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Pareto optimal time-frequency resource allocation for selfish wireless cooperative multicast networks

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Abstract In selfish wireless cooperative multicast networks (WCMNs), a source node wants to achieve the optimal benefit (i.e., rate gain), while the relaying nodes are willing to get fairness rewards (i.e., rate gains) from the source for the cooperative relaying. In this paper, we implement these two different objectives for the source and the relays through the Pareto optimal resource allocation. Define the cooperative strategy of a node as the fraction of a data-frame that it is willing to contribute to its cooperative partners. Consider the rational decision made by one node will definitely affect its cooperative partners' choice. Then, we can formulate this resource sharing problem as a Nash bargaining problem (NBP), and the Nash bargaining solution (NBS) to the NBP encapsulates the Pareto optimality naturally. Finally, to enable the nodes to be capable of computing the NBS cooperative strategies rapidly as the wireless channel changes, we propose a fast particle swarm optimizer (PSO) algorithm to search for the NBS. Simulation results show that the two specified objectives of the source and the relays can be implemented in the Pareto optimal sense, i.e., the source can achieve a significant performance gain in comparison with direct multicast and the relays can get a fair reward by the source according to the level of contribution it has made to improve the performance of the source.

Keywords wireless cooperative multicast, resource allocation, Nash bargaining problem, Nash bargaining solution, particle swarm optimizer

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1 Introduction

Wireless multicast is a bandwidth efficient communication technique, where the transmission-frames of a source node are delivered to multiple destination nodes simultaneously [1] (Figure 1). To guarantee that destinations with bad channels could receive the frames correctly, the source may have to use a low transmission-rate, thus greatly limiting the network performance. Recently, cooperative multicast (CM) [2] has emerged as an effective technique to tackle this problem. In wireless cooperative multicast networks (WCMNs), the receiving nodes with good channels could help the source relay its frames. Therefore, the benefits of spatial diversity among the receiving nodes can be exploited, and the network performance, e.g. the bit error rate (BER) or the transmission rate, can be greatly improved.

In most existing CM strategies (see e.g. [2,3]), it is assumed that the receiving nodes will cooperate unconditionally and always forward data when selected as relays. However, in commercial applications, a

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user node tends to be "selfish" in consuming its channel resources (e.g., time-slot in time division multiple access (TDMA) system or frequency-bandwidth in frequency division multiple access (FDMA) system) solely to maximize its own benefit. Therefore, a CM strategy should jointly consider the benefits of the source and the relay nodes.

Recently, cooperation incentive mechanisms for WCMNs based on pricing-mechanisms [4,5] are proposed. In pricing-mechanisms, a relay is usually assumed to have temporarily idle resources such that it has opportunity to sell the resource to other nodes, and thereby, generate revenue. The revenue can later be used by the relay to encourage others to cooperate. Although pricing-mechanisms could motivate selfish nodes to use system resources more efficiently, it suffers some major drawbacks:

• The price, which is used as a signal to indicate the state of supply and demand of communication resources between the relays and the sources bears little concrete physical meaning and thus it is difficult to find its way directly into practical network applications.

• In full-loaded situations where a relay's transmission demand (e.g., the minimum transmission rate requirement) cannot be fulfilled, there will be no more resources left for selling to other nodes.

• Pricing-mechanisms always rely on the use of tamper-proof hardware to store and check credit [6]. This strategy may hinder their ability to find wide-spread acceptance.

Without resorting to the pricing-mechanisms, we consider one node can trade its communication resources for its partner's cooperation directly. Thus, the tamper-proof hardware used in pricing-mechanisms is avoided. In addition, the resource-exchange based mechanism also takes effect in full-loaded situations, since it will lead to a win-win situation by improving the performances of both the source and the relays.

