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A suboptimal joint bandwidth and power allocation for cooperative relay networks: a cooperative game theoretic approach

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Abstract In commercial networks, user nodes operating on batteries are assumed to be selfish to consume their resources (i.e., bandwidth and power) solely maximizing their own benefits (e.g., the received signal-to-noise ratios (SNRs) and datarates). In this paper, a cooperative game theoretical framework is proposed to jointly perform the bandwidth and power allocation for selfish cooperative relay networks. To ensure a fair and efficient resource sharing between two selfish user nodes, we assume that either node can act as a source as well as a potential relay for each other and either node is willing to seek cooperative relaying only if the datarate achieved through cooperation is not lower than that achieved through noncooperation (i.e., direct transmission) by consuming the same amount of bandwidth and power resource. Define the cooperative strategy of a node as the number of bandwidth and power that it is willing to contribute for relaying purpose. The two node joint bandwidth and power allocation (JBPA) problem can then be formulated as a cooperative game. Since the Nash bargaining solution (NBS) to the JBPA game (JBPAG) is computationally difficult to obtain, we divide it into two subgames, i.e., the bandwidth allocation game (BAG) and the power allocation game (PAG). We prove that both the subgames have unique NBS. And then the suboptimal NBS to the JBPAG can be achieved by solving the BAG and PAG sequentially. Simulation results show that the proposed cooperative game scheme is efficient in that the performance loss of the NBS result to that of the maximal overall data-rate scheme is small while the maximal-rate scheme is unfair. The simulation results also show that the NBS result is fair in that both nodes could experience better performance than they work independently and the degree of cooperation of a node only depends on how much contribution its partner can make to improve its own performance.

Keywords cooperative relay, resource allocation, cooperative game theory, Nash bargaining solution, Pareto optimal

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1 Introduction

The basic idea of cooperative relay is to allow nearby user nodes to help relay information for each other [1]. So the spatial diversity which is available in the relay channels can be exploited. Various cooperative protocols, such as the amplify-and-forward (AF) protocol and the decode-and-forward (DF) protocol have been proposed in [2]. The physical layer performance, e.g., the channel capacity and the symbol error rate for these protocols have been extensively studied in [1,2]. In the network layer, if a collection of available relay nodes are allowed to be selected, the relay selection schemes are classified into two categories [3]: (1) selection cooperation which restricts forwarding to only one relay node from the potential relay nodes set [3–5] and (2) selection relaying which allows a subset of potential relay nodes to forward the source node's data to the destination [6].

However, the above studies are based on the assumption that all nodes are fully cooperative. This assumption is only reasonable in the relief and military environments, where networks are mainly designed to cooperate on some joint tasks, such as minimizing the total energy consumption for life extension in wireless sensor networks (WSNs) [7] and satisfying given system throughput and delay requirements [6]. In these applications, the system efficiency rather than the per-node fairness, such as minimizing energy consumption of individual user node, is emphasized.

Consider in commercial network where the user nodes with independent entities act highly autonomously. Since cooperative relaying represents a cost of resource, e.g., bandwidth [8–11] and power [12–16], the user nodes have the incentive to consume their resources solely to maximize their own benefits. In such cases, the two network objectives, i.e., fairness and efficiency, should be simultaneously considered [8–16]. To tackle this problem, game theory about how the autonomous nodes interact and cooperate with each other is a natural and powerful tool.

In the selection relaying networks, Huang et al. [16] and Zhang et al. [9] studied the problem of how a relay should allocate its power and bandwidth among multiple competing user nodes using auction theory [17] and noncooperative game theory [18], respectively. Based on the noncooperative Stackberg game theory [18], Wang et al. [15] studied another case in which multiple relays compete with each other in terms of price to gain the highest profit from offering power to a single user.

In the selection cooperation networks, Zhang et al. [8] and Zhang et al. [12–14] apply the cooperative game theory [18] to perform the bandwidth and the power allocation, respectively. In their symmetric models, either of the two cooperative user nodes can act as a source as well as a potential relay for each other. So both the nodes could trade their own resource for the partners' cooperation directly. However, ref. [8] only perform the bandwidth allocation with a fixed transmission power. And, ref. [13,14] only perform the power allocation with a fixed transmission bandwidth.

In this paper, in contrast to [9–11, 15, 16], [8] and [12–14], we will study the joint bandwidth and power allocation (JBPA) problem in the time duplex multiple access (TDMA) based selection cooperation networks. In the considered symmetric JBPA model [8,13,14], two cooperative user nodes can act as a source as well as a potential relay for each other, and consequently each node can trade its own bandwidth and power for the partner's cooperative relaying directly. Since the nodes are energy limited, they are willing to cooperate only if the data-rate achieved through cooperation will be not lower than that achieved without cooperation by consuming the same amount of resources. Define the cooperative strategy of a selfish user node as the number of symbols (i.e., the bandwidth in the TDMA-based systems) and power that it is willing to contribute for relaying purpose. The JBPA problem can be formulated as a cooperative game. Since the Nash bargaining solution (NBS) to the JBPA game (JBPAG) is computationally complex and difficult to obtain, we divide it into two subgames, i.e., the bandwidth allocation game (BAG) and the power allocation game (PAG). We prove that both the subgames have unique NBS. The suboptimal NBS to the JBPAG can then be achieved by solving the BAG and PAG sequentially. Assuming the AF cooperation protocol is utilized in the system, the performance of the proposed cooperative game is evaluated by extensive computer simulations.

