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Distributed Coalition Formation Algorithms for Cooperative Broadcast Networks with SWIPT

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(invited paper)

***Abstract*—This paper addresses the application of coalitional game theory to cooperative broadcast networks with simultaneous wireless information and power transfer (SWIPT). To improve the reception reliability of destinations with poor channel conditions, we first divide destinations in the network into two types. The first type, Type I, refers to the destinations with the capability of successful decoding. They will help other users by first performing SWIPT and then relaying the source messages with the harvested energy. The second type of nodes, Type II, have poor connections to the source and hence compete to obtain help from Type I destinations. In order to maximize the data transmission rate of Type II destinations in a distributed manner, we model the cooperative scenario as a coalitional game and propose two coalition formation approaches with different payoff functions. One payoff function is based on how much help a destination can contribute or receive. The other payoff function considers the targeted data rate and ensures much better fairness among destinations. Finally, we propose a distributed coalition formation algorithm where destinations decide individually which coalition to join. Simulation results show that the proposed two cooperative schemes outperform the non-cooperative scheme, and the cooperative scheme II performs better than the cooperative scheme I as expected.**

I. Introduction

Energy harvesting, a technique of converting the ambient energy into electricity, is a cost-efficient way to prolong the lifetime of energy-constrained networks. Apart from conventional energy sources such as solar and wind power, the ambient radio frequency (RF) signal is an alterative new source for simultaneous wireless information and power transfer (SWIPT). The concept of SWIPT was first proposed in [1] and [2], where it was assumed that the receiver can concurrently perform information decoding (ID) and energy harvesting (EH). In [3], separated ID and EH receivers were proposed in a three-node wireless MIMO broadcasting system for SWIPT. More recently, practical receiver architectures for SWIPT were investigated. In [4], the power-splitting receiver splits the received observations into two portions, one portion for ID and the other for EH. In [5], the time-switching receiver switches between the two modes of ID and EH periodically. The rate and energy performance in a two-hop MIMO relay system was studied with different channel state information (CSI) conditions in [6]. In [7], the application of SWIPT to cooperative networks with energy harvesting relays was studied, where the random distances can be captured by using stochastic geometry. In [8], a multi-user scenario with multiple source-destination pairs was considered, where the impact of various power allocation strategies has been studied.

It is worth noting that coalitional game theory, an important branch of game theory, has been employed to design distributed relaying strategies, as shown in [7]. Coalitional game theory is a powerful tool for designing fair, robust and efficient cooperation strategies [9], which can be realized in a distributed manner. In [10], coalitional game theory was applied to study cooperation among single antenna wireless nodes in a hoc networks. In [11], a merge and split algorithm for coalition formation was constructed to model cooperation among single antenna transmitters, acting as a virtual antenna array. In [12], a distributed coalition formation approach was developed to optimize the profits of network operators in green cellular networks.

In this paper, we investigate the application of SWIPT to wireless communication networks by adopting coalitional game theory. We focus on a broadcast network with one source and multiple randomly located destinations. The destinations are divided into two types, referred to as Type I and Type II. Type I destinations, which can decode the source messages successfully, carry out the approach of SWIPT and play as relays powered by the harvested energy. Type II destinations cannot decode the source messages successfully and compete for the help from Type I destinations. We model the cooperation between destinations of two types as a coalitional game. Then, we propose two coalition formation approaches with different payoff functions. The first payoff function quantifies the signal-to-noise ratio that a destination receives or contributes. Then, the payoff function is modified with regards to the targeted data rate, promising much better fairness. Afterwards, we propose a distributed coalition formation algorithm for destinations to determine which coalition to join. Finally, simulation results demonstrate that the cooperative schemes can improve the quality of communications.

