III-B since all $p_{m,n} = 0$ before the inter-transmitter competition by means of a Vickrey auction ensues. T_n can next compute its bid to its favorite receiver, R_m, as

$$(r^*_{n,m}, p^*_{n,m}) = \underset{(r_{n,m},p_{n,m})\geq 0}{\arg\max} \ \bar{u}_{m|n}(r_{n,m}, p_{n,m}) \tag{22a}$$

$$\text{s.t.} \qquad u_{n|m}(r_{n,m}, p_{n,m}) \geq 0. \tag{22b}$$

We solve (22) by first solving it in $p_{n,m}$ for any $r_{n,m}$. We observe that $\bar{u}_{m|n}(r_{n,m}, p_{n,m})$ is increasing in $p_{n,m}$ for a given $r_{n,m}$ and $u_{n|m}(r_{n,m}, p_{n,m})$ is decreasing in $p_{n,m}$. In other words, $p_{n,m}$ must be as large as possible while constraint (22b) is satisfied. Therefore, we set (22b) to zero and obtain

$$p^*_{n,m}(r_{n,m}) = \frac{\lambda_n r_{n,m}}{\sigma_n} - \frac{1}{h_{n,m}}\left(2^{2r_{n,m}} - 1\right) \tag{23}$$

which guarantees that constraint (22b) is satisfied for any $r^*_{n,m}$. Problem (22) becomes

$$r^*_{n,m} = \underset{r_{n,m}\geq 0}{\arg\max} \ \bar{u}_{m|n}(r_{n,m}, p^*_{n,m}(r_{n,m})) \tag{24}$$

which is a convex problem with a unique maximizer. Here, we define

$$\psi_{n,m} \triangleq \frac{1}{\ln 2}\left(\frac{\bar{\lambda}_m}{\bar{\sigma}_m} - \beta_m + \frac{h_{n,m}\eta_m\lambda_n}{\sigma_n}\right). \tag{25}$$

The unique optimal solution of (24) is identified as the $r^*_{n,m}$ value that satisfies

$$c_m\alpha_m 2^{\alpha_m r^*_{n,m}} + 2\eta_m 2^{2r^*_{n,m}} = \psi_{n,m}. \tag{26}$$

In general, (26) is a nonlinear equation, in fact, an exponential polynomial equation [38] which can be solved numerically. Note that when α_m is an integer, (26) reduces to a polynomial equation. For the special case of $\alpha_m = 0$, i.e., linear processing cost for the receivers, the solution of (26) is found as

$$r^*_{n,m} = \frac{1}{2}\log\left(\frac{\psi_{n,m}}{2\eta_m}\right) \tag{27}$$

and for the special case of $\alpha_m = 2$, the solution of (26) is found as

$$r^*_{n,m} = \frac{1}{2}\log\left(\frac{\psi_{n,m}}{2(c_m + \eta_m)}\right). \tag{28}$$

This completes the characterization of all bids $(r^*_{n,m}, p^*_{n,m})$ received by R_m. Suppose R_m has received proposals from all $T_n \in \mathcal{T}_m \subset \mathcal{T}$. R_m then finds the best proposal as

$$(r^*_{n^\dagger,m}, p^*_{n^\dagger,m}) = \underset{\substack{(r^*_{n,m},p^*_{n,m}):\\ T_n\in\mathcal{T}_m}}{\arg\max} \ \bar{u}_{m|n}(r^*_{n,m}, p^*_{n,m}) \tag{29}$$

and the runner-up as

$$(r^*_{n^\ddagger,m}, p^*_{n^\ddagger,m}) = \underset{\substack{(r^*_{n,m},p^*_{n,m}):\\ T_n\in\mathcal{T}_m\setminus\{T_{n^\dagger}\}}}{\arg\max} \ \bar{u}_{m|n}(r^*_{n,m}, p^*_{n,m}) \tag{30}$$

which are optimization problems with finite feasible sets. Finally, R_m identifies $T_{n^\dagger}$ as its favorite transmitter which has to provide only $\bar{u}_{m|n}(r^*_{n^\ddagger,m}, p^*_{n^\ddagger,m})$, which is necessarily less than $\bar{u}_{m|n}(r^*_{n^\dagger,m}, p^*_{n^\dagger,m})$. Thus, $T_{n^\dagger}$ can lower $p^*_{n^\dagger,m}$ to provide $\bar{u}_{m|n}(r^*_{n^\ddagger,m}, p^*_{n^\ddagger,m})$ only and obtain a positive utility for itself as well.

In order to solve $(\{\mathcal{T},\mathcal{R}\},\{\succ_n,\bar{\succ}_m\})$ for an optimal matching in this case, we modify Algorithm 1 to incorporate the inter-transmitter competition, which we model as a Vickrey auction, into our solution. The solution is given in Algorithm 2.

Remark 3: The standard marriage problem of Gale and Shapley [5] has strict preference relations for all agents, but not utilities. Essentially, all utilities are non-negative. Since the utilities in our model can be negative and a node matched to itself receives a utility of zero, it makes sense to eliminate matches with negative utilities without even proposing to them. This, along with the introduction of bidding, is our modification to the DAA. The convergence of our modification is guaranteed since we are only skipping some proposals which would not change the outcome of the standard DAA. The stability is guaranteed since the eliminated proposals would violate stability under standard DAA as the nodes would prefer to be matched to themselves.

IV. One-to-Many Matching Games

In this section, we extend the results of Section III to the case of one-to-many matchings where one transmitter can be matched to multiple receivers.

A. Preliminaries

The definition of matchings extends to the one-to-many case as follows [7], [10], [11].

Definition 5: A one-to-many matching is a function $\mu\colon \mathcal{T}\cup\mathcal{R} \to \mathcal{T}\cup 2^{\mathcal{R}}$ satisfying

1) $\mu(T_n) = \mathcal{R}_n \subset \mathcal{R}$ if and only if $\mu(R_m) = T_n$ for all $R_m \in \mathcal{R}_n$, $n \in \mathcal{N}$,

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Algorithm 2 Optimal solution of $(\{\mathcal{T}, \mathcal{R}\}, \{\succ_n, \bar{\succ}_m\})$ with energy cooperation.