The remainder of this paper is organized as follows. Section 2 introduces the symmetric selection cooperation network model. Section 3 illustrates the network objectives, i.e., fairness and efficiency. In

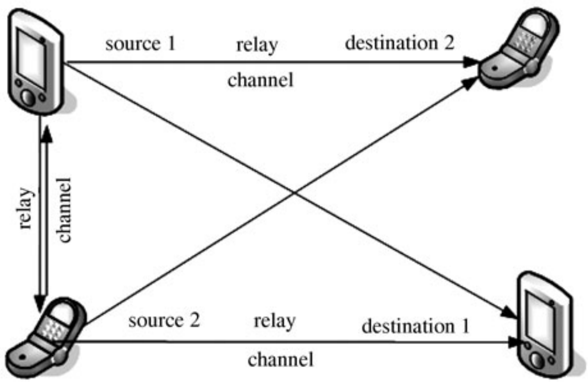

Figure 1 Symmetric selection cooperation system model.

Section 4, we formulate the JBPA problem as a two-node cooperative game. Then, in Section 5, we develop a suboptimal algorithm to search for the NBS to the JBPAG. Simulation results are presented in Section 6. Finally, some conclusions are drawn in Section 7.

2 System model

The considered symmetric selection cooperation system model [8,13,14] is illustrated in Figure 1. Nodes 1 and 2 look on nodes 3 and 4 as their final destinations, respectively. A node pair consisting of a source node i (i=1, 2) and its destination node $d(i)$ ($d(i)$=3 if i=1, and $d(i)$=4 if i=2) is denoted by a user i. Since node $j(j \neq i)$ may have better channel gains to node $d(i)$ than node i, and vice versa, node i and node j can choose each other as their partners for cooperative transmission.

Without loss of generality, we employ the AF cooperation protocol [2] in the system. Different from [8,13,14], we assume that all nodes use TDMA to share the channels and each node is allocated W hertz bandwidth for transmission. Suppose that (1) different users communicate independent information over the orthogonal channels; (2) a TDMA time slot has a length of T second and each transmission frame consists of one time slot and (3) the time length of transmission frame is short compared with the channel coherence time such that all channel gains are fixed during the time of interest. Using the AF protocol, the cooperative transmission of user i helped by relay j occurs in the following two time slots.

In the 1st time slot, source i broadcasts its own information to both destination $d(i)$ and relay j. The received signals $Y_{i,d(i)}$ and $Y_{i,j}$ at destination $d(i)$ and relay j can be expressed as

$$Y_{i,d(i)} = \sqrt{p_i^s g_{i,d(i)}} X_i^s + Z_{i,d(i)}, \tag{1}$$

and

$$Y_{i,j} = \sqrt{p_i^s g_{i,j}} X_i^s + Z_{i,j}, \tag{2}$$

respectively, where p_i^s denotes the transmission power at source i, X_i^s is the broadcast information symbol with unit energy from source i to destination $d(i)$ and relay j, $g_{i,d(i)}$ and $Z_{i,d(i)}$ are the channel gain and the additive white Gaussian noise (AWGN) from source i to destination $d(i)$, respectively, and $g_{i,j}$ and $Z_{i,j}$ are the channel gain and the AWGN from source i to relay j, respectively.

We assume that the noise variance is the same for all wireless links in the system and denote it by σ^2. In this phase, without relay j's help, the SNR resulting from the direct transmission from source i to destination $d(i)$ can be expressed by

$$\gamma_{i,d(i)} = \frac{p_i^s g_{i,d(i)}}{\sigma^2}. \tag{3}$$

In the 2nd time slot, relay j amplifies the signal $Y_{i,j}$ received in the 1st time slot and forwards it to destination $d(i)$ with retransmission power p_j^r. The received signal at destination $d(i)$ is

$$Y_{j,d(i)} = \sqrt{p_j^r g_{j,d(i)}} X_j^r + Z_{j,d(i)}, \tag{4}$$

where

$$X_j^r = \frac{Y_{i,j}}{|Y_{i,j}|} \tag{5}$$

is the transmitted symbol from relay j to destination $d(i)$ that is normalized to have unit energy, and $g_{j,d(i)}$ and $Z_{j,d(i)}$ are the channel gain and the AWGN from relay j to destination $d(i)$ respectively. Substituting (2) into (5), we can rewrite (4) as

$$Y_{j,d(i)} = \frac{\sqrt{p_j^r g_{j,d(i)}}\left(\sqrt{p_i^s g_{i,j}} X_i^s + Z_{i,j}\right)}{\sqrt{p_i^s g_{i,j} + \sigma^2}} + Z_{j,d(i)}. \tag{6}$$

By (6), the relayed SNR at destination $d(i)$ helped by relay j in the 2nd time slot is

$$\gamma_{i,j,d(i)} = \frac{p_i^s g_{i,j} p_j^r g_{j,d(i)}}{\sigma^2\left(p_i^s g_{i,j} + p_j^r g_{j,d(i)} + \sigma^2\right)}. \tag{7}$$

Now, destination $d(i)$ can combine the signal received from source i in the 1st and the AF replica received from relay j in the 2nd time slot using maximal ratio combining (MRC) [19,20] to obtain the cooperative diversity. The effective SNR of the AF cooperative channel from source i to destination $d(i)$ is [16]

$$\boldsymbol{\Gamma}_{i,d(i)} = \gamma_{i,j,d(i)} + \gamma_{i,d(i)}. \tag{8}$$

3 Bandwidth and power resource

We assume each node uses uncoded multilevel quadrature amplitude modulation (MQAM) to transmit information bits with a frame energy constraint of E joule. Consider a well defined MQAM signal constellation with a symbol period T_0 second, and assume ideal Nyquist data pulses for each constellation. The channel bandwidth is computed as $W \approx 1/T^0$ [21], and the number of symbols that can be transmitted within a frame is $N = T/T^0 \approx W \cdot T$.

