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Resource Allocation Scheme for *One-to-Many* Cooperative Wireless Systems Using the Bidding Game Strategy

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Authors' contributions

This work was carried out in collaboration between both authors. Author OA proposed the title of the work, designed the outlines, carried out the analysis and wrote the first and final drafts of the manuscript. Author WB provided very helpful inputs throughout the study and managed the analysis of the study as well as the literature. Both authors approved the final manuscript.

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ABSTRACT

In this paper, we propose a new scheme for optimal resource (i.e, power) allocation in a cooperative wireless communication system, using a type of game called the Bidding game. Previous related works have all considered networks with multiple source nodes interacting with either single or multiple relays, without paying so much attention to how partners are selected for cooperation. However because of the importance of partner selection as an integral part of an efficient cooperative communication network, which also includes resource allocation, we propose this new game-based resource allocation scheme, in which the conventional theories of economic bidding are applied. In this work, we model the cooperative communication network as a single-user, multi-relay system in which the source acts as the auctioneer while the relays or partners act as the

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bidders in the game. The resource being auctioned here is power. The relay which offers the highest bid in terms of price is first selected by the source node and then allocated power by the source node. Our proposed scheme is aimed at answering the question of how maximally or optimally the power should be allocated in the network by the source node so as not to violate the power constraint. We show that there exists bidding and pricing mechanisms or strategies that lead to the maximization of network throughput or utility in cooperative communication networks. We also see in our simulation results that there is convergence to the Nash equilibrium which proves the correctness of our scheme.

Keywords: Cooperative communication; auction; bidding game; optimum; power allocation.

1. INTRODUCTION

In the last few years, cooperative wireless communication has been seen as a veritable signal transmission technique aimed at exploiting spatial diversity gains over single antenna nodes in wireless communication networks. In this technique, several nodes act as partners or relays and share their resources to forward other nodes' data to the destination. It has also been ascertained that this cooperation gives a significant improvement in system performance and reliability over the non-cooperative systems [1]. To fully take hold of the benefits of cooperative diversity or communication, appropriate partner selection and an efficient resource allocation are very essential, because, apart from the fact that these aid the harnessing of the benefits, the performance of cooperative communication as a whole depends on them.

Recently, several works have dealt with the issue of partner selection and resource allocation in cooperative communications. These works are found to be in two categories namely, centralized (for example, [2-4]) and decentralized (e.g. [5-12]). There have been more researches on the distributed systems because they are more favorable in practical terms since they require only the local information of the nodes, unlike the centralized systems which require the global channel state information, and thus incur higher signaling overhead [13]. For instance, in [6], the authors proposed a partner selection scheme for distributed systems based on limited instantaneous SNR. The authors in [7] proposed a distributed power control framework for a single-source, multiple-relay system to optimize multihop diversity. In the last few years, game theory has grown to be a veritable tool in the analysis of distributed systems due to their autonomous and self-configuring capability. For instance, in [5] a non-cooperative game known as Stackelberg was employed to develop a power allocation algorithm. The network is modeled as a single user, multi-relay system in which the source acts as the buyer and the relays act as the sellers of resource (i.e. power). The authors in [14] studied and developed an auction-based power allocation scheme for a distributed cooperative network. In this work where there are many sources and only one relay, the source nodes acts as the bidders while the relay acts as the auctioneer.

Still on researches using the auction theory or the bidding game, the authors in [13] developed a multi-source, multi-relay cooperative network for the purpose of optimal allocation of power. But unlike [14], each user acts as both a bidder and an auctioneer. In [1], the authors proposed a distributed ascending-clock auction-based algorithm for multi-relay power allocation where the source nodes are also many. A design of an auction-based power allocation scheme for many-to-one (multi-user, single-relay) cooperative adhoc networks was implemented in [15]. Furthermore, the authors in [14] extended their work to cover many users as well. It is also worthy of note that non-linear optimization tools were employed in the analysis by the authors in [13-15]. This is due to the fact that power as a resource is being maximized or optimized by either the source or the relay node. It is also noteworthy that in all these aforementioned auction-based works, tools of optimization have been employed in the analyses.

However, unlike the work in [5] where a *buyer-seller* game is used in which a source node selects a partner node that gives it the highest utility by offering it a low price and at the same time develop an optimal power allocation scheme, in this work we propose a new power allocation scheme which is based on the bidding game in which a partner node that offers the highest price is selected by the source node. In this proposed game, the source is the auctioneer while the relays are the bidders. Moreover, unlike the works in many researchers [1,13-15] in which multiple source nodes are involved, and no much attention is actually given to the selection of cooperating partners or relays before allocating resources, we propose a single-user, multi-relay system, which we call single-auctioneer, multi-bidder bidding game in which we focus on the selection of the most suitable partner node as a prelude to resource allocation. This work intends to propose a new power allocation scheme based on the bidding theory with a single source node, rather than multiple source nodes so as to concentrate the entire transmit power from the source for the cooperative process rather than have it shared among multiple source nodes. In addition, since we are also concerned with how the cooperating relays are selected by the source nodes, we propose a scheme based on a single source interacting with multiple relay nodes.

The rest of this paper is organized as follows: Section II presents the background to this work. The proposed power allocation scheme is described in Section III while Section IV gives the results and discussion. The conclusion is given in Section V.

2. BACKGROUND

2.1 Cooperative System Model

We consider a simple cooperative model as depicted in Fig. 1(a) where there is one relay and one source node in time division mode. The schematic in Fig. 1(b) shows a single source node, which, in our work, acts as the auctioneer and *N*-relay nodes, which act as the bidders in our proposed auction or bidding game.