Define the cooperative strategy of a node as the fraction of a data-frame that is willing to contribute to its cooperative partners. We can formulate the proposed resource-exchanging problem for WCMNs as a Nash bargaining problem (NBP) [7]. By solving the Nash bargaining solution (NBS) [7] of the NBP, the cooperative payoff (i.e., rate gains) can be distributed fairly and efficiently between the source and the relays in the Pareto optimal sense (Definition 1 in Section 3). The NBS result also has a concrete physical meaning, i.e., each energy-constraint node is willing to cooperate only if the transmission rate achieved through cooperation will be not lower than that achieved without the cooperation by consuming the same amount of energy

The remainder of this paper is organized as follows. Section 2 introduces the considered selfish WCMN model. In Section 3, we formulate the cooperative resource allocation problem as an NBP. Then, in Section 4, we develop a fast particle swarm optimizer (PSO) [8] algorithm to solve the NBS. Simulation results are presented in Section 5. Finally, conclusions are drawn in Section 6.

2 System model

The considered wireless multicast network model is shown in Figure 1 [3]. Two groups of user nodes are randomly moving within two far apart circular areas, respectively. Without loss of generality, we assume that the nodes within a group are closed to each other, and a source node s in Group A multicasts its data frames to a group of $L+1$ nodes (i.e., nodes $\{r_1, \ldots, r_L\}$ and d) in Group B. Since the distance between node s and each node in Group B is much larger than the average distance between any pair of nodes in Group B, the worst channel gain between nodes s and d will act as the transmission rate bottleneck for the wireless multicast.

To enhance the system performance, we consider that some nodes in Group B may serve as relays for node s and use the cooperative multicast (CM) technology to help forward information to its destination d. Assuming the half-duplex amplify-and-forward protocol [9] is employed by the system, the CM occurs in the following two stages. In Stage 1, node s transmits its information, and, due to the broadcast nature of the wireless channels, all the nodes in Group B can receive the information. In Stage 2, some selected relays help node s by amplifying and forwarding the received signal. In both stages, we assume that the source and the relays transmit their signals through orthogonal channels using the TDMA technology and each frame consists of one time-slot (Figure 2).

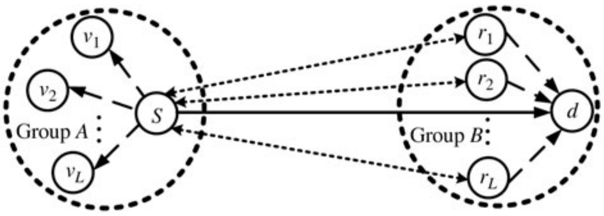

Figure 1 Cooperative multicast network model.

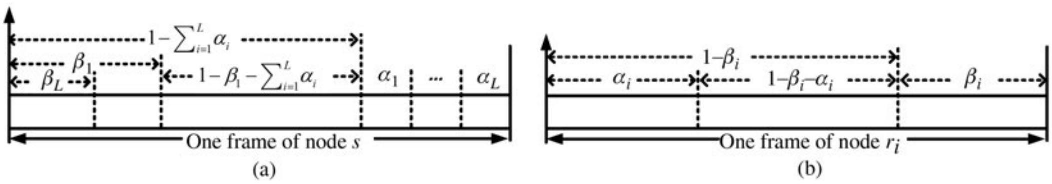

Figure 2 (a) The frame structure of node; (b) the frame structure of node r_i.

In the considered selfish network environments, if node r_i ($\forall i \in \{1,\dots,L\}$) serves as a relay and provides some cooperation benefits for node s, node s should reward node r_i for the relaying. Considering the selected node r_i has its own frames to transmit to destination node v_i in Group A, since the path from node s to node v_i is with good channel condition, node s can use some of its own channel resources to relay frames originating from node r_i as the reward. Thus, node r_i has an incentive to form a coalition with node s for the cooperation. If node s cannot reward node r_i through the resource exchanging, node r_i will quit the coalition to save its energy. Therefore, we make the following assumptions:

• If node r_i is willing to take out $\beta_i (0 \leqslant \beta_i < 1)$ fraction time of a frame to relay the data originating from node s, it will relay β_i fraction data of a frame of node s. Then, as the reward, node s should take out α_i ($0 \leqslant \alpha_i < 1$) fraction time of a frame to relay α_i fraction data of a frame of node r_i.