II. System Model

Consider a cooperative transmission scenario with one source and multiple destinations. Particularly, we introduce a disc $\mathcal{D}$ with radius R_d to model the network topology. The source is located at the origin, and the destinations are randomly located inside the disc. The source broadcasts messages to destinations with constant transmission power P at a data transmission rate R. Let d_k and h_k be the distance and the fading channel gain between the source and the k-th destination, respectively. We assume the the path fading model d_k^* is

$$d_k^* = \begin{cases} 1 & \text{if} \quad d_k < d_0 \\ d_k^{\alpha} & \text{otherwise} \end{cases}, \tag{1}$$

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where d_0 is the threshold distance which promises no fading, and α is the path loss exponent. According to whether destinations can decode the source messages successfully, N destinations can be categorized into the following two types:

- **Type I**: This type of destinations can decode the source messages correctly, i.e., $\frac{|h_k|^2}{d_k^*} \geq \frac{2^{2R}-1}{\rho}$, where $\rho = \frac{P}{P_n}$ is the receive SNR, and P_n is the noise power. They can harvest energy from the observations intended for other destinations. Naturally, their roles in a coalition are acting as relays to help other destinations. In the coalition formation process, a Type I destination joins the coalition where it provides more help, since it will get more reward for the cooperation.
- **Type II**: This type of destinations have poor source-destination channel conditions, i.e., $\frac{|h_k|^2}{d_k^*} < \frac{2^{2R}-1}{\rho}$. In this case, Type II destinations cannot decode their messages. Naturally, in order to maximize their transmission data rate, they compete with each other to get help from Type I destinations. In the coalition formation process, a Type II destination joins the coalition where it receives more help.

The notations for the coalitions are given in the following. N destinations form M coalitions, represented by $\mathcal{S}_m, 1 \leq m \leq M$. Each coalition set $\mathcal{S}_m$ can be further separated into two subsets, denoted by $\mathcal{G}_{\mathcal{S}_m,1}$ and $\mathcal{G}_{\mathcal{S}_m,2}$. More specifically, $\mathcal{G}_{\mathcal{S}_m,1}$ contains all the Type I destinations in $\mathcal{S}_m$, and $\mathcal{G}_{\mathcal{S}_m,2}$ is composed of all the Type II destinations in $\mathcal{S}_m$.

Considering the case of N destinations, $2N$ time slots are required for the cooperative transmission. We divide $2N$ time slots into two phases: the first N time slots as phase one and the remaining N time slots as phase two.

A. Phase one

During each time slot of phase one, all destinations listen to the source. Each destination first tries to decode the received messages. If decoding successfully, it performs energy harvesting by directing the rest observation flows to an energy harvesting circuit. For Type II destinations, they only perform information decoding (ID). For Type I destinations, besides decoding the message intended for themselves, they perform energy harvesting (EH) from the observations intended for other destinations. We assume that the time-switching strategy is adopted, and τ_k, $0 \leq \tau_k \leq 1$, denotes the percentage of time allocated to EH during each time slot. For a k-th destination, $k \in \mathcal{G}_{\mathcal{S}_m,1}$, during the $(1-\tau_k)$ portion of the i-th time slot, $i \neq k$, the k-th destination directs the following observation to the detection circuit:

$$y_{k,i} = \frac{h_k \sqrt{P} s_i}{\sqrt{d_k^*}} + n_k, \tag{2}$$

where s_i is the normalized source message broadcast to the i-th destination. For simplicity, the channel state as well as the additive noise for each destination are assumed to remain unchanged during the entire $2N$ time slots. Therefore, the data rate at destination k for message s_i is

$$R_k = \frac{1-\tau_k}{2} \log(1 + \frac{|h_k|^2 \rho}{d_k^*}). \tag{3}$$

To ensure successful decoding at destination k for message s_i, the supported data rate should be greater than the targeted data rate R, i.e., $R_k \geq R$. Therefore, the threshold time-switching coefficient τ is set as

$$\tau_k = max \left\{ 0, 1 - \frac{2R}{\log(1 + \frac{|h_k|^2 \rho}{d_k^*})} \right\}. \tag{4}$$