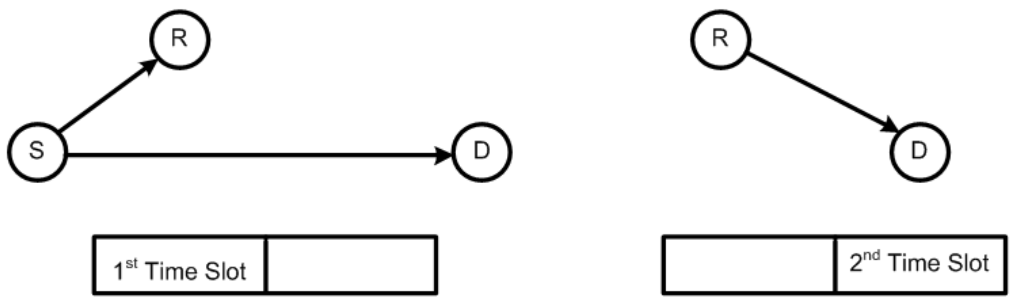

Fig. 1a. A 3-node cooperative system model in the time division mode

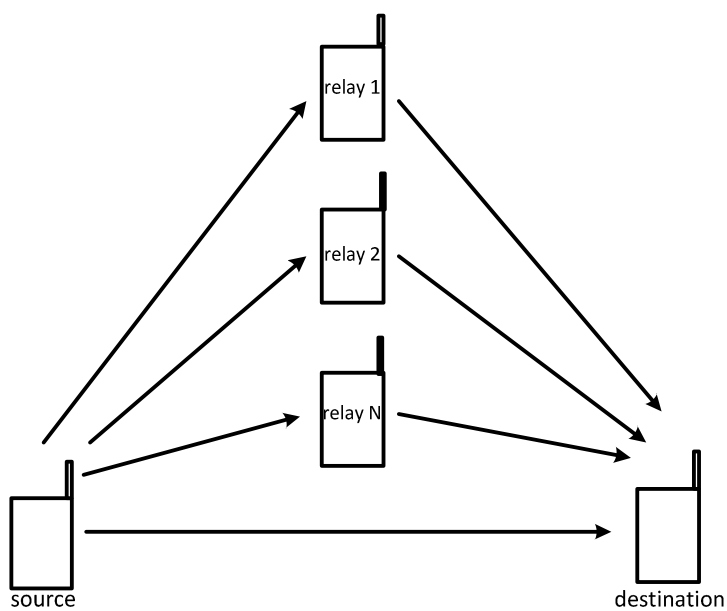

Fig.1b. A *One-to-Many* model of a cooperative wireless communication network

In the first time slot or Phase 1 (in Fig.1a), the source node broadcasts its information, and is received by the both the partner (r) and destination (d) nodes as follows:

$$Y_{sd} = (P_s G_{sd})^{0.5} X_s + \eta_d \quad (1)$$

$$Y_{sr_i} = (P_s G_{sr_i})^{0.5} X_s + \eta_{r_i} \quad (2)$$

where Y_{sd} and Y_{sr} respectively represent the received signal from the source to destination, *d* and from source to relay, *r*. P_s represents the power transmitted from the source node while X_s represents the transmitted data with normalized to unit energy. G_{sd} and G_{sr} denote channel gains from *s* to *d* and from *s* to *r* respectively, and the AWG noises are given as η and denoted by *n*.

During the first time slot, the SNR obtained at the destination node is given as

$$\gamma_{sd} = \frac{P_s G_{sd}}{n} \quad (3)$$

Moreover, during the second time slot, the Y_{sr_i} is amplified and forwarded to the destination node; thus the signal received at the destination during the second time slot is given as

$$Y_{r_i d} = (P_r G_{r_i d})^{0.5} X_{r_i d} + \eta'_d \quad (4)$$

Where $G_{r_i d}$ is the channel gain from relay to destination nodes while η'_d is the noise received during the second phase, and

$X_{r_i d} = \frac{Y_{sr_i}}{|Y_{sr_i}|}$ is the signal of unit energy that the relay receives from the source node and which it forwards to the destination node.

Now, using $X_{r_i d}$ and (2), we rewrite (4) as follows:

$$Y_{r_i d} = \frac{(P_{r_i} G_{r_i d})^{0.5}\left((P_s G_{sr_i})^{0.5} X_s + \eta_r\right)}{(P_s G_{sr_i} + n)^{0.5}} + \eta'_d \quad (5)$$

And using (5), we obtain the SNR through relaying, at the destination node as follows:

$$\gamma_{sr_i d} = \frac{P_{r_i} P_s G_{r_i d} G_{sr_i}}{n\left(P_{r_i} G_{r_i d} + P_s G_{sr_i} + n\right)} \quad (6)$$

Next, the achievable transmission rate at the destination node will then be obtained. From the analysis above, the source has two options in this case:

Option1: the source node uses only the Phase1 transmission and obtains the rate

$$C_{sd} = W \log_2(1 + \gamma_{sd}) \quad (7)$$

Where *W* is the bandwidth of the transmitted signal from the source node

Option 2: the source node uses the two phases, and at the combining output (using MRC), achieves the following achievable transmission rate capacity *C*:

$$C_{sr_i d} = \frac{W}{2} \log_2\left(1 + \gamma_{sd} + \gamma_{sr_i d}\right) = C_s \quad (8)$$

It can be seen in (8) that the $\gamma_{sr_i d}$ is the additional SNR increase when compared with the non-cooperative case, i.e. $\Delta SNR \approx \gamma_{sr_i d}$.

Comparing option 1 above with option 2, the rate increase obtainable by the source node is given as follows:

$$\Delta C = \max\left\{C_{sr_i d} - C_{sd}, 0\right\} \quad (9)$$

We make the assumption that the P_s (source node's power) is fixed and that the power that would be allocated to a particular relay node would be a function of the amount of bid placed by that relay.