To trade for node j's relaying, source i is willing to take out n_i ($0 \leqslant n_i \leqslant N$) symbols in one frame to relay n_i symbols originating from source j. Assuming the relaying power is p_i^r, source i can transmit its own data using only the remaining $N - n_i$ symbols with power p_i^s in which only n_j ($0 \leqslant n_j \leqslant N-1$) symbols will be relayed by source j. It means that only the data carried on n_j symbols of source i can be transmitted in a cooperative manner, while the remaining $N - n_i - n_j$ symbols will be directly transmitted to destination $d(i)$ without any cooperation. For simplicity, we make the following assumptions: (1) one data symbol originating from a node can only be relayed by one symbol of the other node, and (2) each node will only relay the symbols originating from the other and will not relay the symbols originating from itself and then relayed by the other. For user i and his partner user j, we then have $n_i \leqslant N - n_j$ and $n_j \leqslant N - n_i$, which both yield

$$n_i + n_j \leqslant N. \tag{9}$$

In practical networks, a transmission node is not only energy limited but also power limited. It always has several discrete power levels p^1, p^2, ..., p^L ($p^1 < p^2 < \cdots < p^L$) for transmission. If node i agrees to relay n_i symbols for its partner node j, it should at least transmit these symbols at the minimum power level $p_i^r = p^1$. To keep within the energy limit, the maximum power that node i can use to transmit the remaining $N - n_i$ symbols of its own can be computed as

$$\bar{p}_i^s = \frac{E - p^1 n_i T_0}{(N - n_i) T_0}. \tag{10}$$

To remain within the peak-power constraint, the condition $\bar{p}_i^s \leqslant p^L$should be satisfied. Substituting it into (10), we can get

$$n_i \leqslant \frac{p^L T - E}{T_0(p^L - p^1)}. \tag{11}$$

If node i retransmits these n_i symbols at the maximum power $p_i^r = p^L$, it can only transmit its own $N - n_i$ symbols at the minimum power

$$\underline{p}_i^s = \frac{E - p^L n_i T_0}{(N - n_i)T_0}. \tag{12}$$

Since the condition $\underline{p}_i^s \geqslant p^1$ should also be satisfied by node i, we have

$$n_i \leqslant \frac{E - p^1 T}{T_0(p^L - p^1)}. \tag{13}$$

Considering (11) and (13) jointly, given the system parameters E, T, T_0, p^1, and p^L, the maximum number of symbols that node i can contribute to user j in a transmission frame for relaying purpose is

$$n_i^{Thr} = \left\lfloor \min\left(\frac{p^L T - E}{T_0(p^L - p^1)}, \frac{E - p^1 T}{T_0(p^L - p^1)} \right) \right\rfloor. \tag{14}$$

It ensures that the energy and power limitations of a node are both satisfied.

In selfish commercial networks, an autonomous user node could make decisions according to its own willingness. As for the symmetric selection cooperation networks, any user node i has two choices at a given transmission time, that is,

(1) Work independently by setting n_i=0 and $p_i^s = E/T$ to achieve the noncooperative data-rate/payoff as

$$R_i^{NC} = \frac{N \cdot T_0}{2T} \log_2\left(1 + \frac{p_i^s g_{i,d(i)}}{\sigma^2}\right) = \frac{N}{2T \cdot W} \log_2\left(1 + \frac{E}{T}\frac{g_{i,d(i)}}{\sigma^2}\right). \tag{15}$$

(2) Work cooperatively by setting $n_i(0 \leqslant n_i \leqslant N-1)$ and $p^1 \leqslant p_i^r \leqslant p^L$to achieve the cooperative data-rate/payoff as

$$R_i^C = \frac{1}{2T \cdot W}\left[n_j \log_2\left(1 + \varGamma_{i,d(i)}\right) + (N - n_i - n_j)\log_2\left(1 + \gamma_{i,d(i)}\right)\right]. \tag{16}$$

The coefficient 1/2 in (15) and (16) is due to the fact that the transmission time of a user node whether in cooperative or noncooperative situations will occupy two time slots.

4 The cooperative game theoretic framework

Define the cooperation strategy of node i as the number of relaying symbols n_i and the applied relaying power p_i^r. By (16), the cooperative payoff of a node is determined not only by its own strategy in the 1st time slot, but also by the strategy of its cooperative partner in the 2nd time slot, suggesting that the rational decision made by one node will definitely affect its partner's choice in the symmetric selection cooperation networks. A selfish user is willing to seek cooperative relaying only if the data rate/payoff achieved through cooperation will not be lower than that achieved through noncooperation by consuming the same amount of energy resource (efficiency). And both the users expect an optimal tradeoff between their resources payout and payoff (fairness). These two network objectives, i.e., efficiency and fairness, have motivated us to resort to the cooperative game theory [18], which is a natural and powerful tool to study how the selfish nodes interact and cooperate with each other. In a cooperative game, selfish players could negotiate transactions and cooperate in making the decisions. It helps to achieve the user cooperation stimulating strategy profiles, which will result in an efficient and fair resource sharing in the Pareto optimal sense. A payoff allocation is said to be Pareto optimal, if it is not possible to increase the payoffs of some of the users without hurting that of any other users [14,22]. The Pareto optimal payoff allocation can be obtained by solving the Nash bargaining solution (NBS) to a K-person cooperative game.