// The transmitters identify their preference relations $\succ_n$.
for $n = 1, 2, \ldots, N$ **do**
  Initialize $\mathcal{R}' = \mathcal{R}$.
  while $\mathcal{R}' \neq \emptyset$ **do**
    Find R_{m_1} and R_{m_2} using (13) and (14).
    Identify the favorite receiver as $R_m = R_{m_1}$ or R_{m_2}.
    Update $\mathcal{R}' := \mathcal{R}' \setminus \{R_m\}$.
    Update $\succ_n$ such that $R_m \succ_n R_{m'}$, $\forall R_{m'} \in \mathcal{R}'$.
  end while
end for
// The Modified Deferred Acceptance Algorithm.
Initialize $\mathcal{R}_n = \mathcal{R}$, $\forall n \in \mathcal{N}$; $\mu(K) = K$, $\forall K \in \mathcal{T} \cup \mathcal{R}$.
Remove all R_m yielding $u_{n|m}(r^*_{n,m}) < 0$ from $\mathcal{R}_n$, $\forall n$.
while $\exists n \in \mathcal{N}$: $\mu(T_n) = T_n$ and $\mathcal{R}_n \neq \emptyset$ **do**
  for $n = 1, 2, \ldots, N$ **do**
    if $\mu(T_n) = T_n$ and $\mathcal{R}_n \neq \emptyset$ **then**
      T_n finds its favorite $R_m \in \mathcal{R}_n$ and its proposal using (22).
      Update $\mathcal{R}_n := \mathcal{R}_n \setminus \{R_m\}$.
    end if
  end for
  for $m = 1, 2, \ldots, M$ **do**
    if $\mathcal{T}_m \neq \emptyset$ **then**
      R_m finds its favorite $T_n \in \mathcal{T}_m \cup \{\mu(R_m)\}$ using (29) and (30).
      if $\bar{u}_{m|n}(r^*_{n,m}) \geq 0$ **then**
        Set $T'_m = \mu(R_m)$, and update $\mu(T'_m) = T'_m$.
        Update $\mu(R_m) = T_n$, $\mu(T_n) = R_m$.
      end if
    end if
  end for
end while

2) $\mu(T_n) \subset \mathcal{R}$ or $\mu(T_n) = T_n$ for all $n \in \mathcal{N}$,
3) $\mu(R_m) \in \mathcal{T}$ or $\mu(R_m) = R_m$ for all $m \in \mathcal{M}$,
4) $\mu(T_n) \cap \mu(T_{\tilde{n}}) = \emptyset$ for all $n, \tilde{n} \in \mathcal{N}, n \neq \tilde{n}$.

In other words, each transmitter is matched to either itself or a set of receivers, no pair of transmitters can be matched to the same receiver, and each receiver is matched to either itself or a transmitter. As for the preference relations, the transmitter preferences $\succ_n$ will now be on $2^{\mathcal{R}}$, ranking all subsets of the receivers whereas the receiver preferences are as defined in Section III-A.

Definition 6: One-to-many matching μ is stable if there exists no $(T_n, \mathcal{R}_n) \in \mathcal{T} \times 2^{\mathcal{R}}$ such that $\mu(T_n) \neq \mathcal{R}_n$, but $\mathcal{R}_n \succ_n \mu(T_n)$, and $T_n \bar{\succ}_m \mu(R_m)$ or $T_n = \mu(R_m)$ for all $R_m \in \mathcal{R}_n$. In other words, there does not exist a transmitter and a group of receivers where the transmitter is not matched to at least one of the receivers, but all of the nodes in question wish to be matched together.

Similar to Section III, there may turn out to be multiple stable one-to-many matchings, but there can be only one stable matching that is optimal for the transmitters. In the sequel, we aim to find this matching without or with energy cooperation.

B. A One-to-Many Matching Game

Consider a communication model where each transmitter can multi-cast its data to a subset of the receivers. This is done in a way that every receiver can decode the same data. That is, there is only a common message which is broadcast with sufficient power so that the receiver with the lowest channel gain in the subset can decode it. Therefore, the transmission cost of the transmitter depends only on the weakest link in the subset. We consider that the reward that the transmitter gets is proportional to the number of receivers it to which the transmitter multi-casts.

Suppose T_n is matched to the receivers in $\mathcal{R}_n \subset \mathcal{R}$ after proposing rate $r_{n,\mathcal{R}_n}$ to them. The utility of T_n can be given as

$$u_{n|\mathcal{R}_n}(r_{n,\mathcal{R}_n}) = |\mathcal{R}_n|\lambda_n r_{n,\mathcal{R}_n} - \frac{\sigma_n}{\min_{m:R_m \in \mathcal{R}_n} h_{n,m}}(2^{2r_{n,\mathcal{R}_n}} - 1). \tag{31}$$

The receiver utilities are unaffected by the channel gains of the other receivers or by the number of receivers their matched transmitter is multi-casting to. This is because the receivers do not experience any interference: they do not receive any signal intended for another subset of receivers matched to a different transmitter due to orthogonality, and within their subset, they all try to decode the same message. Thus, the utility of R_m given that it is matched to T_n with rate $r_{n,\mathcal{R}_n}$ can be given as

$$\bar{u}_{m|n}(r_{n,\mathcal{R}_n}) = \bar{\lambda}_m r_{n,\mathcal{R}_n} - \bar{\sigma}_m(c_m 2^{\alpha_m r_{n,\mathcal{R}_n}} + \beta_m r_{n,\mathcal{R}_n} + \gamma_m). \tag{32}$$

Similar to Section III-B, we initially assume that the transmitters do not know the utility or the available strategies for any other node. What T_n does know is the channel gains from itself to all receivers. Thus, the best strategy for T_n is to maximize its utility by choosing the following rate proposal for $\mathcal{R}_n$.

