Topology-Aware Incentive Mechanism for Cooperative Relay Networks

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***Abstract*—A properly designed incentive mechanism is important for cooperative relay networks, as it will encourage relays assisting sources' data transmissions. However, previous related studies didn't give enough consideration to the *topology effect*, i.e., how the network topology can substantially influence the relay selection and profit distribution in cooperations. In this paper, we quantify the topology effect in multi-source-multi-relay networks analytically, by using a multi-node Nash bargaining framework based on the network exchange theory. The proposed multi-node Nash bargaining outcome guarantees not only the individual satisfaction for each node, but also the social optimality for the entire network (of all nodes). Then, we propose a distributed incentive mechanism, named as natural algorithm, which enables each node to take advantage of the network topology to reach a multi-node Nash bargaining outcome through proper source/relay selection and payment bargaining. Simulation results illustrate the profit distribution among relays and sources under different network topologies.**

I. Introduction

A. Background and Motivations

Cooperative relay network can effectively improve the wireless transmission performance, reduce the transmission cost, and extend the wireless network coverage [1]–[5]. In cooperative relay systems, relay nodes assist source nodes through forwarding their data to their destinations. In a more flexible system design with a lower deployment cost of relays, mobile users can act as *mobile relays* for data forwarding. On the other hand, cooperations can lead to additional spectrum, time, and energy costs of relays, hence raise concerns on how to incentivize selfish nodes to serve as relays. Moreover, in general, different mobile users may not belong to the same service provider, in which case centralized algorithms may not be applicable. The above reasons motivate the design of distributed incentive mechanism for cooperative relay systems in recent years.

Some recent studies have considered the incentive mechanism design for the cooperative relay networks with different network structures [2]–[4]. For a simple cooperative relay network with one source-destination pair (or simply called source) and one relay, Xie *et al.* in [2] introduced a distributed mechanism based on the Rubinstein-Stahl bargaining game, to determine the power allocation and utility division between the source and the relay. For a network with one source and multiple relays, Duan *et al.* in [3] considered relays' private channel state information (CSI), and proposed a contract-theoretic approach to promote relays to truthfully share the cost for data forwarding and compute the proper prices for cooperation. For a network with multiple sources and one relay, Wang *et al.* in [4] proposed an auction-based scheme for the power allocation of the relay, to strike a balance between the quality-of-service (QoS) of sources and the energy consumption of itself. However, analysis and mechanism design in more general networks with *multiple sources and multiple relays* has been relatively under studied in the literature. In fact, the impact of network topology on the network performance has not been fully understood yet.

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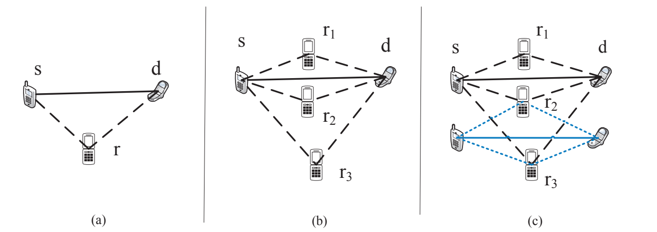

Fig. 1. Illustration on Topology Effect (s: Source, r: Relay, d: Destination)

In this paper, we focus on how network topology influences the relay selection and payment negotiation in cooperative relay networks. The *network topology* is defined as the connection properties between nodes in the network, which depends on a variety of factors such as the locations of nodes, the channel states, the network types, the number sources, the number of relays, and so forth.

Fig. 1 illustrates the influence of network topology. In Fig. 1 (a), there is one source (denoted by "s") and one relay (denoted by "r"), hence they are symmetric in topology and have a similar negotiation power. When the network extends to one source and multiple relays as shown in Fig. 1 (b), the source is the "monopoly buyer" in the network and has a larger market power than the relays. When another source arises in the network as shown in Fig.1 (c), each source is no longer the monopoly since relays also have multiple choices. From this figure, we can see that network topology influences on the relay selection and payment negotiation in cooperative networks, where nodes with more and better connections with others will have a larger bargaining power and can gain more from the cooperation. For convenience, we refer to such an impact of network topology as *topology effect*.

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B. Contributions

In this paper, we define a multi-node Nash bargaining framework according to network exchange theory (NET), to demonstrate how topology effect affects relay selection and the payment negotiation in multi-source-multi-relay cooperative networks. Moreover, we provide a distributed algorithm, named as natural algorithm, which enables each source and each relay to decide how to utilize the topology to reach the multi-node Nash bargaining outcome.