Next, we first formulate the joint cooperative bandwidth and power allocation (JBPA) problem as a two-person cooperative game. Then we use the NBS method to find the win-win strategy profile for the Pareto optimal payoff allocation for both cooperative user nodes.

4.1 Cooperative game model

The basic concepts for the bargaining problem of cooperative game theory has been presented in [14]. Let $K = \{1, 2, \ldots, K\}$ be the set of K players. Let $\Im$ be a closed and convex subset of $\Re^K$ to represent the set of feasible payoff allocations that the players can get if they all work together. Let $U_i^{\min}$ be the minimal payoff that the ith player would expect. If the payoff is smaller than $U_i^{\min}$, the player will not cooperate. Suppose $\{U_i \in \Re^K | U_i \geqslant U_i^{\min}, \forall i \in K\}$ is a nonempty bounded set. Define $\boldsymbol{U}^{\min} = (U_1^{\min}, \ldots, U_K^{\min})$. The triplet $(K, \Im, \boldsymbol{U}^{\min})$ is called a K-person cooperative game Within the feasible set $\Im$, the notion of Pareto optimal as a selection criterion for the game solutions can be defined as follows.

Definition 1. The point $\boldsymbol{U} = (U_1, \ldots, U_K)$ is Pareto optimal, if and only if there is no other allocation U_i' such that $U_i' \geqslant U_i, \forall i \in K$, and $U_i' > U_i, \exists i \in K$.

The interpretation of a Pareto optimal is that there exists no other allocation that leads to superior performance for some players without causing performance deterioration of some other players.

As for the selection cooperation communications, formally, let K={1, 2} be the set of players/users in a cooperative relay game. $U_i = R_i^c$ and $U_i^{\min} = R_i^{NC}$ represent the cooperative payoff and the noncooperative payoff for user i, respectively. By the definition of cooperative game theory [18,23], user i will quit cooperation when his cooperative payoff $U_i = R_i^c$ is less than the noncooperative payoff $U_i^{\min} = R_i^{NC}$. It ensures that both users could benefit from cooperation.

According to Theorem 1 in [14], the JBPA game (JBPAG) $(K, \boldsymbol{U}^{\min})$ will have a unique NBS if and only if $\boldsymbol{U} = (U_1, U_2)$ is a convex set. And the unique NBS to the JBPAG can be achieved by solving the following maximization problem:

$$\{R_1^{C(\text{JBPAG})}, R_2^{C(\text{JBPAG})}\} = \arg\max(R_{1,3}^C - R_{1,3}^{NC})(R_{2,4}^C - R_{2,4}^{NC}), \tag{17}$$

$$\text{subject to } 0 \leqslant n_1, n_2 \leqslant n^{Thr}, \text{ and } n_1 + n_2 \leqslant N,$$
$$p^1 \leqslant p_1^r, p_2^r \leqslant p^L.$$

4.2 Particle swarm optimizer algorithm for solving JBPAG

Although we have proposed the cooperative game theoretical resource allocation framework for the selection cooperation communications in our previous work [24], we cannot provide an efficient centralized optimal algorithm to solve the game. Note that the optimization problem (17) is a combinatorial problem [25] in nature, since it involves four variables n_1, n_2, p_1^r and p_2^r. A low-complexity numerical algorithm particle swarm optimizer (PSO) [13,26] can be used to solve this problem if the unique NBS exits.

Assume that there are M particles in a swarm with S performance parameters to be optimized. $Z_m = \{z_{m,s} | s = 1, 2, \ldots, S\}$ and $V_m = \{v_{m,s} | s = 1, 2, \ldots, S\}$ are the location and flying velocity vectors of the mth particle, $m = 1, 2, \ldots, M$. By calculating fitness value with respect to Z_m using the fitness function , we judge the location of the mth particle. At the $(t+1)-$th iteration, Z_m and V_m are updated according to the rules proposed in [8], which are

$$v_{m,s} = \beta v_{m,s} + \alpha_1 r_1 (x_{m,s} - z_{m,s}) + \alpha_2 r_2 (y_s - z_{m,s}), \tag{18}$$

$$z_{m,s}^{t+1} = z_{m,s}^t + v_{m,s}^{t+1}, \tag{19}$$

where $X_m = \{x_{m,s} | n = 1, 2, \ldots, N\}$ is the best location vector (giving the best fitness value) searched by the mth particle during the whole $t = t^{\max}$ iterations, $Y = \{y_n | n = 1, 2, \ldots, N\}$ is that searched by the whole swarm, β is the particle inertia weight, α_1 and α_2 are the learning factors, and r_1 and r_2 are both uniformly distributed within [0, 1].

In the JBPAG (17), two four-dimension PSO are performed separately by node 1 and node 2 to search for the NBS cooperation strategy profile $\{n_1, p_1^r\}$ and $\{n_2, p_2^r\}$ that maximize the fitness function (17). Thus, $Z_1 = \{n_1, p_1^r\}$, in the first PSO of node 1, and $Z_2 = \{n_2, p_2^r\}$, in the second PSO of node 2. For the detailed PSO algorithm of searching for the NBS cooperation strategy profiles of the JBPAG, please refer to [13].

However, since the cooperative strategies n_1, n_2, p_1^r and p_2^r should be jointly optimized, the problem may become very complex because $\boldsymbol{U}$ is not always a convex set [18]. Suppose the number of power levels of each node is L and the number of data symbols in a TDMA frame is N. The computation complexity of the PSO algorithm is $O(L^2N^2)$.