$$r^*_{n,\mathcal{R}_n} = \arg\max_{r_{n,\mathcal{R}_n} \geq 0} u_{n|\mathcal{R}_n}(r_{n,\mathcal{R}_n}), \tag{33}$$

$$= \frac{1}{2}\log\left(\frac{|\mathcal{R}_n|\lambda_n \min_{m:R_m \in \mathcal{R}_n} h_{n,m}}{2\sigma_n \ln 2}\right), \tag{34}$$

which is obtained by differentiating the objective of (33) with respect to $r_{n,\mathcal{R}_n}$ and setting it to zero. This results in a transmitter utility given as

$$u_{n|\mathcal{R}_n}(r^*_{n,\mathcal{R}_n}) = \frac{|\mathcal{R}_n|\lambda_n}{2}\log\left(\frac{|\mathcal{R}_n|\lambda_n \min_{m:R_m \in \mathcal{R}_n} h_{n,m}}{2e\sigma_n \ln 2}\right) + \frac{\sigma_n}{\min_{m:R_m \in \mathcal{R}_n} h_{n,m}}. \tag{35}$$

T_n can again use (35) to characterize its preference relation $\succ_n$. One way to accomplish this would be to evaluate (35) for all $2^M - 1$ nonempty subsets of $\mathcal{R}$. Though this will not be necessary as we shall explain in the sequel, let us continue with this brute force approach for the moment. After identifying the transmitter preferences, we can solve for the optimal matching by using the results for the one-to-one case in Section III-B as follows.

Consider an ad hoc network, much like the one described in Section II, but with N transmitters and $2^M - 1$ super-receivers.

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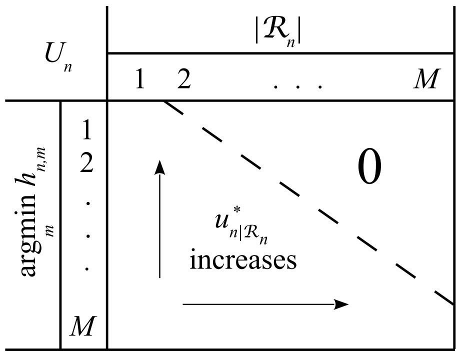

Fig. 2. An example of the utility matrix U_n.

Each super-receiver corresponds to a distinct subset of the receivers in the original model, except for the empty set. That is, each super-receiver is a possible coalition of the receivers in the original model. The transmitters are the same as in the original network. We can run Algorithm 1 for this network to find a stable matching that is optimal for the transmitters. One thing to note is that when a transmitter proposes to a super-receiver, every receiver in the coalition must accept the proposal before the transmitter and the super-receiver can be (temporarily) matched.

We can reduce the time complexity of this solution as follows. Each transmitter has at most $2^M - 1$ options to try before it is either matched or has given up. However, for some of these options (or subsets of the receivers) the transmitter has the same rate proposal and thus the same utility. In fact, the transmitter can have at most $\frac{M(M+1)}{2}$ distinct proposals. In order to clarify this, first suppose for each transmitter that channel gains $h_{n,m}$, $m = 1, 2, \ldots, M$ are reordered so that $h_{n,1} \geq h_{n,2} \geq \cdots \geq h_{n,M}$. We can put all possible $u_{n|\mathcal{R}_n}(r^*_{n|\mathcal{R}_n})$ values in an M-by-M matrix (Fig. 2). Each row corresponds to a different $h_{n,m}$, $m = 1, 2, \ldots, M$, being the lowest channel gain for a given subset of receivers, i.e., the mth row corresponds to $h_{n,m}$ being the lowest channel gain in $\mathcal{R}_n$. The columns correspond to $|\mathcal{R}_n|$. Matrix U_n is lower triangular since the mth row, which corresponds to transmitting at a rate that the receiver with the mth highest channel gain can decode, can have at most m utility values. This is because the transmitter can multi-cast to at most m receivers at this rate (in fact, the receivers with the highest m channel gains). This means that the transmitter has at most $\frac{M(M+1)}{2}$ distinct proposals and it does not have to try all $2^M - 1$ options.

For row m, we have that the lowest channel gain in $\mathcal{R}_n$ is fixed at $h_{n,m}$. The transmitter can be matched to at most m receivers with channel gains $h_{n,1} \geq h_{n,2} \geq \cdots \geq h_{n,m}$. Suppose the transmitter is matched to $\tilde{m} < m$ receivers. We can investigate what happens to the rate proposal and the transmitter utility if the transmitter adds one more receiver to $\mathcal{R}_n$ where we denote the new coalition by $\tilde{\mathcal{R}}_n$. We have that

$$r^*_{n,\tilde{\mathcal{R}}_n} \geq r^*_{n,\mathcal{R}_n} \tag{36}$$

since $\min_{m:R_m \in \mathcal{R}_n} h_{n,m}$ in (34) is fixed and $|\tilde{\mathcal{R}}_n| \geq |\mathcal{R}_n|$. For the transmitter utility, we have

$$u_{n|\tilde{\mathcal{R}}_n}(r^*_{n,\tilde{\mathcal{R}}_n}) \geq u_{n|\tilde{\mathcal{R}}_n}(r^*_{n,\mathcal{R}_n}) \geq u_{n|\mathcal{R}_n}(r^*_{n,\mathcal{R}_n}) \tag{37}$$

where the first inequality is due to the fact that $r^*_{n,\tilde{\mathcal{R}}_n}$ is optimal for $u_{n|\tilde{\mathcal{R}}_n}$ and the second one is due to the fact that $u_{n|\mathcal{R}_n}$ is increasing in $|\mathcal{R}_n|$. Therefore, each row of U_n in nondecreasing in the column index.

For column m, $|\mathcal{R}_n|$ is fixed at m. As the row index increases within this column, $\min_{m:R_m \in \mathcal{R}_n} h_{n,m}$ decreases. We have that

$$r^*_{n,\tilde{\mathcal{R}}_n} \leq r^*_{n,\mathcal{R}_n} \tag{38}$$

since $r^*_{n,\mathcal{R}_n}$ is increasing in $\min_{m:R_m \in \mathcal{R}_n} h_{n,m}$. For the transmitter utility, we have that

$$u_{n|\tilde{\mathcal{R}}_n}(r^*_{n,\tilde{\mathcal{R}}_n}) \leq u_{n|\mathcal{R}_n}(r^*_{n,\tilde{\mathcal{R}}_n}) \leq u_{n|\mathcal{R}_n}(r^*_{n,\mathcal{R}_n}) \tag{39}$$

where the first inequality follows from the fact that $u_{n|\mathcal{R}_n}$ is increasing in $\min_{m:R_m \in \mathcal{R}_n} h_{n,m}$ and the second one follows from the fact that $r^*_{n,\mathcal{R}_n}$ is optimal for $u_{n|\mathcal{R}_n}$. Therefore, each column of U_n in nonincreasing in the row index and each diagonal element in U_n is the maximum of its row and column.