When the channel condition is poor, i.e., $\tau_k = 0$, the entire i-th time slot is allocated for information decoding. Therefore, for Type II destinations, τ_k is always zero, and no energy can be harvested. For Type I destinations, $\tau_k > 0$, the transmission power harvested in this time slot on the basis of (4) is

$$\tilde{P}_k = \eta \frac{\tau_k |h_k|^2 P}{d_k^*} = \eta \left(\frac{|h_k|^2}{d_k^*} P - \frac{2RP|h_k|^2}{d_k^* \log(1 + \frac{|h_k|^2 \rho}{d_k^*})} \right), \tag{5}$$

where constant $\eta \in [0,1]$ represents the efficiency in harvesting and storing energy, assuming to be identical for all destinations. It is worth pointing out that the received signals and harvested energy at the destinations can be stored. More specifically, each destination in $\mathcal{G}_{\mathcal{S}_m,1}$ accumulates their harvested energy for the relay transmission in phase two. We assume the message intended for the destination itself is not used for energy harvesting. Therefore, for the k-th destination, it harvests a same amount of energy at each i-th time slot, $1 \leq i \leq N, i \neq k$, and the total amount of harvested energy is $(N-1)\tilde{P}_k$.

B. Phase two

Phase two is a cooperative phase for relay transmission. Considering a destination $i \in \mathcal{G}_{\mathcal{S}_m,2}$, during the $(N+i)$-th time slot, it receives help from destinations in $\mathcal{G}_{\mathcal{S}_m,1}$ which perform distributed beamforming. Note that the decode-and-forward strategy is used at the relays. Without loss of generality, we assume that each Type I destination offers an equal help to Type II destinations in the same coalition. For instance, the k-th destination, $k \in \mathcal{G}_{\mathcal{S}_m,1}$, equally partitions the total harvested energy into $|\mathcal{G}_{\mathcal{S}_m,2}|$ portions, where $|S|$ denotes the number of destinations located in the coalition S. Mathematically, on the basis of (5), $\forall i \in \mathcal{G}_{\mathcal{S}_m,2}$, the transmission power that the k-th destination employs for relay transmission to the i-th destination is

$$P_k = \frac{N-1}{|\mathcal{G}_{\mathcal{S}_m,2}|} \tilde{P}_k. \tag{6}$$

In terms of relay transmission, we assume that the CSI between different destinations are available, denoting the distance and channel state between destinations as c_{ki} and g_{ki}. Then, each destination k in $\mathcal{G}_{\mathcal{S}_m,1}$, transmits $\frac{g_{ki}^*}{|g_{ki}|}\sqrt{P_k} s_i$ to the i-th destination. As a result, with maximum ratio combining, the i-th destination observes

$$y_i' = \left(\sum_{k \in \mathcal{G}_{\mathcal{S}_m,1}} \frac{\sqrt{P_k}|g_{ki}|}{\sqrt{c_{ki}^*}} \right) s_i + n_i. \tag{7}$$

Considering the message extended for itself ($y_i = \frac{h_i s_i \sqrt{P}}{\sqrt{d_i^*}} + n_i$), the resulting SNR at the destination i is

$$SNR_{i,\mathcal{S}_m} = \frac{|h_i|^2\rho}{d_i^*} + \left(\sum_{k\in\mathcal{G}_{\mathcal{S}_m,1}} \frac{\sqrt{P_k}|g_{ki}|}{\sqrt{c_{ki}^*}}\right)^2. \quad (8)$$

For a Type I destination k, $k \in \mathcal{G}_{\mathcal{S}_m,1}$, since it does not need help from others, the last part in (8) is zero. Therefore, the receive SNR for a Type I destination k is

$$SNR_{k,\mathcal{S}_m} = \frac{|h_k|^2\rho}{d_k^*}. \quad (9)$$

III. Coalition Formation

A. Coalition formation approach I

In this section, we propose a coalition formation approach for the modeled scenario. We define the payoff function of destinations to judge their reward in a coalition, taking both gains and costs of cooperation into account. Given a particular coalition $\mathcal{S}_m$, the Type II destinations in $\mathcal{G}_{\mathcal{S}_m,2}$ receive help from the Type I destinations in $\mathcal{G}_{\mathcal{S}_m,1}$, while the destinations in $\mathcal{G}_{\mathcal{S}_m,1}$ only help others. The payoff function for a j-th destination, $j \in \mathcal{N}$, to join the coalition $\mathcal{S}_m$ based on (8) and (9) is defined as follows