To make the problems more tractable so that the user nodes could compute the NBS strategies rapidly as the wireless channel changes, we divide the JBPAG into two subgames, i.e., the bandwidth allocation game (BAG) and the power allocation game (PAG). By this way, we can not only prove that both the BAG and PAG have unique NBS, but also reduce the computation complexity to $O(L^2 + N^2)$, because the number of variables in the objective functions of both the subgames is reduced by half. In subsection 5.1, we discuss the BAG. In subsection 5.2, we present the PAG.

5 Suboptimal algorithm to solve BPAG

5.1 Symbol allocation game (SAG)

We discuss the SAG by assuming a fixed power allocation $p_i^s = p_i^r = E/T$. From (16), we note that for a given channel state information (CSI) the payoff U_i for user i is only a function of n_i and n_j. We need to prove that $\boldsymbol{U} = (U_1, U_2)$ is a convex set such that the SAG will have a unique NBS strategy $\{n_1^*, n_2^*\}$ according to Theorem 1 in [14]. The convexity of the set $\boldsymbol{U} = (U_1, U_2)$ requires that, for any $\theta(0 \leqslant \theta \leqslant 1)$, if $\boldsymbol{U}^\alpha = (U_1^\alpha, U_2^\alpha) \in \boldsymbol{U}$ and $\boldsymbol{U}^\beta = (U_1^\beta, U_2^\beta) \in \boldsymbol{U}$, then $\theta\boldsymbol{U}^\alpha + (1-\theta)\boldsymbol{U}^\beta \in \boldsymbol{U}$ [12].

Proof. Substituting (16) into $\theta U_1^\alpha + (1-\theta)U_1^\beta$, we can get

$$\begin{aligned}\theta U_1^\alpha + (1-\theta)U_1^\beta &= \frac{\theta}{2T\cdot W}[n_2^\alpha \log_2(1+\mathit{\Gamma}_{1,3}) + (N - n_1^\alpha - n_2^\alpha)\log_2(1+\gamma_{1,3})] \\ &\quad + \frac{1-\theta}{2T\cdot W}[n_2^\beta \log_2(1+\mathit{\Gamma}_{1,3}) + (N - n_1^\beta - n_2^\beta)\log_2(1+\gamma_{1,3})] \\ &= \frac{1}{2T\cdot W}\{[(1-\theta)n_2^\beta + \theta\cdot n_2^\alpha]\log_2(1+\mathit{\Gamma}_{1,3}) + \{N - [(1-\theta)(n_1^\beta + n_2^\beta) \\ &\quad + \theta(n_1^\alpha + n_2^\alpha)]\}\log_2(1+\gamma_{1,3})\}. \end{aligned} \tag{20}$$

From (4) and (9), we have $0 \leqslant n_2^\alpha, n_2^\beta \leqslant n^{Thr}$and $0 \leqslant (n_1^\alpha + n_2^\alpha), (n_1^\beta + n_2^\beta) \leqslant N$. It is easy to derive that

$$0 \leqslant [(1-\theta)n_2^\beta + \theta\cdot n_2^\alpha] \leqslant n^{Thr}, \tag{21}$$

and

$$0 \leqslant [(1-\theta)(n_1^\beta + n_2^\beta) + \theta(n_1^\alpha + n_2^\alpha)] \leqslant N. \tag{22}$$

Thus, we can prove that $\theta U_1^\alpha + (1-\theta)U_1^\beta \in U_1$. By the same method, we can also prove that $\theta U_2^\alpha + (1-\theta)U_2^\beta \in U_2$. Therefore, $\theta\boldsymbol{U}^\alpha + (1-\theta)\boldsymbol{U}^\beta \in \boldsymbol{U}$, and then $\boldsymbol{U} = (U_1, U_2)$ is a convex set.

According to Theorem 1 in [14], a unique NBS payoff allocation $\{U_1^{\mathrm{SAG}} = R_1^{C(\mathrm{SAG})}, U_2^{\mathrm{SAG}} = R_2^{C(\mathrm{SAG})}\}$ of the BAG can be obtained by solving the following maximization problem:

$$\{R_1^{C(\mathrm{SAG})}, R_2^{C(\mathrm{SAG})}\} = \arg\max(R_{1,3}^C - R_{1,3}^{NC})(R_{2,4}^C - R_{2,4}^{NC}), \tag{23}$$

$$\text{subject to } 0 \leqslant n_1, n_2 \leqslant n^{Thr}, \text{ and } n_1 + n_2 \leqslant N.$$

5.2 Power allocation game (PAG)

After performing the SAG, a certain symbol allocation $\{n_1^*, n_2^*\}$ is determined. The PAG has to be performed to obtain the suboptimal NBS to the JBPAG. In the PAG, the payoff U_i of node i is only a function of p_i^s and p_j^r. We need to prove that the PAG has a unique NBS. Similar to the proof in the SAG, we need to prove that, for any $\theta(0 \leqslant \theta \leqslant 1)$, if $\boldsymbol{U}^\alpha = (U_1^\alpha, U_2^\alpha) \in \boldsymbol{U}$ and $\boldsymbol{U}^\beta = (U_1^\beta, U_2^\beta) \in \boldsymbol{U}$ then $\theta\boldsymbol{U}^\alpha + (1-\theta)\boldsymbol{U}^\beta \in \boldsymbol{U}$ [12].