As far as we know, we are the first to quantitively define the topology effect in cooperative relay networks. The main contributions of this paper are summarized as follows:

- *Topology Effect Exploration:* We explore the topology effect in cooperative relay networks quantitively by using a multi-node Nash bargaining framework. The proposed bargaining outcome guarantees both the individual satisfaction for each node and the social optimality for the entire network (of all nodes).
- *Distributed Algorithm Design:* We design a distributed incentive mechanism called natural algorithm to achieve the bargaining outcome in a distributed manner.
- *Simulation Illustrations:* Simulation results illustrate the topology effect. For example, the sum utility of relays is on average 54% of the total utility of all nodes in the network with 5 relays and 5 sources, and drops dramatically to 16% in the network with 15 relays and 5 sources.

The rest of this paper is organized as follows. In Section II, we introduce the system model. In Section III, we elaborate on the limitations of the existing non-cooperative games and cooperative games in analyzing multi-source-multi-relay networks. In Section IV, we use the network exchange theory to illuminate the topology effect in cooperative relay networks. In Section V, we provide a natural algorithm on how to achieve the bargaining outcome in a distributed way. We provide the simulation results in Section VI, and conclude in Section VII.

II. System Model

We consider a cooperative relay network with a set of N source-destination pairs (or simply called sources), denoted by $(\mathcal{S},\mathcal{D}) = \{(s_1,d_1),(s_2,d_2),...,(s_N,d_N)\}$, and a set of M relays, denoted by $\mathcal{R} = \{r_1,r_2,...r_M\}$, as shown in Fig. 2. Each source s_i transmits data to its destination d_i with the help of a relay node (who does not have its own data to transmit), according to a pre-defined cooperative communication protocol. In this work, we adopt the half-duplex amplify-and-forward (AF) protocol [1], where each relay node amplifies and forwards the source data without decoding and recoding. Moreover, we assume that an orthogonal frequency division multiple access (OFDMA) for the source system, where each source is allocated with an orthogonal channel with W-Hz bandwidth [6]. Hence, there is no mutual interference among sources. This assumption allows us to focus on the impact of network topology.

A. Rate Improvement via Cooperation

For each source node, there are two modes for data transmission: the direct transmission mode (DTM) and the

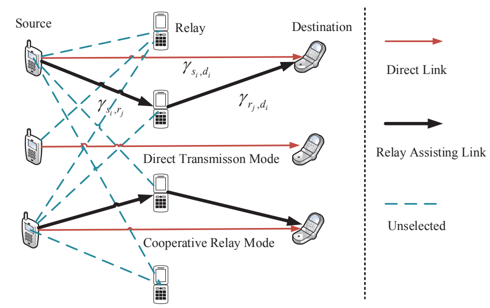

Fig. 2. System Model

cooperative relay mode (CRM). In the CRM, the source can select a relay for transmission assistance. When the source fails to find a proper relay node, it works in the DTM to transmit data directly without the relay's assistance. For simplicity, we assume that each relay works with single-input-single-output module where each relay can assist at most one source simultaneously. Next, we compute the data rates for both DTM and CRM.

1) Direct Transmission Mode: In the DTM, s_i transmits its data directly to d_i. The data rate $R_{i,0}$ can be calculated based on the Shannon capacity:

$$R_{i,0} = W\log_2(1+\gamma_{s_i,d_i}), \tag{1}$$

where $\gamma_{s_i,d_i} = \frac{p_{s_i}h_{s_i,d_i}}{\sigma^2}$ is the signal-to-noise ratio (SNR) on destination d_i, which is determined by the source transmit power p_{s_i}, the channel between source and destination h_{s_i,d_i}, and the noise power σ^2.

2) Cooperative Relay Mode: In the AF-based CRM, the data transmission consists of two phases. In the first phase, the source node s_i selects a relay node (say r_j) and transmits its data to both the selected relay node r_j and its destination d_i. In the second phase, the relay r_j amplifies and forwards the received data to the destination node d_i. According to [1], the data rate of this two-phase process is given as follows:

$$R_{i,j} = \frac{1}{2}W\log_2\left(1+\gamma_{s_i,d_i}+\frac{\gamma_{s_i,r_j}\gamma_{r_j,d_i}}{\gamma_{s_i,r_j}+\gamma_{r_j,d_i}+1}\right), \tag{2}$$

where $\gamma_{s_i,r_j} = \frac{p_{s_i}h_{s_i,r_j}}{\sigma^2}$ is the SNR on relay r_j in the first phase (where h_{s_i,r_j} is the channel between the source s_i and the relay r_j), and $\gamma_{r_j,d_i} = \frac{p_{r_j}h_{r_j,d_i}}{\sigma^2}$ is the SNR on destination d_i in the second phase (where p_{r_j} is the transmission power of relay r_j, and h_{r_j,d_i} is the channel between the relay r_j and the destination d_i). For more details, please refer to [1] and the references therein.