$$\phi_j(\mathcal{S}_m) = \underbrace{\sum_{i\in\mathcal{G}_{\mathcal{S}_m,2}, i\neq j} \left(SNR_{i,\mathcal{S}_m} - SNR_{i,\mathcal{S}_m/j}\right) +}_{T_1} \underbrace{SNR_{j,\mathcal{S}_m}}_{T_2} - \underbrace{\mu(|\mathcal{S}_m|-1)}_{T_3}, \quad (10)$$

where $SNR_{i,\mathcal{S}_m/j}$ denotes the receive SNR of the i-th destination when the j-th destination is removed from the coalition $\mathcal{S}_m$. T_1 stands for the contribution of destination j to other players in coalition $\mathcal{S}_m$. T_2 indicates the help that the j-th destination obtains from other members in the same coalition. T_3 represents the cost of forming coalitions which is assumed to be related to the size of coalition, and μ is the proportional coefficient to measure such cost. If there is only one member in the coalition, no cost is spent to form the coalition, i.e., $T_3 = 0$. Note that destination j can be either Type I or Type II. The value of the coalition $\mathcal{S}_m$ is the total payoff achieved by members in this coalition, i.e.,

$$v(\mathcal{S}_m) = \sum_{j\in\mathcal{S}_m} \phi_j(\mathcal{S}_m). \quad (11)$$

However, the payoff function in (10) has not referred to the fact that it is not always beneficial to increase a destination's SNR. Note that the receive SNR of the destination determines its capacity, i.e., $C = \frac{1}{2}log(1 + SNR)$. Since the source communicates with destinations at the fixed data rate R, each destination's capacity only needs to be larger than the targeted data rate, i.e., $C_{i,\mathcal{S}_m} > R$. Corresponding to the threshold capacity, there is a threshold SNR, denoted by τ, $\tau = 2^{2R}-1$. Consequently, when the SNR of a Type II destination exceeds τ in the help of some Type I destinations, there is no need for more Type I destinations to help it.

B. Coalition formation approach II

In this section, we propose another coalition formation approach by defining a different payoff function for destinations. Taking the threshold SNR into consideration, we modify the SNR expression into

$$\widehat{SNR}_{j,\mathcal{S}_m} = \min\left\{\tau, SNR_{j,\mathcal{S}_m}\right\}. \quad (12)$$

For Type I destinations, $\widehat{SNR}_{j,\mathcal{S}_m}$ is always τ. For Type II destinations, $\widehat{SNR}_{j,\mathcal{S}_m}$ first increases if there is any help from Type II destinations, and then reaches the peak value τ when it receives enough help. Accordingly, the payoff function for the j-th destination to join the coalition $\mathcal{S}_m$ is defined as follows

$$\hat{\phi}_j(\mathcal{S}_m) = \underbrace{\sum_{i\in\mathcal{G}_{\mathcal{S}_m,2}, i\neq j} \left(\widehat{SNR}_{i,\mathcal{S}_m} - \widehat{SNR}_{i,\mathcal{S}_m/j}\right) +}_{T_1} \underbrace{\widehat{SNR}_{j,\mathcal{S}_m}}_{T_2} - \underbrace{\mu(|\mathcal{S}_m|-1)}_{T_3}. \quad (13)$$

In addition, the value of the coalition $\mathcal{S}_m$ is defined as

$$v(\mathcal{S}_m) = \sum_{j\in\mathcal{S}_m} \hat{\phi}_j(\mathcal{S}_m). \quad (14)$$

The above definitions in (13) and (14) ensure a much fair help allocation. That is, Type I destinations assist destinations who need help most, and Type II destinations receive a proper amount of help only to meet the targeted data rate requirement.