•A node will only relay the data originating from its cooperative partner and will not relay the data originating from itself and then relayed by the partner node. Thus, the relaying loop is avoided.

Suppose that the transmission power of each node is fixed at p W, and node s arranges the involved L relays in a descending order according to their cooperation strategy. Then we have $\beta_1 \geqslant \cdots \geqslant \beta_L$. The designed frame structures for both nodes s and r_i are shown in Figure 2(a) and Figure 2(b), respectively.

From Figure 2(a) we know that node s can use $1-\sum_{i=1}^{L}\alpha_i$ fraction time of a frame to transmit its own data, in which only β_1 fraction data will be transmitted in a cooperative manner, while the remaining $1-\beta_1-\sum_{i=1}^{L}\alpha_i$ fraction data can only be directly transmitted to node d without any cooperation. Hence, we have

$$0 \leqslant 1-\beta_1-\sum_{i=1}^{L}\alpha_i \leqslant 1. \tag{1}$$

From Figure 2(b), we also know that node r_i can transmit its own data using $1-\beta_i$ fraction time of a frame, in which only α_i fraction data will be relayed by node s and the data carried on the remaining $1-\beta_i-\alpha_i$ fraction transmission time can only be directly transmitted to its destination node v_i without any cooperation. Hence, we have

$$0 \leqslant 1-\beta_i-\alpha_i \leqslant 1. \tag{2}$$

Since $\beta_1 \geqslant \beta_i$ and $\sum_{i=1}^{L}\alpha_i \geqslant \alpha_i$ ($1 \leqslant i \leqslant L$), combining (1) and (2), we can then have

$$\sum_{i=1}^{L}\alpha_i + \beta_1 \leqslant 1. \tag{3}$$

Let $\gamma_{x,y}$ denote the signal-to-noise ratio (SNR) of the channel between any pair of nodes x and y ($y \neq x$). Using the traditional direct transmission, the noncooperative (NC) channel capacities achieved by nodes s and r_i can be expressed as

$$R_s^{\mathrm{NC}} = \frac{1}{1+L}\log_2(1+\gamma_{s,d}) \quad \text{and} \quad R_{r_i}^{\mathrm{NC}} = \frac{1}{1+L}\log_2(1+\gamma_{r_i,v_i}), \tag{4}$$

respectively, where 1+L is the bandwidth factor [9].

Using the CM, at destination node d, the signal received at Stage 1 and the k ($0 \leqslant k \leqslant L$) signals received at Stage 2 are combined using maximal ratio combining (MRC). The SNR at the output of the MRC is $\gamma_{s,d} + \sum_{i=1}^{k} \gamma_{s,r_i,d}$, where $\gamma_{s,r_i,d} = \frac{\gamma_{s,r_i} \cdot \gamma_{r_i,d}}{1+\gamma_{s,r_i}+\gamma_{r_i,d}}$ [9]. For an easy expression, we define $\beta_{L+1} = 0$. The cooperative channel capacity of node s can then be expressed by

$$R_s^C = \frac{1}{L+1}\Bigg[\sum_{k=2}^{L+1}(\beta_{k-1} - \beta_k)\log_2\left(1 + \gamma_{s,d} + \sum_{i=1}^{k-1}\gamma_{s,r_i,d}\right) + \left(1 - \beta_1 - \sum_{i=1}^{L}\alpha_i\right)\log_2(1 + \gamma_{s,d})\Bigg], \quad (5)$$

where the first term tells us that β_1 fraction data of a frame of node s is transmitted to node d in a cooperative manner, and the second term means that the remaining $1 - \beta_1 - \sum_{i=1}^{L}\alpha_i$ fraction data of the frame of node s can only be transmitted to node d directly. We can think of (5) as the sum of transmission rates of L+1 "parallel" channels, one from node s to the destination node d and the other from the set of L involved relays to node d.