3) Rate Improvement: The data rate improvement for the source s_i with the help of relay r_j is denoted by

$$\theta_{i,j} = R_{i,j} - R_{i,0}. \tag{3}$$

B. Utility Functions

When a relay assists a source's data transmission, the relay incurs certain cost (e.g., the energy consumption), and hence will request some payment from the source. When a source gets assistance from a relay, the source gains certain benefit (e.g., the rate improvement), and needs to offer some payment

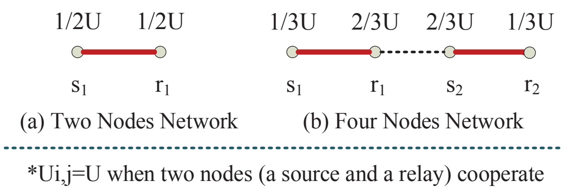

Fig. 3. Illustration of Solutions

to the relay. In order to highlight the influence of topology, we assume that the transmit power of each relay r_j is fixed: $p_{r_j} = p_j$.[1] We denote the payment that the source s_i would like to pay to the relay r_j as $\mu_{i,j}$, and the payment that relay r_j requires from s_i as $\nu_{i,j}$. Then, similar as in [3], we define the utility as follows.

1) Source Utility: The utility of source s_i, denoted by $U_{s_i}^{r_j}(\theta_{i,j}, \mu_{i,j})$, consists of its data rata improvement $\theta_{i,j}$ and the payment $\mu_{i,j}$ it offers to relay r_j, i.e.,

$$U_{s_i}^{r_j}(\theta_{i,j}, \mu_{i,j}) = \theta_{i,j} - \mu_{i,j}. \tag{4}$$

2) Relay Utility: The utility of relay r_j, denoted by $U_{r_j}^{s_i}$, consists of the payment $\nu_{i,j}$ it requires from source s_i and its power cost p_j, i.e.,

$$U_{r_j}^{s_i}(\nu_{i,j}, p_j) = \nu_{i,j} - p_j. \tag{5}$$

Note that when a source s_i and r_j settle down a cooperation successfully, we have: $\mu_{i,j} = \nu_{i,j}$.

3) Pairwise Utility (Cooperation Gain): The total achieved utility of source s_i and relay r_j under a successful cooperation is $U_{i,j}$, which is given by

$$U_{i,j} = \left[U_{s_i}^{r_j}(\theta_{i,j}, \mu_{i,j}) + U_{r_j}^{s_i}(\nu_{i,j}, p_j)\right]^+ = [\theta_{i,j} - p_j]^+, \tag{6}$$

where $[\cdot]^+ = \max\{0, \cdot\}$. Here the pairwise utility is lower-bounded by zero, as a source and a relay will never form a cooperative group when such cooperation leads to a negative total benefit.

C. Problem Formulation

For each source s_i, it wants to maximize its utility through a proper relay selection and a payment negotiation. For each relay r_j, it wants to maximize its utility through choosing the proper source that with the highest payment. Thus, it's natural to model each node as a game player, and study the problem from a game-theoretic perspective. The strategy of each node (denoted as ϕ) consists of two parts: selecting a cooperation pair and negotiating on the payments.

III. Explanation with Traditional Game Theory

In this section, we briefly discuss how to use non-cooperative and cooperative games to formulate our problem. We then point out their limitations in analyzing a cooperative relay network with multiple sources and multiple relays.

[1]This also facilitates the practical implementation of the AF cooperative communication protocol.