Proof. Substituting (16) into $\theta U_1^{\alpha} + (1-\theta)U_1^{\beta}$, we can get

$$\begin{aligned}\theta U_1^{\alpha} + (1-\theta)U_1^{\beta} &= \frac{\theta}{2T\cdot W}\{n_2^*\log_2(1+\mathit{\Gamma}_{1,3}^{\alpha}) + (N-n_1^*-n_2^*)\log_2 t(1+\gamma_{1,3}^{\alpha})\}\\ &\quad+\frac{1-\theta}{2T\cdot W}\{n_2^*\log_2(1+\mathit{\Gamma}_{1,3}^{\beta}) + (N-n_1^*-n_2^*)\log_2(1+\gamma_{1,3}^{\beta})\}\\ &=\frac{n_2^*}{2T\cdot W}[\theta\cdot\log_2(1+\mathit{\Gamma}_{1,3}^{\alpha}) + (1-\theta)\cdot\log_2(1+\mathit{\Gamma}_{1,3}^{\beta})]\\ &\quad+\frac{(N-n_1^*-n_2^*)}{2T\cdot W}[\theta\cdot\log_2(1+\gamma_{1,3}^{\alpha}) + (1-\theta)\cdot\log_2(1+\gamma_{1,3}^{\beta})].\end{aligned}\tag{24}$$

From (8), we know that $\mathit{\Gamma}_{1,3}$ is a function of p_1^s and p_2^r, and $\log_2(1+\mathit{\Gamma}_{1,3})$ is a monotonically increasing function of $\mathit{\Gamma}_{1,3}$. For the given CSI and the obtained $\{n_1^*, n_2^*\}$ from the BAG, there must exist at least one point $(\bar{p}_1^s, \bar{p}_2^r)$, $p^1 \leqslant \bar{p}_1^s, \bar{p}_2^r \leqslant p^L$, at which $\mathit{\Gamma}_{1,3}(p_1^s, p_2^r)$ reaches its maximum $\bar{\mathit{\Gamma}}_{1,3}(\bar{p}_1^s, \bar{p}_2^r)$ and, as a result, $\log_2(1+\mathit{\Gamma}_{1,3})$ reaches its maximum $\log_2(1+\bar{\mathit{\Gamma}}_{1,3})$. Also, there must exist at least one point $(\underline{p}_1^s, \underline{p}_2^r)$, $p^1 \leqslant \underline{p}_1^s, \underline{p}_2^r \leqslant p^L$, at which $\mathit{\Gamma}_{1,3}(p_1^s, p_2^r)$ reaches its minimum $\underline{\mathit{\Gamma}}_{1,3}(\underline{p}_1^s, \underline{p}_2^r)$ and, as a result, $\log_2(1+\mathit{\Gamma}_{1,3})$ reaches its the minimum $\log_2(1+\underline{\mathit{\Gamma}}_{1,3})$. Then we can get

$$\log_2(1+\underline{\mathit{\Gamma}}_{1,3}) \leqslant \log_2(1+\mathit{\Gamma}_{1,3}) \leqslant \log_2(1+\bar{\mathit{\Gamma}}_{1,3}).\tag{25}$$

In (24), because $p^1 \leqslant p_1^{s(\alpha)}, p_2^{r(\alpha)} \leqslant p^L$, $\mathit{\Gamma}_{1,3}^{\alpha} = \mathit{\Gamma}_{1,3}^{\alpha}(p_1^{s(\alpha)}, p_2^{r(\alpha)})$, $p^1 \leqslant p_1^{s(\beta)}, p_2^{r(\beta)} \leqslant p^L$ and $\mathit{\Gamma}_{1,3}^{\beta} = \mathit{\Gamma}_{1,3}^{\beta}(p_1^{s(\beta)}, p_2^{r(\beta)})$, we can get $\underline{\mathit{\Gamma}}_{1,3} \leqslant \mathit{\Gamma}_{1,3}^{\alpha} \leqslant \bar{\mathit{\Gamma}}_{1,3}$ and $\underline{\mathit{\Gamma}}_{1,3} \leqslant \mathit{\Gamma}_{1,3}^{\beta} \leqslant \bar{\mathit{\Gamma}}_{1,3}$. And it is easy to derive that $\log_2(1+\underline{\mathit{\Gamma}}_{1,3}) \leqslant \log_2(1+\mathit{\Gamma}_{1,3}^{\alpha}) \leqslant \log_2(1+\bar{\mathit{\Gamma}}_{1,3})$ and $\log_2(1+\underline{\mathit{\Gamma}}_{1,3}) \leqslant \log_2(1+\mathit{\Gamma}_{1,3}^{\beta}) \leqslant \log_2(1+\bar{\mathit{\Gamma}}_{1,3})$.

For any $0 \leqslant \theta \leqslant 1$, we then have

$$\log_2(1+\underline{\mathit{\Gamma}}_{1,3}) \leqslant \theta\cdot\log_2(1+\mathit{\Gamma}_{1,3}^{\alpha}) + (1-\theta)\cdot\log_2(1+\mathit{\Gamma}_{1,3}^{\beta}) \leqslant \log_2(1+\bar{\mathit{\Gamma}}_{1,3}).\tag{26}$$

From (25) and (26), we can conclude that the term $\theta\cdot\log_2(1+\mathit{\Gamma}_{1,3}^{\alpha}) + (1-\theta)\cdot\log_2(1+\mathit{\Gamma}_{1,3}^{\beta})$ in (24) has the same value space as the term $\log_2(1+\mathit{\Gamma}_{i,d(i)})$ in (16) for i=1.

For the term $\log_2(1+\gamma_{1,3})$ in (16), because $p^1 \leqslant p_1^s \leqslant p^L$, we can get the value space of $\gamma_{1,3}$ is $[\frac{p^1 g_{1,3}}{\sigma^2}, \frac{p^L g_{1,3}}{\sigma^2}]$. Since $\log_2(1+\gamma_{1,3})$ is a monotonically increasing function of $\gamma_{1,3}$. The value space of $\log_2(1+\gamma_{1,3})$ is $[\log_2(1+\frac{p^1 g_{1,3}}{\sigma^2}), \log_2(1+\frac{p^L g_{1,3}}{\sigma^2})]$.