Using these properties of U_n, we can improve the solution further, i.e., we can have each transmitter start with the diagonal elements of its utility matrix, next move on to the subdiagonal and so on. In this approach, the transmitters go through their available moves in the order of descending transmitter utilities, just like they did in Section III-B, until they have a match. Additionally, the modification on DAA that we considered in Section III-B extends to the one-to-many case. That is, we can improve the utilities by forbidding the transmitters from making proposals which yield negative utilities for them, i.e., the negative elements of matrix U_n, if any. This modification purges only the matches which would lower the sum utility of the network while leaving the matches with nonnegative utilities intact. We give in Algorithm 3 the optimal solution to the one-to-many matching game described above.

Remark 4: Although we do not consider a quota for the one-to-many matchings, when the number of transmitters or receivers is large, it may be useful to introduce quotas for feasibility of implementation. The approach remains identical in this case: For a quota of q, the matrix in Fig. 2 will have $q \leq M$ columns and each transmitter will have at most $\frac{M(M+1)}{2} - \frac{(M-q)(M-q+1)}{2} \leq \frac{M(M+1)}{2}$ distinct proposals.

We next extend the matching game in Section III-C to the one-to-many case and consider energy cooperation as a way for the transmitters to make more desirable proposals.

C. A One-to-Many Matching Game with Energy Cooperation

Consider the setup in Section IV-B with the addition of the transmitters' knowledge of the receivers' utility functions. The transmitters are now able to offer energy cooperation in their proposals to incentivize their target receiver group into accepting their proposals. We incorporate energy cooperation into the one-to-many multi-cast scheme of Section IV-B as

Algorithm 3 Optimal solution of the one-to-many matching game.

// The transmitters compute matrix U_n.
for $n = 1, 2, \ldots, N$ **do**
  for $m_1 = 1, 2, \ldots, M$ **do**
    for $m_2 = 1, 2, \ldots, m_1$ **do**
      Find $u_{n|\mathcal{R}_n}(r^*_{n,\mathcal{R}_n})$ such that $\min_{m:R_m\in\mathcal{R}_n} h_{n,m} = h_{n,m_1}$ and $|\mathcal{R}_n| = m_2$ using (35).
    end for
  end for
  Generate $\succ_n$ such that $\mathcal{R}^1_n \succ_n \mathcal{R}^2_n$ if $u_{n|\mathcal{R}^1_n}(r^*_{n,\mathcal{R}^1_n}) \geq u_{n|\mathcal{R}^2_n}(r^*_{n,\mathcal{R}^2_n})$.
end for
// The Modified Low-Complexity DAA for the one-to-many case.
Initialize $\mu(K) = K$, $\forall K \in \mathcal{T} \cup \mathcal{R}$.
Remove all negative entries of U_n, i.e., $U_n := \max\{U_n, 0\}$ element-wise, $\forall n$.
while $\exists n \in \mathcal{N}$: $\mu(T_n) = T_n$ and $U_n \neq 0$ **do**
  for $n = 1, 2, \ldots, N$ **do**
    if $\mu(T_n) = T_n$ and $U_n \neq 0$ **then**
      T_n finds the maximum element in U_n and proposes (34).
      T_n replaces the maximum element in U_n with 0.
    end if
  end for
  Initialize $a_n = 0, \forall n \in N$.
  for $m = 1, 2, \ldots, M$ **do**
    if $\mathcal{T}_m \neq \emptyset$ **then**
      R_m finds its favorite $T_n \in \mathcal{T}_m \cup \{\mu(R_m)\}$.
      if $\bar{u}_{m|n}(r^*_{n,\mathcal{R}_n}) \geq 0$ **then**
        Update $a_n = 1$.
      else
        Update $a_n = 0$.
      end if
    end if
  end for
  for $n = 1, 2, \ldots, N$ **do**
    if $a_n = 1$ **then**
      Update $\mu(T_n) = \mathcal{R}_n$.
      for $m : R_m \in \mathcal{R}_n$ **do**
        Set $T'_m = \mu(R_m)$.
        Update $\mu(T'_m) = T'_m$ and $\mu(R_m) = T_n$.
      end for
    end if
  end for
end while

follows. Let $p_{n,\mathcal{R}_n}$ be T_n's energy offer to the receivers in $\mathcal{R}_n$. The transmitter utility is given as

$$u_{n|\mathcal{R}_n}(r_{n,\mathcal{R}_n}, p_{n,\mathcal{R}_n}) = |\mathcal{R}_n|\lambda_n r_{n,\mathcal{R}_n} - \frac{\sigma_n}{\min_{m:R_m\in\mathcal{R}_n} h_{n,m}} \times \left(2^{2r_{n,\mathcal{R}_n}} - 1\right) - \sigma_n p_{n,\mathcal{R}_n} \tag{40}$$

and the receiver utility for all $m \in \mathcal{R}_n$ is given as

$$\bar{u}_{m|n}(r_{n,\mathcal{R}_n}, p_{n,\mathcal{R}_n}) = \bar{\lambda}_m r_{n,\mathcal{R}_n} - \bar{\sigma}_m(c_m 2^{\alpha_m r_{n,\mathcal{R}_n}} + \beta_m r_{n,\mathcal{R}_n} + \gamma_m - p_{n,\mathcal{R}_n} h_{n,m}\eta_m). \tag{41}$$

Note that the transmitter determines a single power value to send energy at to each receiver in $\mathcal{R}_n$; it does not specify different powers. The energy that the receivers can harvest from the energy signal that the transmitter transmits depends on their channel gains and harvesting efficiencies, and thus may be different.