A. Non-cooperative Game (Nash Equilibrium)

In game theory, the Nash equilibrium (NE) [11] is a solution of a non-cooperative game involving two or more players, where each player chooses a strategy and no player can benefit from a unilateral strategy change. In cooperative relay networks in this paper, the Nash equilibrium is given as follows:

$$\begin{cases} \phi_{s_i}^* = (r_j^*, \mu_{i,j}^*) = \arg \max\limits_{r_j \in \mathcal{R}, \mu_{i,j}} U_{s_i}^{r_j}(\theta_{i,j}, \mu_{i,j}), \ \forall s_i \in \mathcal{S}, \\ \phi_{r_j}^* = (s_i^*, \nu_{i,j}^*) = \arg \max\limits_{s_i \in \mathcal{S}, \nu_{i,j}} U_{r_j}^{s_i}(\nu_{i,j}, p_j), \ \forall r_j \in \mathcal{R}, \\ \mu_{i,j}^* = \nu_{i,j}^*, \quad \forall s_i \in \mathcal{S}, r_j \in \mathcal{R}. \end{cases} \tag{7}$$

An example of Nash equilibrium is given in Fig. 3(a), where the source and the relay get half of the total utility U generated. However, there exist infinite Nash equilibria in this particular network, i.e., any (U_{s_1}, U_{r_1}) ranging from $(U, 0)$ to $(0, U)$. Hence, an NE fails to determine the most meaningful utility division between a pair of cooperative nodes.

B. Cooperative Game (Nash Bargaining Solution)

Nash bargaining solution (NBS) is a cooperative game solution, and provides guidelines regarding how to divide the total utility fairly in a given cooperation [12]. In the cooperative relay network considered in this paper, given a set $\mathcal{M}$ of cooperative pairs, an NBS is reached when the following equations is satisfied:

$$\begin{aligned} &\max_{\mu_{i,j}, \nu_{i,j}} \prod_{(s_i, r_j) \in \mathcal{M}} \left(U_{s_i}^{r_j}(\theta_{i,j}, \mu_{i,j}) - d_{s_i}^{r_j}\right)\left(U_{r_j}^{s_i}(\nu_{i,j}, p_j) - d_{r_j}^{s_i}\right), \\ &\text{s.t.} \ \ \mu_{i,j} = \nu_{i,j}, U_{s_i}^{r_j}(\theta_{i,j}, \mu_{i,j}) \geq d_{s_i}^{r_j}, \ U_{r_j}^{s_i}(\nu_{i,j}, p_j) \geq d_{r_j}^{s_i}, \\ &\qquad \forall (s_i, r_j) \in \mathcal{M}, \end{aligned} \tag{8}$$

where $d_{s_i}^{r_j}$ and $d_{r_j}^{s_i}$ are the utilities of source s_i and r_j, respectively, when they break up the cooperation. In our model, $d_{s_i}^{r_j} = d_{r_j}^{s_i} = 0$. Hence, for each cooperation pair $(s_i, r_j) \in \mathcal{M}$, in an NBS, s_i and r_j share the total utility equally, i.e.,

$$U_{s_i}^{r_j}(\theta_{i,j}, \mu_{i,j}) = U_{r_j}^{s_i}(\nu_{i,j}, p_j) = \frac{1}{2} U_{i,j}. \tag{9}$$

However, an NBS can neither determine how the cooperative pair assignment $\mathcal{M}$ is formulated, nor explain why each source and relay agree on the cooperative pair in $\mathcal{M}$. Moreover, an NBS cannot reflect the topology effect, even given a cooperative pair assignment. An example is given in Fig. 3(b), where NBS leads $U_{s_1}^{r_1} = U_{r_1}^{s_1}$, although r_1 deserves to gain more according to its topology superiority to s_1, since r_1 has two cooperator options and s_1 only has one.

To overcome the limitations of NE and NBS and obtain a rational outcome in general multi-source-multi-relay cooperative networks that reflect the influence of topology, we will define and study a multi-node Nash bargaining framework based on the network exchange theory in the next section.

IV. Topology Effect in Cooperative Relay Networks

In this section, we first briefly introduce the multi-node Nash bargaining framework based on the network exchange theory. Then we use this framework to demonstrate the topology effect in cooperative relay networks.

A. Multi-node Nash Bargaining Framework

In this work, we will adopt the multi-node Nash bargaining framework proposed in [9] for cooperative relay networks. For convenience, we denote the payoff of each source s_i as U_{s_i} and each relay as U_{r_j}, which represent their utilities respectively after cooperator selection and payment bargaining. For example, when s_i selects r_j for cooperation, we have $U_{s_i} = U_{s_i}^{r_j}(\theta_{i,j}, \mu_{i,j})$, $U_{r_j} = U_{r_j}^{s_i}(\nu_{i,j}, p_j)$, and $\mu_{i,j} = \nu_{i,j}$. Correspondingly, all the cooperation pairs form a set M, where $(s_i, r_j) \in M$ if and only if s_i selects r_j for cooperation. When a source s_i or a relay r_j cannot find a cooperation pair, we have $U_{s_i} = 0$ or $U_{r_j} = 0$. Thus, a multi-node Nash bargaining outcome is given as follows:

Definition 1: In a multi-source-multi-relay network, an outcome is called a *multi-node Nash bargaining outcome* (MNBO), if it satisfies the following properties:

$$\begin{cases} U_{s_i} + U_{r_j} \geq U_{i,j}, \\ U_{s_i} - \max\limits_{k \in \partial i \setminus \{j\}} [U_{i,k} - U_{r_k}]^+ \\ = U_{r_j} - \max\limits_{l \in \partial j \setminus \{i\}} [U_{l,j} - U_{s_l}]^+, \quad \forall (s_i, r_j) \in M, \end{cases} \tag{10}$$

where ∂i denotes the set of neighbors of node i.

- The first inequation indicate that there exists no uncooperating pair in the network that can improve their sum payoff through breaking up their current cooperation pair respectively and forming a new pair. In comparison with the NE and NBS, these inequations explain the consequence of cooperator selection, in which each node selects the best cooperator.

- The second equation indicates that each player thinks that it obtains a fair value division from this cooperation: when two nodes in a cooperation pair break the cooperation and turn to other nodes for cooperations, their utility losses will be the same. In comparison with the NBS in (9), $\max_{k \in \partial i \setminus \{j\}} (U_{i,k} - U_{r_k})_+$ is the maximum utility of s_i when breaking the cooperation with r_j and $\max_{l \in \partial j \setminus \{i\}} (U_{l,j} - U_{s_l})_+$ is that of r_j.

The MNBO guarantees that each player selects its best cooperator and obtains a fair utility considering the topology effect. An MNBO is illustrated in Fig. 3(b), where s_1 selects r_1 for cooperation and s_2 selects r_2 with $U_{s_1} = \frac{1}{3}U$, $U_{r_1} = \frac{2}{3}U$, $U_{s_2} = \frac{2}{3}U$, $U_{r_2} = \frac{1}{3}U$. They all find their best cooperators, since $U_{s_1} + U_{r_1} = U$, $U_{s_2} + U_{r_2} = U$, and $U_{r_1} + U_{s_2} = \frac{4}{3}U > U$. In addition, topology effect is reflected by the fact that the nodes r_1 and s_2 are located at powerful positions (with superiority in topology) get higher payoffs.

B. Bargaining Outcome and Properties

We at first prove that for any cooperative relay network, there always exists at east one MNBO. Moreover, any MNBO satisfies the NE conditions defined in (7), implying that the MNBO is a stronger solution than the NE.

Theorem 1: There exists at least one MNBO outcome in a cooperative relay network.

Proof: In the cooperative relay networks, the nodes can be separated into two sets: sources and relays. Hence, the network can be abstracted as a bipartite graph (as a cooperation edge can only occur between a source and a relay). In a bipartite graph, there exists at least one MNBO [9]. ■

Theorem 2: An MNBO satisfies the NE conditions in (7).

Proof: Under an NE, each node cannot unilaterily change its strategy to obtain a higher payoff. For each source s_i who obtain a payoff U_{s_i} in cooperation (s_i, r_j), it may change its strategy in two ways: 1) stay in the same cooperation and negotiate with the cooperator r_j to obtain a different (hopefully higher) payoff U'_{s_i}, or 2) choose to cooperate with another relay r_k. When s_i stays in the same cooperation, s_i can obtain at most $U'_{s_i} = U_{i,j} - U_{r_j} \leq U_{s_i}$ according to equation (10). When s_i chooses to cooperate with another relay r_k, to obtain a payoff U'_{s_i}, and r_k obtains U'_{r_k}. Such a new cooperation will be possible only if relay r_k can receive a new payoff that is no smaller than its current payoff, i.e., $U'_{r_k} \geq U_{r_k}$. Based on the second inequation in (10), we have $U'_{s_i} + U'_{r_k} = U_{i,k} \leq U_{r_k} + U_{s_i}$. Hence, we have $U'_{s_i} \leq U_{s_i}$ no matter how source s_i changes its strategy. This indicates that s_i cannot unilaterally change its strategy to improve its payoff. With the similar analysis on sources without cooperation and relays with and without cooperation, we can derive that each node cannot improve its utility through strategy alternation. Thus, the MNBO guarantees an NE. ■

We then show that an MNBO can also achieves the social optimality of the entire network.