2.2 Non-linear Optimization

A Non-Linear Optimization problem is a type of optimization problem that is defined by a system of equalities and inequalities, collectively known as constraints, over a set of unknown real variables, along with an objective function to be maximized or minimized, where some or all the constraints or the objective functions are nonlinear. It is the branch of mathematical optimization that deals with nonlinear problems.

A general nonlinear optimization problem is given as follows:

max *f*(x) *to maximize some variable, e.g utility*

OR

min *f*(x) *to minimize some variable, e.g price*

Where $f(x): R^n \to R$
$x \in R^n$

s.t (*subject to*)

$$g_j(x) = 0, j \in J$$
$$h_k(x) \le 0, k \in K$$

Methods of solving an Optimization problem

1. Where the objective function *f* is linear and the constraint set is a polytope, the problem is a linear optimization problem, which may be solved using well known linear optimization solutions.
2. Where the objective function is concave (maximization problem), or convex (minimization problem) and the constraint set is convex, then the problem is convex and general methods from convex optimization can be used in most cases.
3. If the objective function is a ratio of a concave and a convex function (in the maximization case) and the constraints are convex, then the problem can be transformed to a convex optimization problem using fractional optimization techniques.

Under differentiability and constraint qualifications, the Karush–Kuhn–Tucker (KKT) conditions provide necessary conditions for a solution to be optimal. And since this work involves optimization of some resource, the KKT conditions would be very useful in this regard. Under convexity, these conditions are also sufficient. If some of the functions are non-differentiable, subdifferential versions of the Karush–Kuhn–Tucker (KKT) conditions are available [16].

2.3 Karush-Kuhn-Tucker (KKT) Conditions

For a solution in a nonlinear optimization problem to be optimal, there are some necessary conditions to be satisfied. These are referred to as the first order necessary conditions and are called the Karush-Khun-Tucker (KKT) conditions. Where nonlinear constraints are involved (as in NLO), the KKT approach to nonlinear optimization makes use of and generalizes the method of Langrange multipliers, which conventionally are used in solving equality-constrained optimization problems.
We now briefly consider a nonlinear optimization problem in order to explain the applications of the KKT conditions

$$\min f(x) \text{ or } x^* = \arg\min_x f(x) \quad (10)$$

$$\text{s.t } g_i(x) - b_i \ge 0 \quad i = 1,\ldots k \quad (11)$$

$$h_i(x) - b_i = 0 j = 1,\ldots m \quad (12)$$

Where (1) is the objective function while (2) and (3) are the inequality and equality constraints respectively. In word form, we wish to find the solution that minimizes *f(x)*, provided the inequalities $g_i(x) \ge b_i$ and equalities $h_i(x) = b_i$ hold true. For this kind of nonlinear optimization, the necessary KKT conditions are as follows:

(i) $g_i(x^*) - b_i$ is feasible, where x^* represents optimal value. This condition applies to (1)

(ii) $\nabla f(x^*) - \sum_{i=1}^{m} \lambda_i^* g_i(x^*) = 0$. This condition applies to (1), (2) and (3)

(iii) $\lambda_i^*(g_i(x^*) - b_i) = 0$, *i* = 1,…*k*. This applies to (2)

(iv) $\lambda_i^* \ge 0$, *i* = 1,…*k*. This applies to (2)

3. GAME THEORY-BASED RESOURCE ALLOCATION

3.1 Bidding Game Model

The main essence of a bidding game is auction. An auction is a decentralized economic mechanism for allocation of resources. In an auction, the players are the bidders and auctioneers, the strategies are the bids while allocations and prices are the bids' functions. For our work, the source is the auctioneer who desires to sell bids to the highest bidder, the relay nodes are the bidders who wish to pay for the bids and the good or resource to be bought is power. According to Han et al. [17], there are four components which determine the outcome of an auction. These components are (1) the information available to the bidders and auctioneer, (2) the bids placed by the bidders to the auctioneer, (3) the allocation of good or resource by the auctioneer, based on the placed bids, and (4) the payments made to the auctioneer by the bidder after the successful bidding.

In the cooperative scenario being considered here, and as mentioned earlier, power is the good or resource that the bidders(relays) are going to bid for, from among which the source (auctioneer) would select the highest bidder (the relay that places the highest value in the bid profile). Fig.3 shows a bidding game model for a cooperative system being considered.

Modeling the bidding game with these components, we have:

- Information: The source node (auctioneer) announces a non-negative bid threshold B_{th} and a price $p > 0$ to all relays prior to the commencement of the bidding process;

Bids, b_i: Relay r_i places a bid (which is a scalar), $b_i \geq 0$ to the source node. After an iterative process to get the highest bidder, the source selects the most suitable relay;

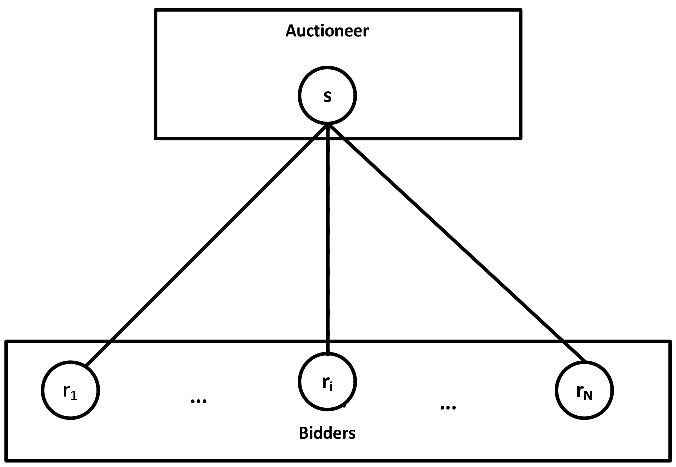

Fig. 2. Illustration of the bidding interaction between the auctioneer and the bidders