We model the competition between the transmitters as a Vickrey auction similar to Section III-C. The transmitters will now bid to sets of receivers, or super-receivers, by setting their own transmitter utilities to zero. Suppose T_n's favorite set of receivers is $\mathcal{R}_n$. Note that T_n can generate matrix U_n to find its preference relation over all subsets of the receivers and determine $\mathcal{R}_n$. In order for T_n to obtain this maximum utility, all of the receivers in $\mathcal{R}_n$ must agree to be matched with T_n. For this reason, T_n's proposal should be desirable to all receivers in $\mathcal{R}_n$ and its energy offer should be high enough to provide a competitive utility for all receivers in $\mathcal{R}_n$. Therefore, T_n calculates its energy offer in a way to achieve max-min fairness between the receivers in $\mathcal{R}_n$, i.e.,

$$(r^*_{n,\mathcal{R}_n}, p^*_{n,\mathcal{R}_n}) = \underset{(r_{n,\mathcal{R}_n}, p_{n,\mathcal{R}_n})\geq 0}{\arg\max} \; \min_{m:R_m\in\mathcal{R}_n} \bar{u}_{m|n}(r_{n,\mathcal{R}_n}, p_{n,\mathcal{R}_n}), \tag{42a}$$

$$\text{s.t.} \qquad u_{n|\mathcal{R}_n}(r_{n,\mathcal{R}_n}, p_{n,\mathcal{R}_n}) \geq 0. \tag{42b}$$

Given $r_{n,\mathcal{R}_n}$, $\bar{u}_{m|n}(r_{n,\mathcal{R}_n}, p_{n,\mathcal{R}_n})$ is increasing in $p_{n,\mathcal{R}_n}$ for all m such that $R_m \in \mathcal{R}_n$, and $u_{n|\mathcal{R}_n}(r_{n,\mathcal{R}_n}, p_{n,\mathcal{R}_n})$ is decreasing in $p_{n,\mathcal{R}_n}$. Thus, T_n will offer a $p_{n,\mathcal{R}_n}$ that is as high as possible while T_n's own utility is nonnegative, which we find by solving $u_{n|\mathcal{R}_n}(r_{n,\mathcal{R}_n}, p_{n,\mathcal{R}_n}) = 0$ as

$$p^*_{n,\mathcal{R}_n}(r_{n,\mathcal{R}_n}) = \frac{|\mathcal{R}_n|\lambda_n r_{n,\mathcal{R}_n}}{\sigma_n} - \frac{1}{\min_{m:R_m\in\mathcal{R}_n} h_{n,m}}\left(2^{2r_{n,\mathcal{R}_n}} - 1\right) \tag{43}$$

which satisfies constraint (42b) for all $r_{n,\mathcal{R}_n}$. Problem (42) can be simplified as

$$r^*_{n,\mathcal{R}_n} = \underset{r_{n,\mathcal{R}_n}\geq 0}{\arg\max} \; \min_{m:R_m\in\mathcal{R}_n} \bar{u}_{m|n}(r_{n,\mathcal{R}_n}, p^*_{n,\mathcal{R}_n}(r_{n,\mathcal{R}_n})) \tag{44}$$

which is a convex problem that we solve numerically to find the optimal proposal for T_n.

After all rate and energy offers are calculated and proposed, each receiver finds the best proposal and the runner-up, i.e., the two proposals that yield the two largest utilities for the receiver. The receiver accepts the best proposal and similar to Section III-C, the transmitter with the best proposal has to provide the second largest receiver utility. At this point, each transmitter knows what it needs to provide for each receiver that it is matched to, and can lower its energy offer $p^*_{n,\mathcal{R}_n}$ so long as all of its matches receive the promised utility.

We can now solve this game by using Algorithm 2 with a minor modification where the transmitters use (43) and (44) instead of (34) to compute their bids.

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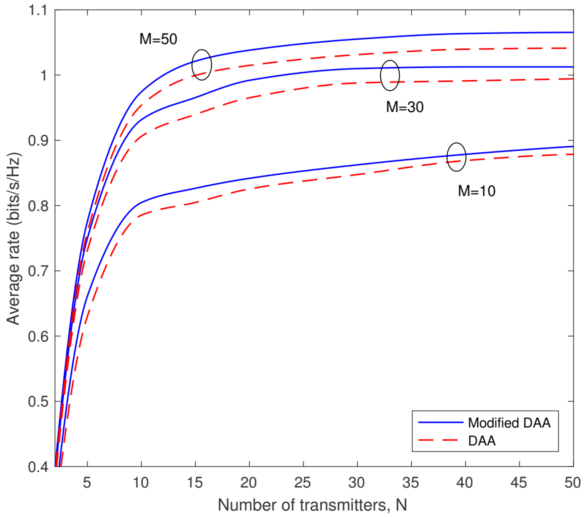

Fig. 3. Average rate per matched transmitter versus N and M for the one-to-one game in Section III-B.

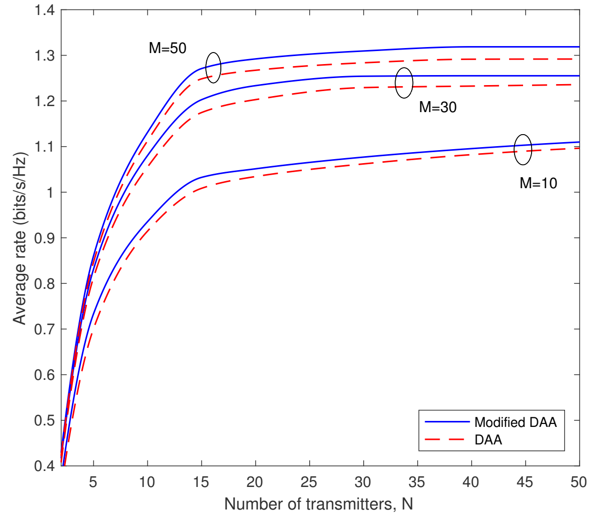

Fig. 4. Average rate per matched transmitter versus N and M for the one-to-one game in Section III-C.

V. Numerical Results

In this section, we present numerical results for the games in Section III and Section IV. We consider a simulation setup of N transmitters and M receivers uniformly placed on a 100 m $\times$ 100 m square with a 1 MHz band for each orthogonal link, carrier frequency 900 MHz, noise density 10^{-19} W/Hz, and Rayleigh fading. Consequently, the mean fading level between two nodes which are d m apart is computed as -40 dB$/d^2$ [39], [40]. For processing costs, we assume $c_m = 5$ mW, $\alpha_m = 2$ (bps)$^{-1}$, $\beta_m = 5$ mW/bps, and $\gamma_m = 50$ mW for all receivers [29], [30], [41]. In addition, σ_n and $\bar{\sigma}_m$ are uniform in $[0, 0.1]$ bps/W, η_m is uniform in $[0, 1]$, $\lambda_n = 1$, and $\bar{\lambda}_m = 1$ for all nodes. We average our findings over 10^5 realizations of this setup.