IV. Coalition Formation Algorithm

A. Coalition formation concepts

As aforementioned, each destination tries to join a coalition where they either benefits or contributes most. Thus the proposed game can be classified as a coalitional game with transferrable payoff. According to the definitions in the above coalition formation approaches, i.e., in (10) and (13), we can observe that the payoff of a destination depends solely on the members of its current coalition. Therefore, the proposed game can be modeled as a hedonic coalition formation game. First, we introduce some important definitions.

Definition 1: A coalition partition, or namely coalitional structure, is defined as the set $\Omega = \{\mathcal{S}_1, \mathcal{S}_2, ...\mathcal{S}_M\}$. It partitions the grand set $\mathcal{N}$ into disjoint coalitions, i.e., $\forall \mathcal{S}_m \in \Omega$, $\bigcup_{m=1}^{M} \mathcal{S}_m = \mathcal{N}$.

Definition 2: Given a particular partition Ω, $\mathcal{S}_\Omega(j)$ is the current coalition where the j-th destination belongs to, i.e., $\mathcal{S}_\Omega(j) = \mathcal{S}_m$, with $j \in \mathcal{S}_m$ and $\mathcal{S}_m \in \Omega$.

Definition 3 (The Preference Relation): The $preference$ is an important metric for an destination to valuate the set of possible coalitions it may join. Particularly for any destination $j \in \mathcal{N}$, the preference relation, represented by $S_m \prec_j S_n$, implies that the j-th destination strictly prefers to stay in S_n rather than S_m, where $j \in S_m$ and $j \in S_n$. For this purpose, the following two criteria are used to quantify the preference:

$$S_m \prec_j S_n \Leftrightarrow \begin{cases} C1 : \phi_j(S_m) < \phi_j(S_n) \\ C2 : v(S_m) + v(S_n \setminus j) < \\ \qquad v(S_m \setminus j) + v(S_n), \end{cases} \quad (15)$$

where $S \setminus j$ denotes a subset of S created by removing the j-th destination. The first expression in (15) indicates that a destination prefers a coalition where it has a higher payoff. The second expression in (15) takes the overall network benefits into account. This criterion promises that the value of the new partition will not be reduced if the destination stays in S_n instead of S_m. There may be contradictions in these two criteria, but only when both are satisfied will the preference stand. In summary, one destination builds its preference over different coalitions by taking both individual and overall benefits into consideration.

Definition 4 (The hedonic shift rule): Given a partition $\Omega = \{\mathcal{S}_1, \mathcal{S}_2, ...\mathcal{S}_M\}$, any destination $j \in \mathcal{N}$ makes a hedonic shift based on a well-defined preference. The destination decides to leave its current coalition $\mathcal{S}_\Omega(j) = \mathcal{S}_m$ and join another coalition $\mathcal{S}_n \in \Omega \cup \{\emptyset\}$, $\mathcal{S}_n \neq \mathcal{S}_m$, if and only if $\mathcal{S}_n \cup \{j\} \succ_j \mathcal{S}_m$ is satisfied. Mathematically, we have $\{\mathcal{S}_m, \mathcal{S}_n\} \to \{\mathcal{S}_m \backslash \{j\}, \mathcal{S}_n \cup \{j\}\}$.

The shift rule (that we denote as '$\rightarrow$') provides a mechanism for any destination to leave its current coalition $\mathcal{S}_m$ and join another coalition $\mathcal{S}_n$, given that the new coalition $\mathcal{S}_n \cup \{j\}$ is strictly preferred over $S_\Omega(j)$ based on the preference in (15). Subsequently, after the hedonic shift, the current partition Ω transforms into a new partition $\Omega' = \{\Omega \setminus \{S_m, S_n\}\} \cup \{S_m \setminus \{j\}, S_n \cup \{j\}\}$.