For the term $\theta\cdot\log_2(1+\gamma_{1,3}^{\alpha}) + (1-\theta)\cdot\log_2(1+\gamma_{1,3}^{\beta})$ in (24), because $p^1 \leqslant p_1^{s(\alpha)} \leqslant p^L$ and $p^1 \leqslant p_1^{s(\beta)} \leqslant p^L$, both the value space of $\gamma_{1,3}^{\alpha} = \frac{p_1^{s(\alpha)}\cdot g_{1,3}}{\sigma^2}$ and $\gamma_{1,3}^{\beta} = \frac{p_1^{s(\beta)}\cdot g_{1,3}}{\sigma^2}$ are $[\frac{p^1 g_{1,3}}{\sigma^2}, \frac{p^L g_{1,3}}{\sigma^2}]$. We can prove that, for any $0 \leqslant \theta \leqslant 1$, the term $\theta\cdot\log_2(1+\gamma_{1,3}^{\alpha}) + (1-\theta)\cdot\log_2(1+\gamma_{1,3}^{\beta})$ in (24) and the term $\log_2(1+\gamma_{1,3})$ in (16) for i=1 have the same value space $[\log_2(1+\frac{p^1 g_{1,3}}{\sigma^2}), \log_2(1+\frac{p^L g_{1,3}}{\sigma^2})]$. And then we can prove that $\theta U_1^{\alpha} + (1-\theta)U_1^{\beta} \in U_1$.

By the same method, we can also prove that $\theta U_2^{\alpha} + (1-\theta)U_2^{\beta} \in U_2$. Therefore, $\theta \boldsymbol{U}^{\alpha} + (1-\theta)\boldsymbol{U}^{\beta} \in \boldsymbol{U}$, and then $\boldsymbol{U} = (U_1, U_2)$ is a convex set.

For the given CSI and the symbol allocation of the BAG, a unique NBS $\{U_1^* = R_1^{C*}, U_2^{\mathrm{SAG}} = R_2^{C*}\}$ to the PAG can then be obtained by solving the following maximization problem:

$$\{R_1^{C*}, R_2^{C*}\} = \arg\max(R_{1,3}^{C} - R_{1,3}^{C(\mathrm{SAG})})(R_{2,4}^{C} - R_{2,4}^{C(\mathrm{SAG})}),\tag{27}$$

$$\text{subject to } p^1 \leqslant p_1^r, p_2^r \leqslant p^L.$$

The solution $\{R_1^{C*}, R_2^{C*}\}$ is also the suboptimal NBS to the JSPAG.

5.3 Computation complexity analysis

Both (23) and (27) are combinatorial problems [25], since (23) involves two discrete variables n_1 and n_2, and (27) involves two discrete variables p_1^r and p_2^r. Suppose the number of power levels of each node is L and the number of data symbols in a TDMA frame is N. The computation complexities of (23) and (27) are $O(N^2)$ and $O(L^2)$, respectively. The particle swarm optimizer (PSO) can be used to search the suboptimal NBS by solving the maximization problems (23) and (27) sequentially. And the computation complexity is $O(N^2 + L^2)$. In commercial networks, user nodes are laptops or smart phones which have reasonably enough computing power to solve it.

Note that the knowledge required by a node to perform the JSPAG and use the MRC is the CSI including that for source-destination, source-relay, and relay-destination channels, which can be acquired by the dedicated feedback channels, meaning that no information exchange is needed between different user nodes and thus the centralized information exchange and coordination is avoided. The selfish user node could search for its NBS strategy only based on local information in a distributed manner.

6 Simulation results

In this section, we present simulation results for the proposed games. To evaluate the fairness and efficiency performances of the games, we compare the NBS resource allocations with the maximal-rate optimization. The objective of the maximal-rate optimization is to maximize the overall system rate. This requires that all user nodes be fully cooperative. The maximal-rate cooperative resource allocation can be achieved by solving the following optimization problem:

$$\{\tilde{R}_1^C, \tilde{R}_2^C\} = \arg\max(R_1^C + R_2^C), \tag{28}$$

$$\text{subject to } 0 \leqslant n_1 \leqslant n_1^{Thr}, 0 \leqslant n_2 \leqslant n_2^{Thr}, \text{ and } n_1 + n_2 \leqslant N,$$
$$p^1 \leqslant p_1^r, p_2^r \leqslant p^L.$$

The simulated network is shown in Figure 2. We locate the two destinations (node 3 and node 4) at (1200 m, 0 m) and (0 m, 0 m) and source 2 at (800 m, 0 m). The x coordinate of source 1 is fixed at 400 m while its y coordinate varies from 0 m to 400 m. The path gain is set to $0.097/d^4$ [13,14], where d is the distance between the transmitter and the receiver (in meters), and the noise level is 1×10^{-14}W. We assume that the transmission frame length is T= 5 ms, and each node is under the constraints of an energy level of E=5×10^{-5} J and a transmission bandwidth size of 1 MHz. The minimum and maximum power levels for a transmission node are set to p^1=1 mW and p^L=10 mW, respectively. So, according to (9), the maximal number of symbols that a node can contribute to its partner for relaying in a transmission frame is n^{Thr}=222.