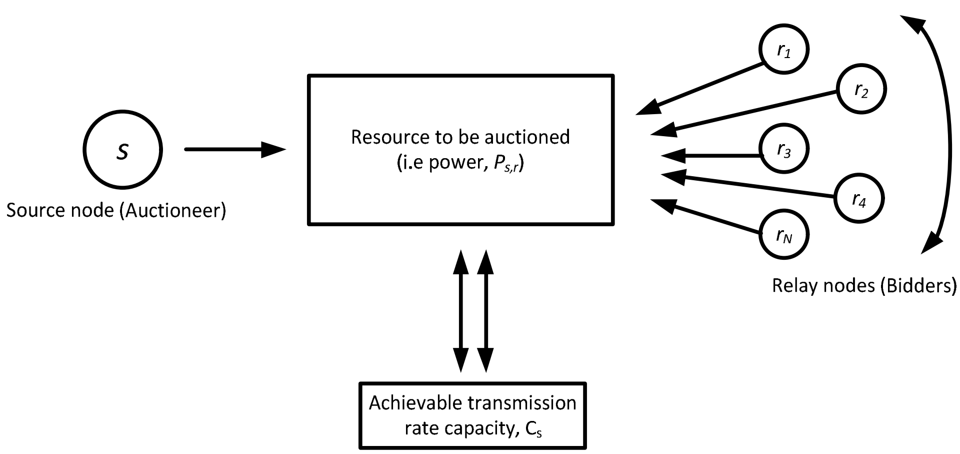

Fig. 3. Model of the bidding game for a cooperative communication system

According to Jianwei et al. [14], a bidding profile defined as vector **b** = (b_1, b_2,…b_N) which contains the bids of the relay nodes, where N is the number of relays involved in the game.

- Allocation, P_{all}: The source, after selecting the relay, allocates power P_{all} based on the bid price placed by the selected relay node.

From the model in Fig. 3, we derive the following:

After a suitable relay r_i with the highest bid has been selected by the source node, s, allocation of power is carried out for the relay node,
Let P = power available to be allocated by the source node
B_{th} = threshold bid placed by the source node at the commencement of the bidding process
b_j = bid placed by the other relay(s) not selected by the source node but among the set of participating relay nodes
If P_{all} = power allocated to the selected relay node, r_i, we have

$$P_{all} = \frac{b_i}{\sum_{j=1}^{N} b_j + B_{th}} P \tag{13}$$

Where $\frac{b_i}{\sum_{j=1}^{N} b_j + B_{th}}$ is the ratio of the selected relay node's bid to the bids of the other relays in the set.

Fig. 2 shows an illustration of the bidding interaction between the auctioneer and the bidders. Let

R_N = {1, 2…N} be a set of relay nodes available for the bidding game. A *1 X N* matrix p_s denotes the source power where p_{s,r_i} (p_{1,r_i} for only one source node) represents the amount of power the source allocates to a relay r_i for forwarding data to the destination node.
The sum of all the elements in the only row of p_s represents the total power consumption or allocation of all participating relays in the network, which is subject to an optimal or peak power constraint $\overline{p}_s$.

Let C_s denote the achievable transmission rate capacity as derived in Eqn.8 in Section II.A for the source node at a given power allocation vector $\{p_{s,r_i}\}_{i=1}^{N}$ which can be applied to different cooperative diversity techniques such as decode and forward, amplify and forward, estimate and forward or compress and forward.

Now, to the objective of this work: to allocate power to each relay node in order to maximize or optimize the total throughput and efficiency of the network. We formulate the optimization problem as follows (which we call NLO):

$$\max C_s \qquad \text{or } p^*_{s,r_i} = \arg\min_{p_{s,r_i}} C_s \tag{14}$$

$$\text{s.t } \sum_{i=1}^{N} p_{s,r_i} \le \overline{p}_s, \quad \forall i \in \text{N} \tag{15}$$

$$\text{variables } p_s \ge 0 \tag{16}$$

The objective function in the NLO above is concave, since C_s is a concave function of the power vector $\{p_{s,r_i}\}_{i=1}^{N}$. It is also obvious that constraint (12) is convex. It can thus be said without loss of generality that the set of the optimization problem in the NLO that is feasible is a convex one. It thus means that the NLO is a convex optimization problem; which solution is given as follows:

For the NLO problem in Eqn. (14) – (16), the Lagrangian is

$$L(p_s,\lambda) = C_s - \sum_{i=1}^{N} \lambda_i \left(\sum_{i=1}^{N} p_{s,r_i} - \overline{p}_s \right) \tag{17}$$

Where $L(p_s,\lambda)$ is the Lagrangian which depends on p_s and λ while $\lambda \ge 0$ is the Lagrange multiplier.