Similarly, we can express the cooperative channel capacity of node r_i helped by node s as

$$R_{r_i}^C = \frac{1}{L+1}[\alpha_i \log_2(1 + \gamma_{r_i,v_i} + \gamma_{r_i,s,v_i}) + (1 - \alpha_i - \beta_i)\log_2(1 + \gamma_{r_i,v_i})], \quad 1 \leqslant i \leqslant L, \quad (6)$$

where $\gamma_{r_i,s.v_i} = \frac{\gamma_{r_i,s} \cdot \gamma_{s.v_i}}{1+\gamma_{r_i,s}+\gamma_{s.v_i}}$. The first term in (6) indicates that α_i fraction data of a frame of node r_i is transmitted to node v_i in a cooperative manner, and the second term indicates that the remaining $1 - \alpha_i - \beta_i$ fraction data of the frame can only be transmitted to node v_i directly.

Since the transmission rate is no larger than the corresponding channel capacity in the following analysis, we use the capacities (4)–(6) to represent the data-rate of nodes s and r_i as in [9,10].

3 Pareto optimal resource allocation

3.1 Cooperative bargaining game model

Formally, a two-user bargaining game consists of a disagreement point $\boldsymbol{R}^{\min} = (R_1^{NC}, R_2^{NC})$ and the set of possible agreements $\boldsymbol{R} = (R_1^C, R_2^C)$. $\boldsymbol{R}$ is also known as a feasibility set, and points in $\boldsymbol{R}$ must all be better than the disagreement point $\boldsymbol{R}^{\min}$. Within $\boldsymbol{R}$, a payoff distribution is said to be Pareto optimal, if there exists no other payoff distribution for which one node can improve its payoff without reducing the payoffs of the other nodes. The goal of bargaining is to choose the feasible agreement in $\boldsymbol{R}$ that would result in Pareto optimal payoff distribution after thorough negotiations. If an agreement between both nodes cannot be reached, the payoffs the nodes will receive are given by the disagreement point.

An NBS is a social optimal solution to a cooperative bargaining game, which ensures that, after each node is assigned with the minimal payoff/capacity, the remaining resources are allocated to the nodes proportionally according to their bargaining abilities (i.e., the channel link conditions.).

3.2 Pareto optimal solution

Using the CM, node s could achieve an optimal rate gain and hence alleviate the bottleneck effect of the multicast system. At the same time, selfish node r_i acting as a relay should get a fairness reward (i.e., rate gain) from node s for the cooperative relaying. These two different objectives of nodes s and r_i can be implemented through the Pareto optimal rate/payoff allocation [7].

Definition 1 (Pareto optimality). Define $U_s = R_s^C$ and $U_{r_i} = R_{r_i}^C$ as the cooperative rates/payoffs for nodes s and r_i in the CM, respectively. A Pareto optimal rate allocation $\boldsymbol{U}^* = \{U_s^*, U_{r_1}^*, \ldots, U_{r_L}^*\}$ states that there is no other allocation $\boldsymbol{U}' = \{U_s', U_{r_1}', \ldots, U_{r_L}'\}$ that can lead to better rate gains for some nodes (i.e., $U_j' > U_j^*$, $\exists j \in \{s, r_1, \ldots, r_L\}$) without causing rate decrease for some other nodes (i.e., $U_j' < U_j^*$, $\exists j \in \{s, r_1, \ldots, r_L\}$) [5].

Let us define $U_s^{\min} = R_s^{NC}$ and $U_{r_i}^{\min} = R_{r_i}^{NC}$ as the noncooperative rates for nodes s and r_i, respectively. By Definition 1 the Pareto optimal rate allocation ensures that (i) node s could achieve an optimal rate gain $U_s^{-} U_s^{\min}$ through the cooperation, and (ii) node r_i could get a fairness reward, i.e., rate gain $U_{r_i}^{-} U_{r_i}^{\min}$ from node s when participating in the cooperation If the achieved rate is less than $U_{r_i}^{\min}$, node r_i could choose to quit the cooperation [7]. Thus, the two specified objectives of nodes s and r_i can be implemented in the Pareto optimal sense.