Let Y denote the y coordinate of node 1. Note that the channel gains of a node represent its ability to bargain with its partner over the cooperative power allocation for cooperative relaying. Figures 3 and 4 show the achieved data-rates of user 1 and user 2 in different adaptive resource allocation schemes, respectively. We can see that both user 1 and user 2 could obtain data-rate increases through the BAG and the JSPAG. And the JSPAG leads to a small improvement compared with the BAG. At the start point (0 m, 0 m) of node 1, both the users achieve the best data-rate increases, since they have the best channel conditions in this situation. As node 1 moves along the line from (0 m, 0 m) to (500 m, 500 m), the data-rate increases of the users gradually decrease as the channel conditions become worse). When node 1 moves across the critical point (0 m, 380 m), it cannot make any further contribution to user 2, since its channel gains become more worse. So node 2 would decrease its cooperation level to 0 selfishly. So Y=380 is the breakpoint. At the breakpoint and beyond this distance, both the nodes are willing to work independently. That also means that node 1 and node 2 should search for new partner nodes for cooperation.

In Figure 5, we show the overall rates of the two users in different resource allocation schemes. And we can see that the performance loss of the game schemes to that of the maximal-rate scheme is small, while the maximal-rate scheme is extremely unfair for individual users (see Figures 3 and 4). Comparing with the NBS resource allocation in Figures 3 and 4, node 2 is willing to contribute more resources for cooperation than node 1 in the maximal-rate optimization. That is because node 2 always has better channel gains than node 1 in the simulations. To increase the system rate, node 2 has to contribute more resources for cooperation unselfishly. Thus, from Figure 4, we can see that user 2 even acquires negative rate increases when $Y > 100$. The individual data rates of user 1 and user 2 in the maximal-rate optimi-

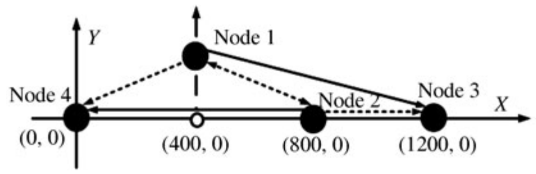

Figure 2 A two user cooperative communication network.

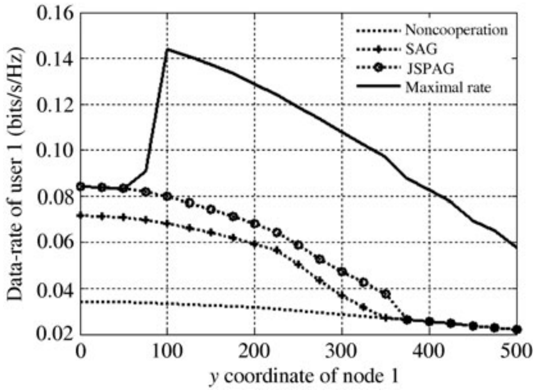

Figure 3 Data-rates of user 1.

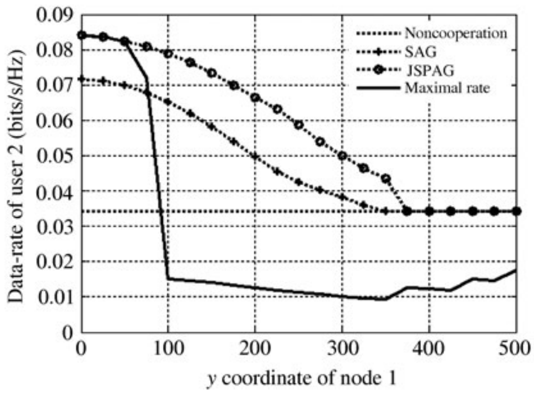

Figure 4 Data-rates of user 2.

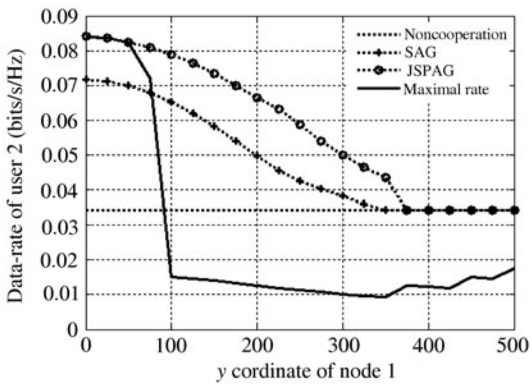

Figure 5 System data-rates.

zation are also shown in Figure 3 and Figure 4, respectively. The maximal-rate optimization is unfair in that user 1 with the worse channel gains always has better performance than user 2. These situations can only happen in the full cooperation networks where the nodes are designed to realize a common goal, e.g., the system rate jointly. However, in a selfish network, why will a user node with better channel gains contribute more resources to help others and get a bad performance? Although the efficiency is maximized, the fairness is lost.

By the simulation results, we can conclude that the proposed games can achieve a good tradeoff between the fairness and the efficiency. Note that the time-varying channel fading is considered in our simulation as in [8–14]. So the y coordinate of node 1 represents the user nodes' channel conditions. If the time-varying fading is considered, the x-axis represents the channel conditions instead of the y coordinate of node 1.

7 Conclusions

In this paper, we have analyzed the cooperation behavior of selfish user nodes in cooperative communication networks. We formulate the energy-efficient resource allocation problem between two cooperating nodes as a cooperative game, and use the Nash bargaining solution (NBS) method to obtain the suboptimal NBS to the game. By comparing with the maximal-rate optimization scheme, simulation results show the NBS resource allocation is efficient in that the performance loss of the NBS to that of the maximal-rate optimization is small while the maximal-rate scheme is extremely unfair. The simulation results also show that the NBS resource allocation is fair in that both nodes could experience better performance than they work independently.

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