Definition 2: The social welfare $W(\mathcal{S}, \mathcal{R})$ is defined as the sum of payoffs of all source nodes and all relay nodes:

$$W(\mathcal{S}, \mathcal{R}) = \sum_{s_i \in \mathcal{S}} U_{s_i} + \sum_{r_j \in \mathcal{R}} U_{r_j}.$$

Theorem 3: An MNBO maximizes the social welfare.

Proof: Given any cooperation set M, the social welfare of the network can be calculated as $W(\mathcal{S}, \mathcal{R}) = \sum_{(s_k, r_l) \in M} (U_{s_k} + U_{r_l}) = \sum_{(s_k, r_l) \in M} U_{k,l}$ according to (6). Under an MNBO, we denote $U^*_{s_k}$ as the utility of each source s_k and $U^*_{r_l}$ as the utility of each relay r_l. With summing up the utilities for all nodes, we can calculate the social welfare under an MNBO as $W^*(\mathcal{S}, \mathcal{R}) = (\sum_{s_i \in \mathcal{S}} U^*_{s_i} + \sum_{r_j \in \mathcal{R}} U^*_{r_j})$, which is no smaller than $\sum_{(s_k, r_l) \in M} (U^*_{s_k} + U^*_{r_l})$. In addition, we have $\sum_{(s_k, r_l) \in M} (U^*_{s_k} + U^*_{r_l}) \geq \sum_{(s_k, r_l) \in M} U_{k,l} = W(\mathcal{S}, \mathcal{R})$, according to (10). Hence, we have $W^*(\mathcal{S}, \mathcal{R}) \geq W(\mathcal{S}, \mathcal{R})$, which indicates that the social welfare achieved under an MNBO is no smaller than the social welfare achieved under any other type of cooperation formation. This implies that the social welfare is maximized under an MNBO. ■

V. Natural Algorithm

In this section, we design an distributed algorithm to achieve an approximate multi-node Nash bargaining outcome. The algorithm enables each node to take advantage of its topology property in cooperator selection and payment bargaining. We name the algorithm as natural algorithm, it is based on the idea of natural dynamics question in [10].

A. Algorithm Design

Our distributed consists of three steps, which is executed iteratively at any state of the network. The first step is for

Algorithm 1: Natural Algorithm

Step 1: Information Exchange

1) Each s_i sends a pilot to d_i and each r_j;
2) Each d_i estimates SNR γ_{s_i,d_i} and γ_{r_j,d_i} and r_j estimates γ_{s_i,r_j};
3) Each r_j estimates its power cost transmitting data to each d_i;
4) Each d_i sends γ_{s_i,d_i} and γ_{r_j,d_i} to s_i and each r_j;
5) Each r_j sends γ_{s_i,r_j} and c_j to s_i;
6) Each source s_i and each relay r_j calculates $U_{i,j}$;

Step 2: Iteration of Selection and Bargaining

Initialization with $t = 0$ and random $Y_{r_j \to s_i}(0)$ and $Y_{s_i \to r_j}(0)$, given a δ and an α;

while *(Inequation (12) is not satisfied)* **do**

1) t=t+1;
2) Calculate outside options of each node with (11);
3) Each source s_i exchanges $\varphi_{s_i \backslash r_j}(t)$ with relay r_j and so does each r_j;
4) Calculate offers of each node with (11);

end

Step 3: Results Extraction

1) Match pair $(s_i, r_j) \in \mathcal{M}$ only when $r_j = arg(\max_{r_k} Y_{r_k \to s_i}(T^*(\delta)))$;
2) Payoff of each source s_i: $U_{s_i} = Y_{r_j \to s_i}(T^*(\delta)),\ (s_i, r_j) \in \mathcal{M}$;
3) Payoff of each relay r_j: $U_{r_j} = Y_{s_i \to r_j}(T^*(\delta)),\ (s_i, r_j) \in \mathcal{M}$;
4) For each pair $(s_i, r_j) \in \mathcal{M}$, payment from s_i to r_j: $\mu_{i,j} = \nu_{i,j} = R_{i,j} - R_{i,0} - U_{s_i}$;

channel state estimation and information sharing, the second step is for cooperator selection and payment bargaining, the third step is for result extraction.

At the first step, sources send control messages to possible cooperative relays and destinations for channel state estimation (CSI). Then they exchange the CSI.

The second step is for each node to bargain with its neighbors on how to divide the pairwise utilities. To clearly elaborate on the second step, we define two parameters for each node (source or relay) i: *offer* $Y_{k \to i}(t)$ and *outside option* $\varphi_{i \backslash j}(t)$, as shown in Definition 3 and Definition 4.