B. Distributed algorithm design

In this section, we propose a distributed coalition formation algorithm, as presented in Table I. This distributed algorithm allows destinations to determine which coalition to join independently. It is assumed that at the beginning of all time, the initial state of the coalition partition is N separate coalition sets without any cooperation. Then, we have the initial partition $\Omega_0 = \{\{1\}, \{2\}, ..., \{N\}\}$. During the iteration phase, each destination takes its turn to determine whether to stay in the current coalition or join a new coalition. As for any destination $j \in N$, it first retrieves the current coalition partition Ω. Afterwards, it searches the potential hedonic shifts based on the defined preferences in (15) over the sets $\{\Omega \setminus \{\mathcal{S}_\Omega(j) \cup h(j)\}\}$. It is worth mentioning that the $j-$th destination will not consider coalitions in the history set $h(j)$, in which case, the same coalition is not visited more than one time during the coalition space search. Specifically, if the destination j is to perform any hedonic shift, it updates its history set $h(j)$ by adding $\{\mathcal{S}_m \setminus \{j\}\}$. Then it leaves the current coalition $\Omega(j) = \mathcal{S}_m$, and joins the new coalition $\mathcal{S}_n$. The iteration runs until no more hedonic shifts possible for all the destinations. At last, we obtain the final partition where no destination would like to leave its current coalition.

V. SIMULATION RESULTS

In this section, we present some simulation results to demonstrate the performance of the proposed coalition formation algorithms, whereas the non-cooperative scheme is used as benchmarking. Specifically, the algorithms based on coalition formation approach I and II in Section III are termed as the cooperative scheme I and the cooperative scheme II, respectively.

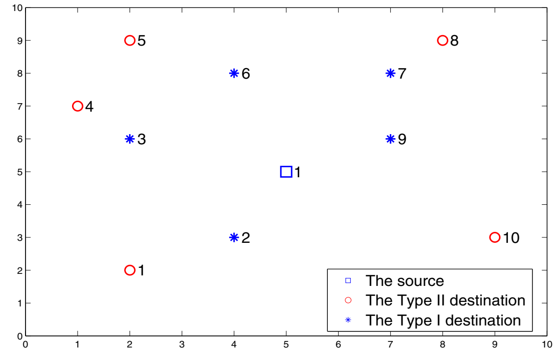

Fig. 1. Final coalition partition of the cooperative scheme I and II, $\Omega_I^* = \{\{4\}, \{5\} \{8\} \{10\} \{1, 2, 3, 6, 7, 9\}\}$ and $\Omega_{II}^* = \{\{3, 4, 5, 6\}, \{1, 2\}, \{7, 8, 9, 10\}\}$. $R_d = 5$m, $\alpha = 2$, $\mu = 0.01$, $\eta = 0.1$.

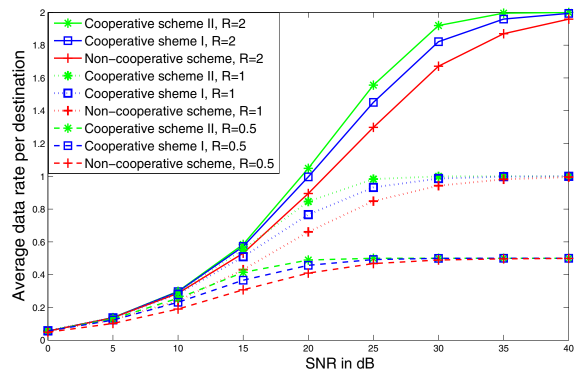

Fig. 2. Simulation results of average data rate per destination versus the targeted data rate, with $N = 10$, $R_d = 5$m, $\alpha = 3$, $\eta = 1$, and $\mu = 0.01$

First, we show a specific case of coalition partition in Fig. 1, verifying intuitively that the cooperative scheme II outperforms the cooperative scheme I. Here, we set the targeted data rate $R = 0.4$ bit per channel use (BPCU) and SNR=10. For the simplicity of discussion, we set the channel state between the source and the destination as well as the ones between different destinations as 1. As shown in this figure, for the cooperative scheme I, Type II destinations 4, 5, 8 and 10 are ignored without any help from Type I destinations, while Type II destination 1 receives crowded help. In contrast, the cooperative scheme II avoids such situation and offers a fair and uniform help as expected.