Using the Karush-Kuhn-Tucker (KKT) theorem and conditions as in [18] and as described in Section II.C, the following necessary and sufficient conditions are obtained for two variables p^* and λ^* which stand for the optimal values of the power and Lagrange multiplier respectively.

$$C_s^{'}\left(p_{s,r_i}{}^{*}\right)=\lambda_i^{*},\ \forall p_{s,r_i}{}^{*}>0,\ i\in \mathrm{N} \qquad (18)$$

$$\lambda_i^{*}\left(\sum_{i=1}^{N} p^{*}{}_{s,r_i}-\overline{p}_s\right)=0,\ \forall i\in \mathrm{N} \qquad (19)$$

$$\sum_{i=1}^{N} p_{s,r_i}{}^{*}\leq \overline{p}_s,\ \forall i\in \mathrm{N} \qquad (20)$$

$$p^{*}\geq 0,\quad \lambda^{*}\geq 0 \qquad (21)$$

Noteworthy is that if $p_{s,r_i}=0,\quad C^{'}\left(p_{s,r_i}{}^{*}\right)=0$; which we obtained by evaluating the derivative of the Lagrangian function in (17) with respect to p_{s,r_i} . This derivative is as follows:

$$\frac{\partial L(P_s,\lambda)}{\partial P_{s,r_i}}=\frac{\partial C_s}{\partial P_{s,r_i}}-\frac{\partial}{\partial P_{s,r_i}}\left[\lambda_i\left(\sum_{i=1}^{N}P_{s,r_i}-\overline{p}\right)\right]$$

$$=C_s^{'}\left(P_{s,r_i}\right)-\lambda_i$$

Thus, $$C_s^{'}(P_{s,r_i}{}^{*})=\lambda_i^{*}$$

where the asterix (*) denotes optimal value. We propose, in the next section, a bidding game-based power allocation scheme to achieve the optimum solution for the optimization problem NLO.

3.2 Proposed Bidding Game-Based Power Allocation Scheme

In the development of this scheme, the first step is to show that there exists auction equilibrium in the proposed bidding game. This is expedient because in any form of analysis using the game-theoretic concepts, a common objective is to ensure there are a convergence to and a unique Nash equilibrium. Then we propose our scheme to achieve the optimum allocation of power.

In this work, we wish to achieve an efficient resource allocation through a single-auctioneer multi-bidder bidding game where the auctioneer is the source node and the relay nodes are the bidders. An interaction between the source node (auctioneer) and the relay nodes (bidders) is illustrated in Fig. 2, in which the auctioneer dynamically announces a bid price to all the bidders and the bidders respond by placing bids so as to attract the auctioneer in selecting a particular bidder to which power would be allocated. The issue we are attempting to address in this section is that of the maximum amount of power that can be allocated to the relay nodes by the source nodes without violating the power constraint.

As mentioned earlier, the auctioneer (source, *s*) announces a price, which we call p_{th} and each bidder (relay, r_i) places or submits a bid b_i to the source, s.

Let p_{th} = price value announced by the auctioneer,

b = bidding matrix or profile where $b_i=\{b_{s,i}\}_{i=1}^{N}$.
However this auctioneer – bidder approach is made up of two main components, which are:

(a) For a given price, p_{th}, each bidder r_i, $\forall i$ determines its demand vector $\{p_{s,r_i}\}_{i=1}^{N}$, then places the corresponding bid vector $\{b_{s,r_i}\}_{i=1}^{N}$ to the auctioneer;
(b) For the collected or submitted bids from the bidders, the auctioneer determines its own supply value as well and allocates the power based on those bids.

In essence, our main challenge is to develop a price value and a bidding matrix or profile so that the outcome of the proposed bidding game is equivalent to the optimum solution of NLO. We thus introduce a 2-sided bidding game rule. One side is the bidder's side while the other is the auctioneer's side.

Side 1: For the bidders' side, each of the bidders r_i, $\forall i$ places a bid in proportion to the price given by the auctioneer and the power it intends to buy from it, i.e. $b_{s,r_i}=p_{th}\cdot p_{s,r_i},\quad \forall i$. Obviously, if $p_{s,r_i}=0\Rightarrow$ no bidding takes place.

Side 2: However, for the auctioneer's side, the auctioneer aims at maximizing the surrogate function $\sum_{i=1}^{N} b_{s,r_i}\log p_{s,r_i}$, using the mechanism in Kelly et al. [19]; the differentiability and concavity in p_{s,r_i} being the factors for selecting the surrogate function.

We propose the following:

Proposition: There is an optimum demand vector $\{p^{*}_{s,r_i}\}_{i=1}^{N}$ from each bidder r_i, $\forall i$, and an optimum supply value from the auctioneer both of which agree with the NLO.

Proof of the proposition: The achievable transmission rate capacity of source, C_s is related only to $\{p_{s,r_i}\}_{i=1}^N$ without having an explicit relationship with $\{p_{r_i,s}\}_{i=1}^N$. Since C_s is jointly concave in $\{p_{s,r_i}\}_{i=1}^N$, bidder r_i has the capability to decide its demand $\{p^*_{s,r_i}\}_{i=1}^N$ which satisfies (15) – (18), with the optimal dual vector λ^* given. From the illustrative graph in Fig.2, the power the auctioneer sells to bidder r_i is equivalent to the power the bidder r_i submits a bid for. This thus means that an optimal demand vector leads to an optimum supply vector. This proposition implies that, if the source and relay nodes simply follow the proposed scheme rather than attempt to compute the local payoff selfishly, the global optimum is achievable.

3.2.1 Bidder problem

We assume that the bidders do not place their bids just to impact the auctioneer's price, especially when there are N bidders at play in the bidding market. There is the tendency for each bidder to want to maximize its utility or surplus (which is the difference between the payoff from buying power from auctioneer and its own payment for the power). From the auctioneer's price, p_{th}, bidder r_i determines its optimum demand according to the following function:

$$\max_{\{p_{s,r_i}\}_{i=1}^N} U_{r_i} = C_s - \sum_{i=1}^N p_{th} p_{s,r_i} \quad (19)$$