Definition 3: Given a network with the pairwise utility $U_{i,j}$ between each pair (i, j) (where one node in (i, j) is a source and the other is a relay), the outside option for node i from node j at the t's iteration is denoted as $\varphi_{i \backslash j}(t)$, which represents the maximum utility i can obtain without j.

Definition 4: $Y_{k \to i}(t)$ denotes the offer from node k to i, which represents the largest payoff that node k would like to give to node i.

The quantitative calculation of $\varphi_{i \backslash j}(t)$ and $Y_{k \to i}(t)$ is given as follows:

$$\begin{cases} \varphi_{i \backslash j}(t) = \alpha \cdot \left(\max\limits_{k \in \partial i \backslash j} Y_{k \to i}(t-1) \right) + (1 - \alpha) \cdot \varphi_{i \backslash j}(t-1), \\ Y_{k \to i}(t) = \left[U_{k,i} - \varphi_{k \backslash i}(t)\right]^+ - \frac{1}{2} \left[U_{k,i} - \varphi_{k \backslash i}(t) - \varphi_{i \backslash k}(t)\right]^+, \end{cases} \tag{11}$$

where $[\cdot]^+ = \max\{0, \cdot\}$, and $\alpha \in (0, 1)$ is a *damping factor* and ∂i is the set of node i's neighbors.

When $t = 0$, for each pair of nodes (s_i,r_j) with $U_{i,j} > 0$, we set random $Y_{r_j \to s_i}(0)$ and $Y_{s_i \to r_j}(0)$ such that they satisfy $Y_{s_i \to r_j}(0) + Y_{r_j \to s_i}(0) = U_{i,j}$. At the tth iteration, for any source node s_i and any relay node r_j with $U_{i,j} > 0$, they calculate the information of their outside options $\varphi_{s_i \backslash r_j}(t)$ and $\varphi_{r_j \backslash s_i}(t)$, and then exchange their outside options and bargain on the offer through (11). The algorithm terminates at the time $T^*(\delta)$, when each node in the network cannot adjust its outside option in a δ restriction as follows:

$$\begin{cases} |(\varphi_{s_i/r_j}(T^*(\delta)) - \varphi_{s_i/r_j}(T^*(\delta) - 1))| < \delta, \forall (s_i, r_j) \\ |(\varphi_{r_j/s_i}(T^*(\delta)) - \varphi_{r_j/s_i}(T^*(\delta) - 1))| < \delta, \forall (s_i, r_j) \end{cases} \tag{12}$$

where δ is small number named as a *convergence decision factor* for convergence, where $\delta \to 0$ when $(T^*(\delta)) \to \infty$.

The third step is to extract the results. Each source s_i selects a relay r_j with the largest $Y_{r_j \to s_i}(T^*(\delta))$. The payoff for each source U_{s_i} and each relay U_{r_j} can be calculated respectively as $U_{s_i} = Y_{r_j \to s_i}(T^*(\delta))$ and $U_{r_j} = Y_{s_i \to r_j}(T^*(\delta))$. For more details, please see Algorithm 1.

B. ε-Property of Natural Algorithm

The algorithm can reach a ε-multi-node Nash bargaining outcome. An ε-multi-node Nash bargaining outcome is defined as follows:

Definition 5: An ε-multi-node Nash Bargaining outcome is an outcome where the properties are satisfied simultaneously:

$$\begin{cases} U_{s_i} + U_{r_j} \geq U_{i,j}, \\ |(U_{s_i} - \max\limits_{r_k \in \partial s_i \backslash r_j} [U_{i,k} - U_{r_k}]^+) \\ \quad - (U_{r_j} - \max\limits_{s_l \in \partial r_j \backslash s_i} [U_{j,l} - U_{s_l}]^+)| < \varepsilon,\ \forall\ (s_i, r_j) \in M, \end{cases} \tag{13}$$

where M denotes the set of cooperation pairs.

The ε-multi-node Nash bargaining outcome guarantees the first inequation in (10), which indicates that the social welfare is maximized according to Theorem 3. However, the approximate bargaining indicates that an ε-divergence happens in terms of how to divide the common value of the cooperation as in the second inequation in (13).

Theorem 4: Algorithm 1 converges to an ε-multi-node Nash bargaining outcome, where $\varepsilon = 6 \cdot M \cdot N \cdot \delta$.