From (5)–(6), we note that the cooperative rate of a node is determined by not only its own cooperative strategy in Stage 1, but also the cooperative strategy of the cooperative partner node in Stage 2. It reflects the fact that nodes s and $\{r_1, \ldots, r_L\}$ should share their resource to seek the cooperation, and the rational decision made by one node will definitely affect its cooperative partners' choice. So, we can formulate this resource sharing problem as a Nash bargaining problem (NBP). The NBP is used to investigate how much collective rate a set of nodes can gain and how to fairly divide this rate among them. Nash demonstrated that there exists a unique solution, called the Nash bargaining solution (NBS) for a NBP, which encapsulates the Pareto optimality. According to [7], a unique NBS for the proposed NBP can be obtained by solving the following maximization problem:

$$\begin{aligned} &\max Q, \quad Q = (R_s^C - R_s^{NC}) \textstyle\prod_{i=1}^{L} (R_{r_i}^C - R_{r_i}^{NC}) \\ &\text{s.t.} \;\; \beta_1 \geqslant \ldots \geqslant \beta_L \quad \text{and} \quad 0 \leqslant 1 - \beta_1 - \textstyle\sum_{i=1}^{L} \alpha_i \leqslant 1, 1 \leqslant i \leqslant L. \end{aligned} \tag{7}$$

Besides Pareto optimal, the NBS also satisfies other five axioms, which are individual rationality, feasibility, independence of irrelevant alternatives, independence of linear transformations, and symmetry. The detailed explanation for these axioms can be found in [7]. The knowledge required by a node is the channel state information (CSI) including that for source-destination, source-relay, and relay-destination channels of its own and the cooperative partner nodes. Assume the channels are slow fading and remain constant over any two stags for the CM, and the CSI can be acquired by each node through the dedicated feedback channels. The NBS can then be computed by each node independently by solving the same problem (7).

Moreover, problem (7) is a multi-objective optimization problem in nature [11], since the cooperative strategies $\{\alpha_1, \ldots, \alpha_L\}$ and $\{\beta_1, \ldots, \beta_L\}$ should be jointly optimized. Thus, a mathematical algorithm for searching for the optimal point of problem (7) may have very high computation complexity of $O(N^{2L})$. To enable the nodes to compute the NBS cooperative strategies rapidly as the wireless channel changes, a fast convergence that takes only a few iterations to the optimal solution of problem (7) is expected.

4 Solving the game

In this section, we propose a particle swarm optimizer (PSO) [8] based low-complexity numerical algorithm to search for the NBS of the proposed game (7).

A basic PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles move around in the search-space according to a few simple formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position and it is also guided toward the best known positions in the search-space, which are updated as better positions found by other particles. The process is repeated until the swarm achieves the best solutions.

Formally, to solve problem (7), we define the objective function Q as the fitness function which must be maximized. Let S be the number of particles in the swarm. Each particle has a position $\boldsymbol{x}_j = \{\alpha_{1,j}, \ldots, \alpha_{L,j}, \beta_{1,j}, \ldots, \beta_{L,j}\}$ and a velocity $\boldsymbol{v}_j$ $(j = 1, \ldots, S)$ with the search-space of $\alpha_{i,j}, \beta_{i,j} \in [0, 1]$. The fitness function takes a candidate solution $\boldsymbol{x}_j$ as argument in the form of a vector of real numbers, and produces a real number $Q(\boldsymbol{x}_j)$ as output which indicates the fitness of the given candidate solution $\boldsymbol{x}_j$. Let $\boldsymbol{y}_j$ be the best known position of particle j and let $\boldsymbol{z}$ be the best known position of the entire swarm. The proposed PSO algorithm for solving for the proposed game (7) is described as in Algorithm 1.