After this, the bidder places its optimum bid to the auctioneer according to that optimal demand and the announced price p_{th} as :

$$b^*_{s,r_i} = p^*_{s,r_i}, \quad \forall i \quad (20)$$

From the rule of concavity, it can be proved that the utility U_{r_i} is jointly concave in $\{p_{s,r_i}\}_{i=1}^N$ where C_s (defined in (8)) is concave in $\{p_{s,r_i}\}_{i=1}^N$. And as a result of the concave nature of the utility, bidder r_i is able to optimize the unique power vector $\{p_{s,r_i}\}_{i=1}^N$ so as to maximize its payoff. Finding the derivative of U_{r_i} in (19) with respect to p_{s,r_i}, the necessary and sufficient first order condition can be obtained as:

$$\frac{\partial U_{r_i}}{\partial p^*_{s,r_i}} = C'_s\left(p^*_{s,r_i}\right) - p_{th} = 0, \quad \forall p_{s,r_i} > 0, i \quad (22)$$

Having another look at (15), which is the KKT condition for the NLO, it can be seen that if the auctioneer announces its price as

$$p^*_{th} = \lambda^*_i = C'_s\left(p^*_{s,r_i}\right), \quad \forall i, \ \forall p_{s,r_i} > 0 \quad (23)$$

it is then obvious that (21) agrees with (15). This clearly shows that the optimum power p^* in the above bidder problem is in agreement with the one in the NLO. It can thus be seen from the above analysis that, with an appropriate pricing and bidding, the individual optimum in the bidder problem in in good agreement with the global optimum.

3.2.2 Auctioneer problem

The next issue we need to address is the auctioneer problem. We can solve the optimum power supply or allocation by the auctioneer by the formulation of auctioneer problem in terms of the following optimization problem:

$$\max \sum_{i=1}^N b_{s,r_i} \log p_{s,r_i} \quad (24)$$

$$\text{s.t} \sum_{i=1}^N p_{s,r_i} \le \overline{p}_s \quad (25)$$

variables $p \ge 0$ (26)

The Lagrangian associated with the problem (24) – (26) is written as follows:

$$L'_s = \sum_{i=1}^N b_{s,r_i} \log p_{s,r} - \lambda_s \left(\sum_{i=1}^N p_{s,r_i} - \overline{p}_s \right) \quad (27)$$

where λ_s denotes the Lagrange multiplier of the auctioneer. From the KKT theorem mentioned earlier, the KKT conditions for the auctioneer problem are as follows:

$$p^*_{s,r_i} = \frac{b_{s,r_i}}{\lambda^*_s}, \ \forall i \in N \quad (28)$$

$$\lambda^*_s \left(\sum_{i=1}^{N} p^*_{s,r_i} - \overline{p}_s \right) = 0 \quad (29)$$

$$\sum_{i=1}^{N} p_{s,r_i} \le \overline{p}_s \quad (30)$$

$$p^* \ge 0, \quad \lambda^*_s \ge 0 \quad (31)$$

If the above problem with its accompanying KKT conditions is compared with the NLO, we see that if $\lambda_i = \lambda_s$ and bids are submitted / placed by bidders as

$$b^*_{s,r_i} = p^*_{s,r_i} C'_s \left(p_{s,r_i} \right)$$
(32)

It can be clearly seen then that (28) – (31) agree with (18) – (21) and the solution of the auctioneer problem is also in agreement with the NLO.

3.3 Algorithm for the Power Allocation Scheme

We now construct an algorithm to show the mechanism for the bidding game-based power allocation scheme we are proposing. This mechanism is iterative.

3.3.1 Algorithm for single-auctioneer multi-bidder power bidding game

Initialize or Start up

Iterative process index is set up at t = 0

For every bidder node, initial mode is set to direct (non-cooperative) transmission

i.e. $p^{(0)}$ = diag ($\overline{p}_1, \overline{p}_2, ...\overline{p}_N$): only diagonal elements are non-zero

A random 1 x N bid matrix, $b^{(0)} \ge 0$ is generated

A random value of auctioneer's price p_{th} is given as the threshold price

Iterate

1. $t \leftarrow t + 1$
2. Allocate power: Source (auctioneer) dynamically allocates power p_{s,r_i} to relay r_i according to
3. $p^{(t)}_{s,r_i} = \dfrac{b^{(t-1)}_{s,r_i}}{p^{(t-1)}_{th}}, \ \forall i \in N$
4. Update bids:

- $t \ge 1;$
- Auctioneer, s = 1;
- **for** each bidder r_i, i = 1:N **do**
- **if** $\dfrac{\partial U^{(t)}_{r_i}}{\partial p^{(t)}_{s,r}} > 0$ **,** OR $C'_s\left(p^{(t)}_{s,r_i}\right) > p^{(t-1)}_{th}$ **then**
- $b^{(t)}_{s,r_i} = p^{(t)}_{s,r_i} C'_s \left(p^{(t)}_{s,r_i} \right)$**;**
- **else**
- $b_{s,r_i}(t) = 0;$
- **end if**
- **end for**

5. Update price: The auctioneer updates its price as follows:

$$p_{th}^{(t)} = p_{th}^{(t-1)} + \psi_{th}\left(\sum_{i=1}^{N} p_{s,r_i}^{(t)} - \overline{p}_s\right)$$

Where ψ_{th} = small constant incremental step-size

Until the price value converges

4. RESULTS AND DISCUSSION

A cooperative communication network consisting of one source node, one destination and four relay nodes is considered, as shown in Fig. 4. The single destination node is situated at (0, 0) in a two-dimensional plane topology, while the relay nodes are randomly located on the network plane. The source node is acting as the auctioneer while the relays are acting as the bidders in the bidding game. It is assumed that all relay nodes have the same maximum power constraints, given as 10 dB. The path loss exponent is also set to be 3.0.