Fig. 3 shows the sum rate of the network resulting from our solution for the game in Section III-B divided by the number of matched transmitters. As can be seen from the figure, our modified DAA algorithm results in an improvement in the average rate of the network as compared to DAA since our solution does not allow any transmitter-receiver pairs to be matched with each other unless said matching results in non-negative utilities for both nodes. As we add more transmitters to the network, the receivers are presented with a larger selection of proposals to choose from. Likewise, the addition of more receivers into the network may result in a new favorite receiver for each transmitter, improving their best option. In other words, larger N and M yields more options for both sides and better matches. As a result, the average rate is increasing in the number of transmitters and the number of receivers in the network.

We repeat this setup for the game in Section III-C with energy cooperation and present our findings in Fig. 4. We observe similar phenomena for this case and note the larger average rate values as compared to Fig. 3. This additional improvement is due to the competition between the transmitters which results from the Vickrey auction we employ for this case. The transmitters are more inclined to compromise their own utilities so that they can propose better offers to their favorite receivers, which yields an overall improvement in the resulting rates.

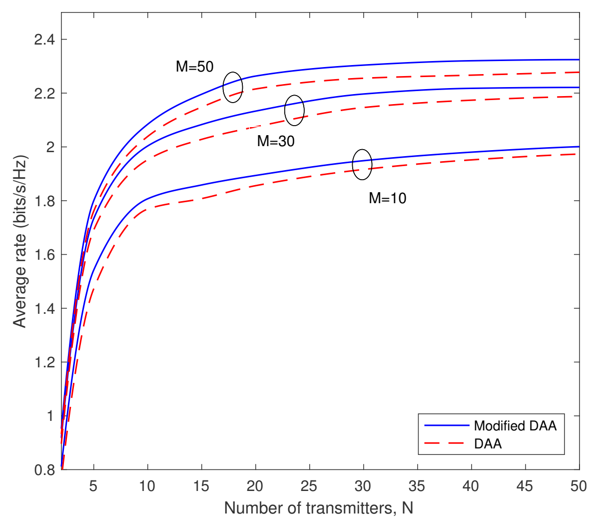

Fig. 5. Average rate per matched transmitter versus N and M for the one-to-many game in Section IV-B.

Figs. 5 and 6 show the average rate per matched transmitter for the one-to-many game without energy cooperation in Section IV-B and the one-to-many game with energy cooperation in Section IV-C. We observe that the improvement introduced by our modification on the DAA extends to the one-to-many case. We also observe larger rates. One reason for this is that the transmitters with good channels to several receivers are no longer limited to sending their data to just one receiver. Likewise, some receivers may find it more desirable to join a receiver coalition than accept a one-to-one proposal which was the only option they had in Section III. Further, the transmitters

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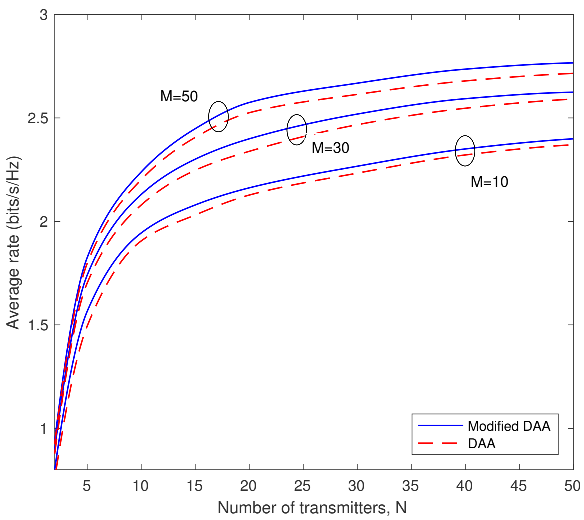

Fig. 6. Average rate per matched transmitter versus N and M for the one-to-many game in Section IV-C.

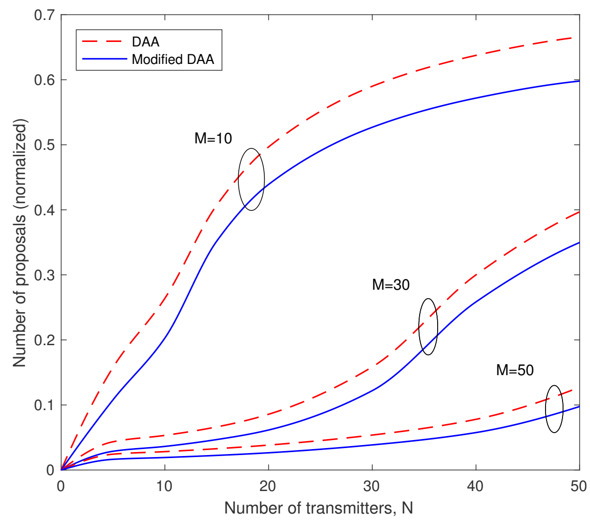

Fig. 8. The normalized number of proposals before an optimal matching is found versus N for the one-to-one game in Section III-C.

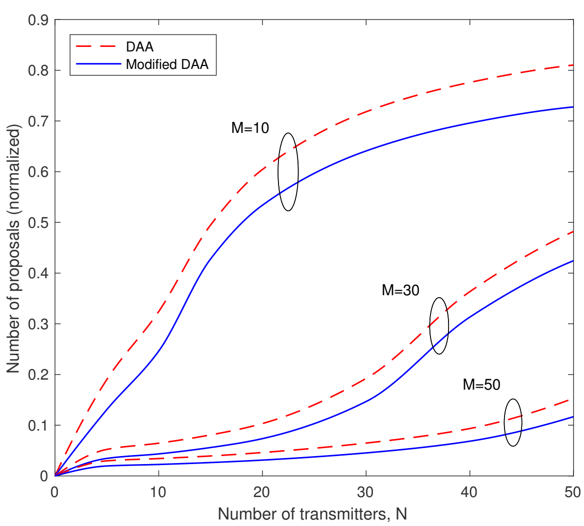

Fig. 7. The normalized number of proposals before an optimal matching is found versus N for the one-to-one game in Section III-B.

are even more inclined to forgo their own utilities in the one-to-many game in Section IV-C since they must satisfy all receivers in their favorite receiver subset.