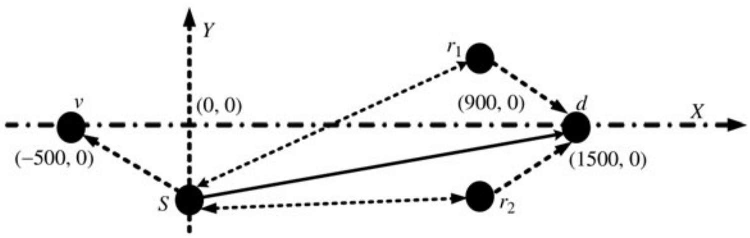

Figure 3 Simulated cooperative multicast system.

Algorithm 1. PSO algorithm for searching for the NBS of the game (7)

1. For each particle $j = 1, \dots, S$ do:
   1) Initialize the particle's position with a uniformly distributed random vector $\boldsymbol{x}_j \sim f(0, 1)$, where $f(\cdot)$ is the uniform distribution function.
   2) Initialize the particle's best known position to its initial position: $\boldsymbol{y}_j \leftarrow \boldsymbol{x}_j$. If $Q(\boldsymbol{y}_j) > Q(\boldsymbol{z})$, update the swarm's best known position: $\boldsymbol{z} \leftarrow \boldsymbol{y}_j$.
   3) Initialize the particle's velocity: $\boldsymbol{v}_j \sim f(-b, b)$ where $b(0 < b < 1)$ is the speed adjustment parameter of the particles.
2. Until a termination criterion, i.e., number of iterations performed is met, repeat:
   1) For each particle $j = 1, \dots, S$ do:
      (1) Pick random numbers: c_1, $c_2 \sim f(0, 1)$.
      (2) Update the particle's velocity: $\boldsymbol{v}_j \leftarrow \rho \boldsymbol{v}_j + \kappa_1 c_1(\boldsymbol{y}_j - \boldsymbol{x}_j) + \kappa_2 c_2(\boldsymbol{z} - \boldsymbol{x}_j)$, where ρ is the particle inertia weight, κ_1 and κ_2 are the learning factors. These parameters ρ, κ_1 and κ_2 are selected by the practitioner to control the behavior and efficacy of the PSO method [6].
      (3) Update the particle's position: $\boldsymbol{x}_j \leftarrow \boldsymbol{x}_j + \boldsymbol{v}_j$.
      (4) If $Q(\boldsymbol{y}_j) < Q(\boldsymbol{x}_j)$, update the particle's best known position: $\boldsymbol{y}_j \leftarrow \boldsymbol{x}_j$.
      (5) If $Q(\boldsymbol{y}_j) > Q(\boldsymbol{z})$, update the swarm's best known position: $\boldsymbol{z} \leftarrow \boldsymbol{y}_j$.
3. Now $\boldsymbol{z}$ holds the best found solution.

5 Simulation results

The simulated system is illustrated in Figure 3. We located node r_1 at (1000 m, 300 m), node r_2 at (1000 m, −300 m), node d at (1500 m, 0 m) and node v at (−500 m, 0 m). The x coordinate of node s is fixed at 0 m, and its y coordinate is varied from −800 m to 800 m. Node s multicasts data-frames to a group of nodes $\{r_1, r_2, d\}$, while the relay nodes $\{r_1, r_2\}$ have the common destination node v. The path gain is set to $0.097/d^4$ [7], where d is the distance between the transmitter and the receiver (in meters) and the noise level of the additive white Gaussian noise channels is set to 10^{-14} W. We set the transmit power for each node to 3 mW.

The performance of the proposed NBS based CM strategy is evaluated and compared with that of the direct multicast (DM) scheme without cooperation. Let Y denote the y coordinate of node 1. Figure 4 shows the rate gains of nodes s, r_1 and r_2 in comparison with the DM scheme. Figure 5 shows the corresponding NBS CM strategies of the nodes, as node s moves.