In Fig. 5, we show the convergence of the source node's power to the Nash equilibrium. It can be recalled that the existence of and convergence to the Nash equilibrium are a necessary condition for the solution of any game-based analysis. The plots equally show the variations of the source power with different price allotments. Fig. 6 shows a similar situation but with the utility of the source node. Fig. 7 shows a comparison of the convergence of the proposed scheme with the work of Yuan et al, 2011, using the bidding price. It shows that our proposed scheme outperforms that other work

We were also able to find from our simulations that the closer a relay is to the destination node, the higher the price it presents and the higher the utility it provides for the source node. For instance, in the 2-D graph in Fig. 4, relay 2 is closest to the destination node, and thus presents the highest utility to the source node. A reason for this is that the closer a relay node is to the destination node, the less the power it would need to forward the source node's data to the destination node against the situation in which the relay node is further away from the destination node. So, the relay node located close to the destination node would most likely as the highest price and thus be the most likely selection candidate for the source node – which would give utility to both the relay and source nodes.

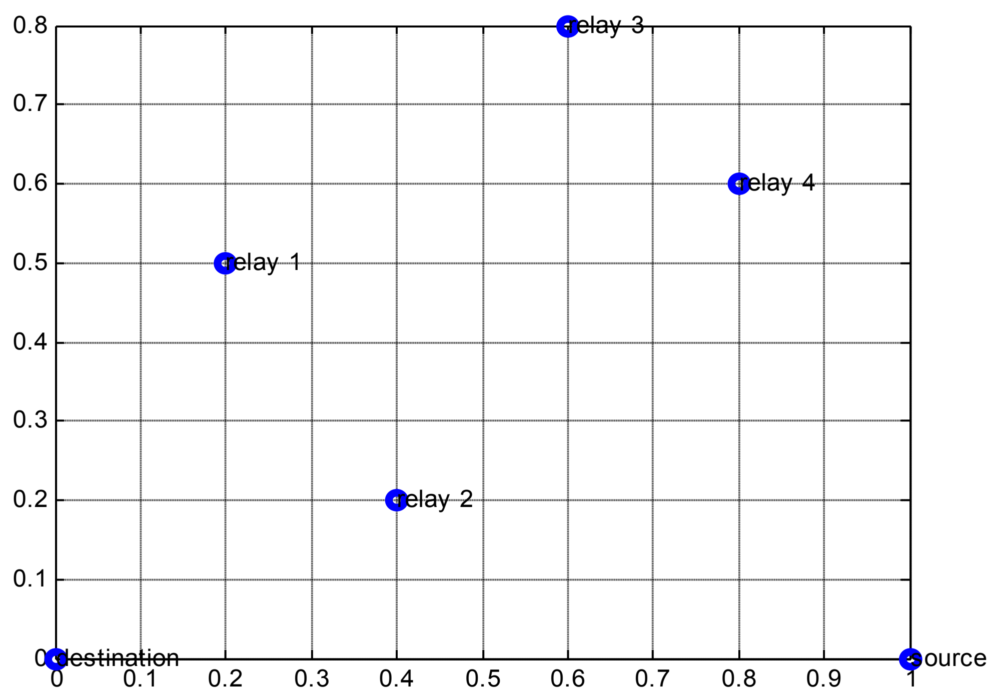

Fig. 4. Graph showing the locations of the source, relay and destination nodes on a 2-D plane

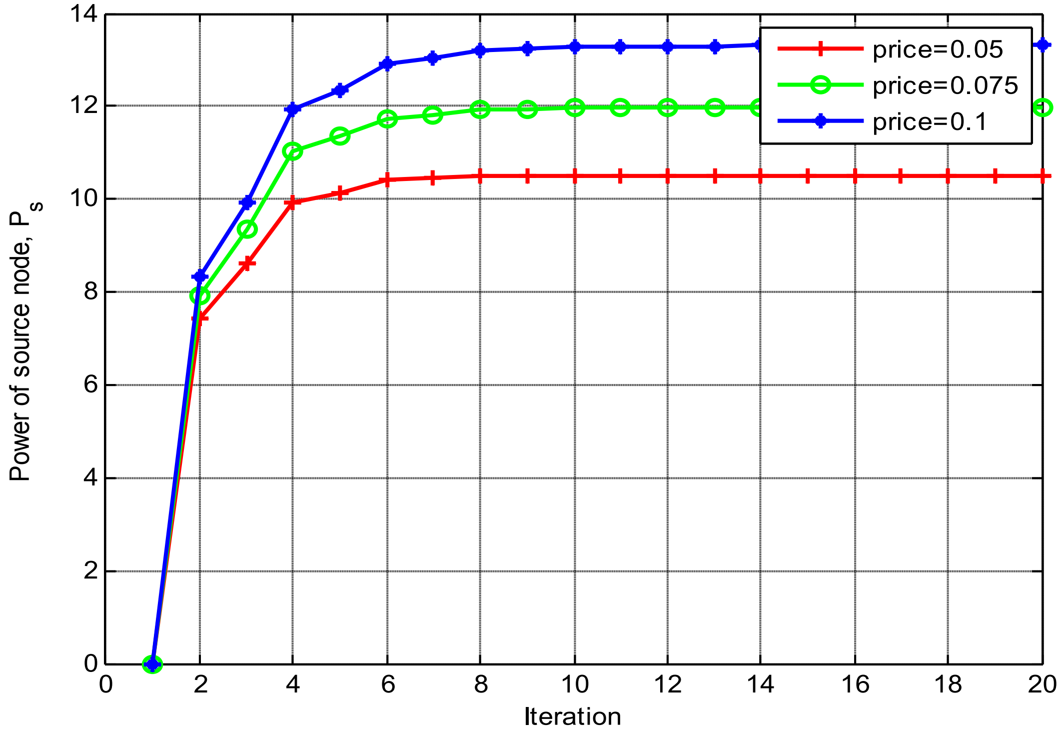

Fig. 5. Plots showing the convergence of the source node power to the Nash equilibrium