The authors in [10] have proved that for a graph $G(V, E)$ with $U_{i,j}$ on each edge the ε-Nash bargaining outcome is guaranteed at iteration T^* when the following equation is satisfied:

$$\sum_{(i,j) \in E} |(\varphi_{i/j}(T^*) - \varphi_{i/j}(T^* - 1))| < \frac{\varepsilon}{6}. \tag{14}$$

Combining (14) with (12), we can show that our algorithm guarantees a ε-Nash bargaining outcome, where $\varepsilon = 6 \cdot M \cdot N \cdot \delta$.

VI. Simulation Results

We first verify the topology effect in cooperative relay networks with numerical results (Fig. 4). Then, we illustrates that our natural algorithm can reach the social optimality (Fig. 5). The simulation parameters are given as follows. The transmit power of each source is 0dBm, and the average noise power is -90dBm. The spectrum resources for each source-to-destination

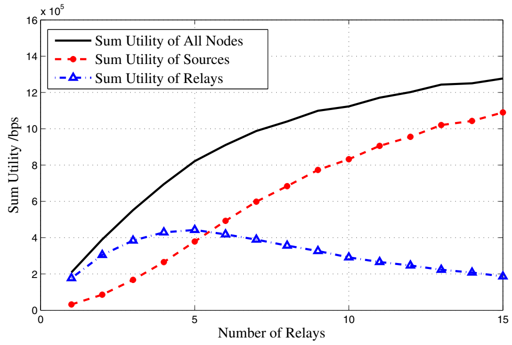

Fig. 4. Sum Utility vs Number of Relays

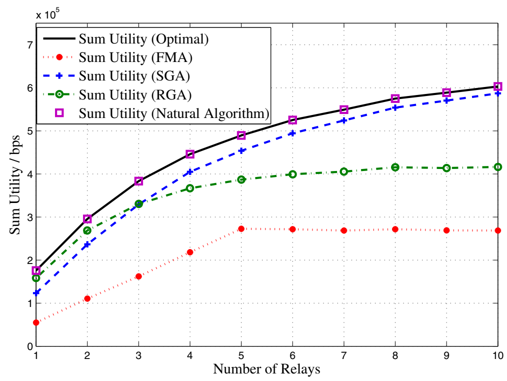

Fig. 5. Sum Utility of All Nodes with Different Distributed Algorithms

pair is 500kHz. We first illustrate the social optimal and the individual optimal with our algorithm. Then, we discuss the topology effect of the networks.

A. Illustration of Topology Effect

Fig. 4 reveals the change of sum utility when the number of relays changes in an MNBO. The region size is 100m$\times$100m containing 10 source-destination pairs. The number of relays varies from 1 to 20. With the number of relays increasing, the potential benefits of cooperation increases, and the sum utility of the whole network is increasing accordingly. Correspondingly, the sum utility of sources increases as well. However, the sum utility of relays at first increases and then decreases. When the number of relays is below 5, having more relays indicates that more cooperation pairs can be constructed to reach a higher sum utility of relays. When the number of relays exceeds 5, having more relays indicates more competition inside the relay set. Such competition drives the relay prices down, resulting in a lower total relay utility. With 5 relays in the network, the sum utility of relays is 54% of the sum utility of all nodes. The number decreases to 16% when 15 relays exist in the network.

B. Social Welfare Comparison

Fig. 5 illustrates the sum utility improvement of the natural algorithm together with other distributed benchmark algorithms. The network consists of 5 sources. The number or relays varies from 1 to 10. The curve of optimal sum utility with relays is drawn by enumerating all possible relay selection schemes and then choosing the one with the maximum data rate in a centralized way. In the fixed matching algorithm (FMA) sources and relays randomly form the cooperation pairs. In the source-side greedy algorithm (SGA), each source s_i selects its best cooperator r_j sequentially. In the relay-side greedy algorithm (RGA), each relay r_j selects its best cooperator s_i sequentially. We can see that our natural algorithm achieves the maximum sum utility among all distributed algorithms.

VII. Conclusion

In this paper, we study the relay selection and payment bargaining in a cooperative relay network with multiple sources and multiple relays. We introduce a multi-node Nash bargaining framework based on the network exchange theory, which can capture the topology effect, and provide nodes with topology priority with larger benefits. In addition, the multi-node Nash bargaining outcome guarantees both the Nash equilibrium and the social optimality. Simulation results illustrate the topology effect and shows that natural algorithm achieves a better performance than other distributed algorithms. There are several interesting directions for extending this work. An important one is to study a more general cooperative relay network model, where each source can employ multiple relays to transmit his data, and each relay can help multiple sources simultaneously.

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