From Figure 4, we can see that the proposed NBS based CM strategy achieves the Pareto optimal rates allocation, since it leads to superior performance to the DM scheme for all the cooperative nodes. We can conclude that the proposed game can stimulate selfish user nodes to cooperate in relaying effectively. When -800 m$< Y < -620$ m, the channel conditions from node s to nodes r_1 and r_2 are poor. It means that node s cannot reward nodes r_1 and r_2 for their cooperation through the game. Hence, nodes r_1 and r_2 refuse to cooperate with node s for the relaying. All nodes prefer to transmit individually, and the rates that the nodes achieve are given by the disagreement point. After that, when node s moves along from the point (0 m, −620 m) to the point (0 m, 0 m), all the cooperative node could achieve higher performance gains, since the channel conditions become better. When 0 m$< Y <$800 m, the situation is the opposite.

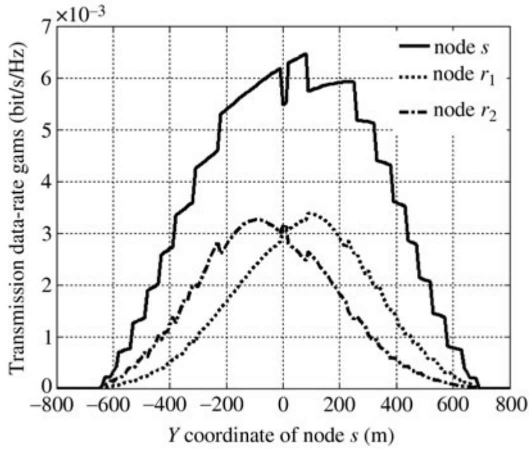

Figure 4 Rate gains of all nodes in the NBP.

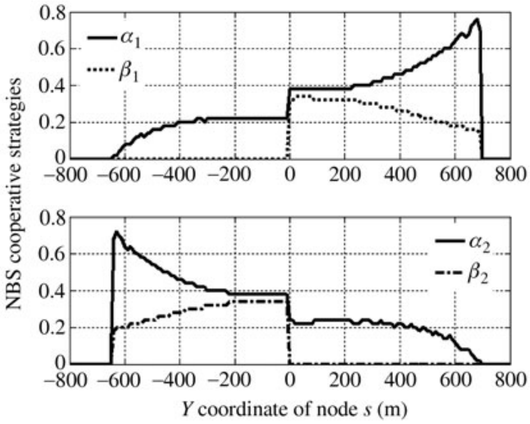

Figure 5 NBS strategies of all nodes in the NBP.

From Figure 5, we can see that, when -800 m$< Y < -620$ m, the channel from node s to node v is poor; as a result, node s cannot reward node r_1 and node r_2 for CM. Hence, node r_1 and node r_2 refuse to form coalition with node s for CM. When -620 m$< Y <0$ m, node s is willing to take out more symbols to exchange for node r_2's relaying than node r_1's, because node r_2's channel is better than that of node r_1 within this region. In return, node r_2 contributes more symbols for relaying for node s than node r_1 (close to 0). When 0 m$< Y <$800 m, the situation is the opposite. Now, we can conclude that the fairness of the proposed scheme is also demonstrated by the fact that the degree of cooperation of a node only depends on how much contribution its partner can make to increase its own rate.

Note that the time-varying channel fading is not considered in this paper, and hence the channel gain is mainly determined by the distance and the propagation loss factor as in [9].

6 Conclusion

In this paper, we propose a bargaining game theoretical framework for stimulating cooperation in selfish CM networks. Simulation results have verified that the NBS-based CM strategy can achieve a Pareto optimal rate allocation among the cooperation nodes, since all nodes could perform better cooperatively than individually. In the future work, we will further study the joint power and channel resource allocation bargaining game for the wireless CM networks.

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