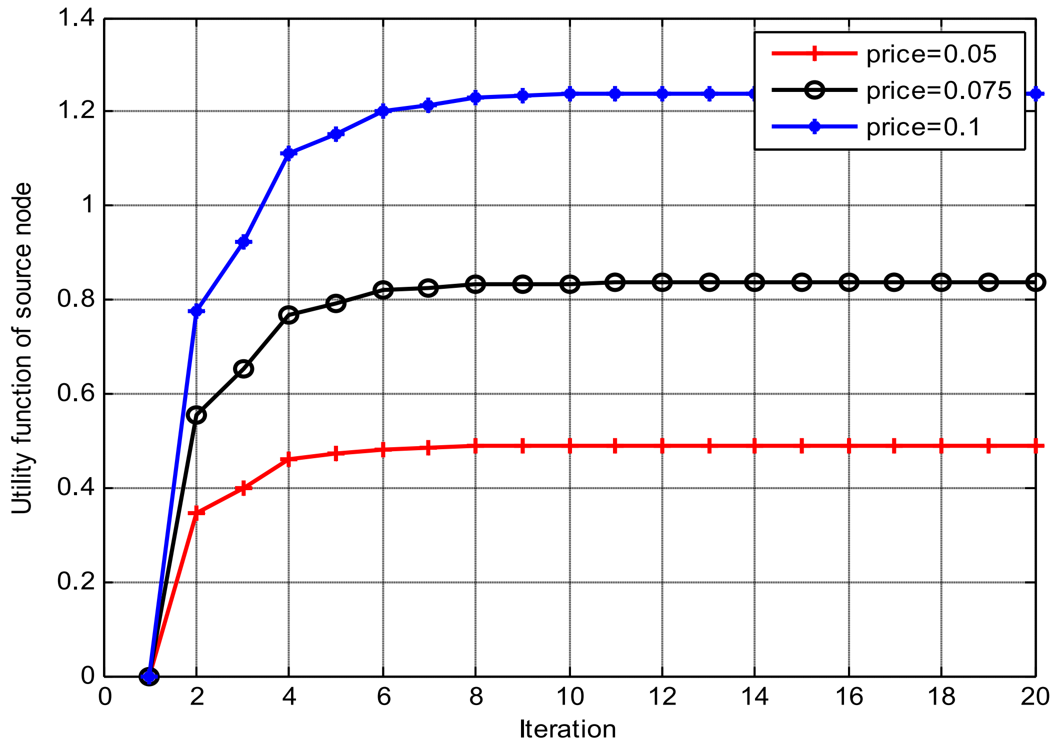

Fig. 6. Plots showing the convergence of the source node's utility to the Nash equilibrium

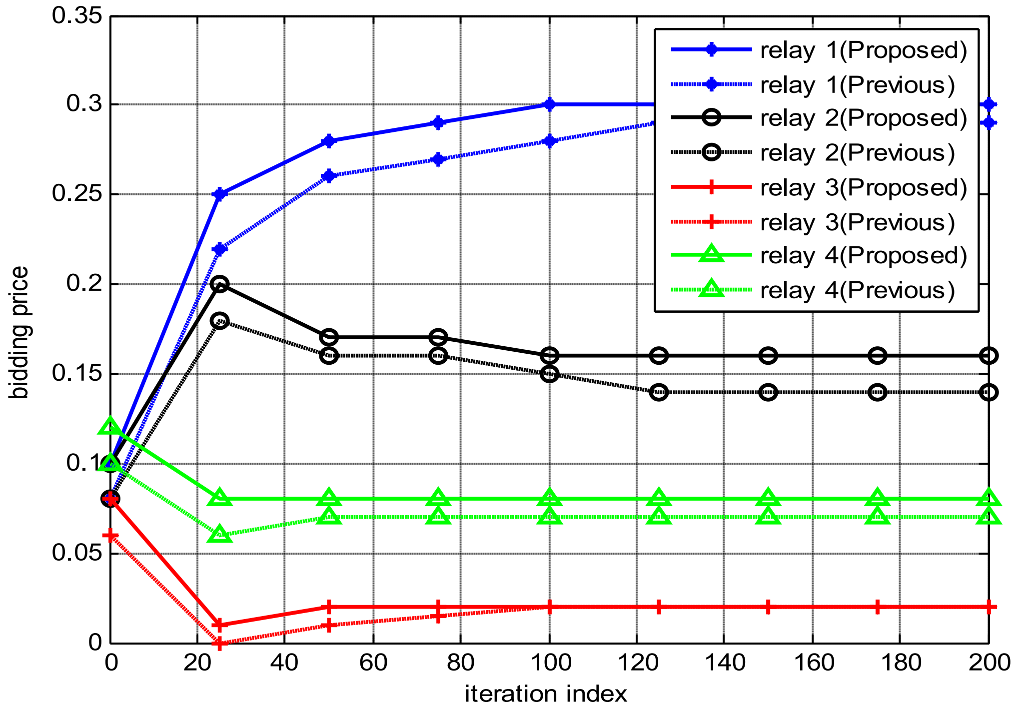

Fig. 7. Comparison of the convergence of the proposed scheme with the work of Yuan et al, 2011, using the bidding price

5. CONCLUSION

In this paper, we have proposed a new scheme for optimum resource allocation in cooperative communication networks using a kind of game known as the bidding game. We were able to solve this problem by mapping a cooperative network into a single-auctioneer multi-bidder game where the source node acts as the auctioneer and the relays act as the bidders. Through the implementation of this proposed power bidding scheme, the user can achieve the optimum in terms of the power bided for and the power sold, without violating the power constraints. Thus the motivation for embarking on this research and the contribution thereof have been achieved, for it will assist designers of future generation of wireless communication infrastructure in the area of efficient utilization of energy.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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