Figs. 7 and 8 show the average number of proposals that must be presented and considered before our solution converges to an optimal matching for the games in Sections III-B and III-C, respectively. Here, we normalize the number of proposals by NM which is the maximum number of proposals and thus corresponds to the worst case scenario. As can be seen, our solution requires a smaller number of proposals as compared to DAA since in our solution, the transmitters automatically eliminate receivers which yield negative utilities whereas they may propose to such receivers in DAA. We observe that both our solution and DAA are efficient in the sense that the addition of more receivers into the system results in a lower number of proposals per receiver required for convergence. Lastly, we observe that the game in Section III-C with energy cooperation requires a smaller number of proposals on average than the one in Section III-B without energy cooperation. This is due to the fact that with energy cooperation, the transmitters can propose better offers to their favorite receivers. Hence, they are more likely to be matched to their favorite receivers and do not need to propose to their second favorite receivers and so on, which results in a lower number of proposals required to converge to a stable matching.

Lastly, Fig. 9 shows the average number of proposals required for convergence for the one-to-many game in Section IV-C. This time, the maximum number of proposals for the worst case scenario is $N(2^M-1)$ which we use to normalize the proposal counts in Fig. 9. The exponential-to-polynomial reduction in the number of proposals that we have shown in Section IV is observed numerically. We finally note that the improvement is magnified further as M is increased.

VI. Conclusion

In this paper, we have considered a wireless ad hoc network composed of N transmitters and M receivers. We have studied a communication scenario where the transmitters collect data which they can deliver to the receivers. We have taken into account the energy consumption of the entire network by modeling the transmission and decoding costs at the transmitters and receivers appropriately, bearing in mind the fact that energy is often not free which may influence the nodes' decisions regarding their operation. We have first formulated a one-to-one matching game between the transmitters and the receivers, and provided analytical expressions for each node's optimal decision with respect to its individual utility. We have next introduced another medium of competition by employing a Vickrey auction among the transmitters. We have shown that the transmitters can offer energy cooperation to the receivers to obtain better matches. We have observed that

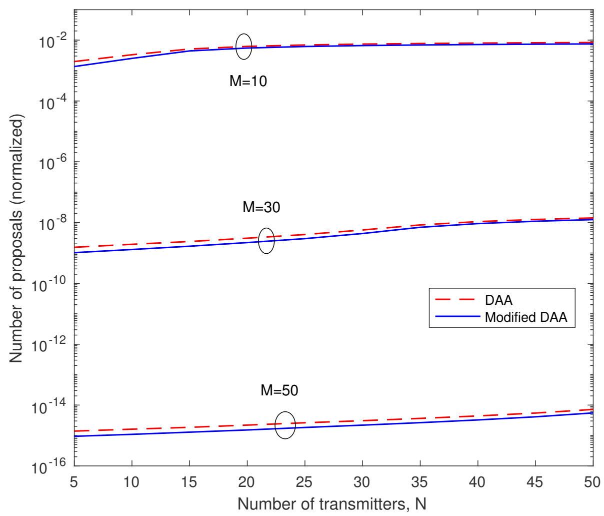

Fig. 9. The normalized number of proposals before an optimal matching is found versus N for the one-to-many game in Section IV-C.

energy cooperation lets the transmitters provide additional incentive to the receivers and results in larger rates for the network. We have next introduced one-to-many matchings to the network and shown that we can lower the complexity of the DAA by eliminating some possible proposals at the transmitter which do not affect the outcome of the algorithm. We have lastly extended energy cooperation to the one-to-many matching case and seen that the transmitters must be able to convince each receiver in their favorite receiver set in a max-min fair fashion.

The insights gained from this study are that we can match transmitters and receivers to increase the network throughput with judicious energy usage despite their selfish nature. Moreover energy transfer can further incentivize selfish nodes towards network formation and improve the overall network performance. Future directions include many-to-many games where transmitters and receivers can form coalitions, and bidirectional energy transfer where receivers can transfer energy to transmitters.

References

[1] B. Varan and A. Yener, "Matching games for wireless networks with energy cooperation," in *Proc. International Symposium on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks Workshop on Green Networks*, May. 2016.

[2] J. Andrews, S. Buzzi, W. Choi, S. Hanly, A. Lozano, A. Soong, and J. Zhang, "What will 5G be?" *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1065–1082, Jun. 2014.

[3] I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Communications Magazine*, vol. 40, no. 8, pp. 102–114, Aug. 2002.

[4] F. Li and Y. Wang, "Routing in vehicular ad hoc networks: A survey," *IEEE Vehicular Technology Magazine*, vol. 2, no. 2, pp. 12–22, Jun. 2007.

[5] D. Gale and L. S. Shapley, "College admissions and the stability of marriage," *American mathematical monthly*, pp. 9–15, 1962.

[6] A. E. Roth and M. A. O. Sotomayor, *Two-sided matching: A study in game-theoretic modeling and analysis*. Cambridge University Press, 1992.

[7] E. Jorswieck, "Stable matchings for resource allocation in wireless networks," in *17th International Conference on Digital Signal Processing*, Jul. 2011.

[8] R. El-Bardan, W. Saad, S. Brahma, and P. K. Varshney, "Matching theory for cognitive spectrum allocation in wireless networks," in *Proc. 50th Conf. on Information Sciences and Systems*, Mar. 2016.

[9] N. Namvar and F. Afghah, "Spectrum sharing in cooperative cognitive radio networks: A matching game framework," in *49th Annual Conference on Information Systems and Sciences*, Mar. 2015.

[10] K. Hamidouche, W. Saad, and M. Debbah, "Many-to-many matching games for proactive social-caching in wireless small cell networks," in *12th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt)*, May 2014, pp. 569–574.

[11] H. Xu and B. Li, "Seen as stable marriages," in *Proceedings of the IEEE INFOCOM*, Apr. 2011, pp. 586–590.