Then, we evaluate the data rate performance of these schemes. The destinations are randomly deployed in the disc, and their channels are assumed to be frequency flat quasi static Rayleigh fading. As shown in Fig. 2, the cooperative scheme II achieves the highest average data rate no matter what the choice of the targeted data rate is, while the use of the non-cooperative scheme results in the worst performance. The average data rate curves are increasing, along with the increase in SNR. Once SNR is high enough, the achievable average data rate approaches R for all schemes. This phenomenon is expected since all destinations become Type I nodes at high SNR.

In Fig. 3, we focus on how the number of destinations influences the data rate. As shown in the figure, when the number of destinations in our scenario is larger, the difference in data rate performance among these schemes is bigger, show-

TABLE I. A DISTRIBUTED COALITION FORMATION ALGORITHM

– **Initial State:** At the beginning of all time, the initial network is $\Omega_0 = \{\{1\}, \{2\}, ..., \{N\}\}$. – **Coalition Formation** **repeat** For any destination j, $1 \leq j \leq N$, $a)$ Destination j retrieves the current partition Ω (in the first round, $\Omega = \Omega_0$). $b)$ Destination j searches the sets $\{\Omega \setminus \{\mathcal{S}_\Omega(j) \cup h(j)\}\}$ for possible hedonic shifts. $c)$ Destination j performs the hedonic shift with the following specific steps: • Destination j adds $\{\mathcal{S}_\Omega(j) \setminus \{j\}\}$ into its history set $h(j)$. • Destination j leaves its current coalition and joins the new coalition. • Update the current partition Ω. • Update the current coalition $\mathcal{S}_\Omega(j)$. **until** No more hedonic shift exists. – **Final State:** A stable partition $\Omega' = \{S_1, S_2, ...S_M\}$.

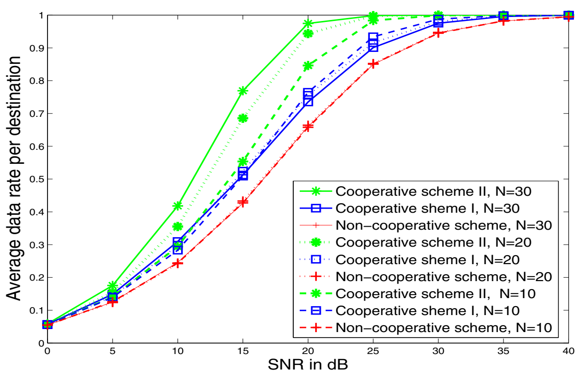

Fig. 3. Average data rate per destination versus the number of destinations , with $R = 1$ BPCU, $R_d = 5$m, $\alpha = 3$, $\eta = 1$, and $\mu = 0.01$

ing that the cooperative scheme II is more preferable among these three schemes. In addition, for the cooperative scheme II, the average data rate is higher with more destinations. This is expected since more users means more opportunities for users to join in more appropriate coalitions. More specifically, with more destinations in the same disc, i.e., a bigger density, the distance between neighboring Type I and Type II destinations is smaller, enabling better cooperation. It is worth pointing out that the proposed game theoretic approaches are implemented in a distributed way, which means that those performance gains in the case with more users are not obtained at a price of more system overhead and complexity.

VI. CONCLUSIONS

In this paper, we introduce a downlink broadcast transmission network with the application of simultaneous wireless information and power transfer. The cooperation scenario for Type I and Type II destinations is formulated as a hedonic coalition formation game. We have proposed two distributed coalition formation algorithms based on different payoff functions. Each destination decides whether join a new coalition based on the well defined preference, taking both individual and overall benefits into consideration. Both the cooperative scheme I and II are superior to the non-cooperative scheme, proving the relay transmission strategy with the harvested energy can improve the network performance. Simulation results demonstrate the superiority of the cooperative scheme II which promises a better achievable data rate.

VII. ACKNOWLEDGEMENT

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