[12] N. Namvar, W. Saad, B. Maham, and S. Valentin, "A context-aware matching game for user association in wireless small cell networks," in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, May 2014, pp. 439–443.

[13] Y. Gu, W. Saad, M. Bennis, M. Debbah, and Z. Han, "Matching theory for future wireless networks: Fundamentals and applications," *IEEE Communications Magazine*, vol. 53, no. 5, pp. 52–59, May 2015.

[14] F. Pantisano, M. Bennis, W. Saad, S. Valentin, and M. Debbah, "Matching with externalities for context-aware user-cell association in small cell networks," in *2013 IEEE Global Communications Conference (GLOBECOM)*, Dec. 2013, pp. 4483–4488.

[15] Z. Chang, L. Zhang, X. Guo, Z. Zhou, and T. Ristaniemi, "User-cell association in heterogenous small cell networks: A context-aware approach," in *2015 IEEE/CIC International Conference on Communications in China (ICCC)*, Nov. 2015, pp. 1–5.

[16] A. Leshem, E. Zehavi, and Y. Yaffe, "Multichannel opportunistic carrier sensing for stable channel access control in cognitive radio systems," *IEEE Journal on Selected Areas in Communications*, vol. 30, no. 1, pp. 82–95, Jan. 2012.

[17] R. W. Irving, P. Leather, and D. Gusfield, "An efficient algorithm for the optimal stable marriage," *Journal of the ACM*, vol. 34, no. 3, pp. 532–543, Jul. 1987.

[18] B. Gurakan, O. Ozel, J. Yang, and S. Ulukus, "Energy cooperation in energy harvesting communications," *IEEE Transactions on Communications*, vol. 61, no. 12, pp. 4884–4898, Dec. 2013.

[19] K. Tutuncuoglu and A. Yener, "Energy harvesting networks with energy cooperation: Procrastinating policies," *IEEE Transactions on Communications*, vol. 63, no. 11, pp. 4525–4538, Nov. 2015.

[20] R. Zhang and C. K. Ho, "MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE Transactions on Wireless Communications*, vol. 12, no. 5, pp. 1989–2001, May 2013.

[21] S. Lee, R. Zhang, and K. Huang, "Opportunistic wireless energy harvesting in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 9, pp. 4788–4799, Sep. 2013.

[22] B. Varan and A. Yener, "Incentivizing signal and energy cooperation in wireless networks," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 12, pp. 2554–2566, Dec. 2015.

[23] K. Huang and E. Larsson, "Simultaneous information and power transfer for broadband wireless systems," *IEEE Transactions on Signal Processing*, vol. 61, no. 23, pp. 5972–5986, Dec. 2013.

[24] C. Zhong, H. Suraweera, G. Zheng, I. Krikidis, and Z. Zhang, "Wireless information and power transfer with full duplex relaying," *IEEE Transactions on Communications*, vol. 62, no. 10, pp. 3447–3461, Oct. 2014.

[25] K. Tutuncuoglu and A. Yener, "Cooperative energy harvesting communications with relaying and energy sharing," in *Proceedings of the 2013 IEEE Information Theory Workshop*, Sep. 2013.

[26] I. Krikidis, S. Timotheou, S. Nikolaou, G. Zheng, D. Ng, and R. Schober, "Simultaneous wireless information and power transfer in modern communication systems," *IEEE Communications Magazine*, vol. 52, no. 11, pp. 104–110, Nov. 2014.

[27] L. Liu, R. Zhang, and K.-C. Chua, "Wireless information and power transfer: A dynamic power splitting approach," *IEEE Transactions on Communications*, vol. 61, no. 9, pp. 3990–4001, Sep. 2013.

[28] R. Yates and H. Mahdavi-Doost, "Energy harvesting receivers: Packet sampling and decoding policies," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 3, pp. 558–570, Mar. 2015.

[29] K. Tutuncuoglu and A. Yener, "Communicating with energy harvesting transmitters and receivers," in *Information Theory and Applications Workshop*, Feb. 2012.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TGCN.2017.2751643, IEEE Transactions on Green Communications and Networking

[30] A. Arafa and S. Ulukus, "Optimal policies for wireless networks with energy harvesting transmitters and receivers: Effects of decoding costs," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 12, pp. 2611–2625, Dec. 2015.

[31] O. Orhan, D. Gunduz, and E. Erkip, "Energy harvesting broadband communication systems with processing energy cost," *IEEE Transactions on Wireless Communications*, vol. 13, no. 11, pp. 6095–6107, Nov. 2014.

[32] J. Xu and R. Zhang, "Throughput optimal policies for energy harvesting wireless transmitters with non-ideal circuit power," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 2, pp. 322–332, Feb. 2014.

[33] O. Ozel, K. Shahzad, and S. Ulukus, "Optimal energy allocation for energy harvesting transmitters with hybrid energy storage and processing cost," *IEEE Transactions on Signal Processing*, vol. 62, no. 12, pp. 3232–3245, Jun. 2014.

[34] W. Vickrey, "Counterspeculation, auctions, and competitive sealed tenders," *Journal of finance*, vol. 16, no. 1, pp. 8–37, 1961.

[35] P. Grover, K. Woyach, and A. Sahai, "Towards a communication-theoretic understanding of system-level power consumption," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 8, pp. 1744–1755, Sep. 2011.

[36] P. Rost and G. Fettweis, "On the transmission-computation-energy tradeoff in wireless and fixed networks," in *2010 IEEE Globecom Workshops*, Dec. 2010, pp. 1394–1399.

[37] M. J. Osborne and A. Rubinstein, *A course in game theory*. MIT press, 1994.

[38] J. F. Ritt, "On the zeros of exponential polynomials," *Transactions of the American Mathematical Society*, vol. 31, no. 4, pp. 680–686, 1929.

[39] A. Goldsmith, *Wireless communications*. Cambridge university press, 2005.

[40] T. S. Rappaport, *Wireless communications: Principles and practice*. Prentice Hall PTR New Jersey, 1996.

[41] S. Cui, A. Goldsmith, and A. Bahai, "Energy-constrained modulation optimization," *IEEE Transactions on Wireless Communications*, vol. 4, no. 5, pp. 2349–2360, Sep. 2005.

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