A Unified Cross-Layer Framework for Resource Allocation in Cooperative Networks

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Abstract—Node cooperation is an emerging and powerful solution that can overcome the limitation of wireless systems as well as improve the capacity of the next generation wireless networks. By forming a virtual antenna array, node cooperation can achieve high antenna and diversity gains by using several partners to relay the transmitted signals. There has been a lot of work on improving the link performance in cooperative networks by using advanced signal processing or power allocation methods among a single source node and its relays. However, the resource allocation among multiple nodes has not received much attention yet. In this paper, we present a unified cross-layer framework for resource allocation in cooperative networks, which considers the physical and network layers jointly and can be applied for any cooperative transmission scheme. It is found that the fairness and energy constraint cannot be satisfied simultaneously if each node uses a fixed set of relays. To solve this problem, a *multi-state cooperation* methodology is proposed, where the energy is allocated among the nodes state-by-state via a geometric and network decomposition approach. Given the energy allocation, the duration of each state is then optimized so as to maximize the nodes utility. Numerical results will compare the performance of cooperative networks with and without resource allocation for cooperative beamforming and selection relaying. It is shown that without resource allocation, cooperation will result in a poor lifetime of the heavily-used nodes. In contrast, the proposed framework will not only guarantee fairness, but will also provide significant throughput and diversity gain over conventional cooperation schemes.

Index Terms—Cooperative networks, cross-layer design, resource allocation, fairness, lifetime, convex optimization.

I. INTRODUCTION

MIMO (Multiple-Input Multiple-Output) systems, where multiple antennas can be used at both the transmit and receive ends, have recently been receiving significant attention because they hold the promise of achieving huge capacity increases and diversity gains over the harsh wireless link [1],

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[2]. As such, MIMO is currently considered as one of the main candidates for meeting the stringent requirement and demand of future wireless networks. Unfortunately, the use of MIMO technology may not be practical in many wireless networks. For instance, nodes in a sensor network are usually small, inexpensive, and have typically severe energy constraints. Cooperative networking or communications is one potential solution that can overcome this limitation. The fundamental idea behind cooperative networks is based on the fact that the signals transmitted by a source node to its destination node can be also received by other nodes in a wireless environment. These nodes can then act as relays to process and re-transmit the signals they receive in a distributed fashion, thereby, creating a virtual antenna array through the use of the relays' antennas without complicated signal design or adding more antennas at the nodes [3-10].

Sendonaris *et al* firstly proposed the idea of cooperative diversity for CDMA cellular networks [3-4]. Laneman *et al* studied various cooperative diversity schemes such as fixed relaying, selection relaying, and incremental relaying [5-6]. The work in [7] compared several cooperation protocols and presented a space-time code design criteria for amplify-and-forward relay channels. In order to increase the power efficiency of ad-hoc networks such as sensor networks, cooperative beamforming via a virtual array was developed in [8-9]. [10] further studied the capacity of cooperative networks from an information-theoretic perspective and showed the feasible position of relays.

The above previous work mainly aimed at enhancing the performance in the physical layer. However, cooperative communication is inherently a network problem, as pointed out in [3], [5-6]. It would be therefore fruitful to take into account additional higher layer network issues. There have been some efforts towards this such as combining node cooperation with ARQ in the link layer [11], routing in the network layer [12], or resource allocation in the MAC layer [13-14]. From a cross-layer perspective, fairness is especially important in cooperative networks since some nodes may have more chances to be relays, or consume more power in cooperative transmissions so that their energy may be used up very fast. In this scenario, not only the heavily-used nodes will suffer from a short lifetime, but also the other nodes will not be able to achieve the expected cooperative gain due to the lack of available relays. More seriously, these self-interested users or heavily-used terminals may refuse to cooperate in order to save their energy. The fairness and lifetime issues

have been considered in wireless networks with network layer cooperation using packet forwarding rather than signal forwarding [15-18]. It was demonstrated in [15] that an over-consumption of some nodes may result in a short network lifetime. In order to stimulate node cooperation and balance energy consumption, both reputation-based and market-based approaches were presented. Using a game-theoretic framework, [16] proposed a generous tit-for-tat strategy for energy-constrained ad-hoc networks. The market-based approach was studied in [17] and [18], where a micro-economic framework was used to maximize the node utility in a distributed fashion. However, user cooperation in the physical layer was not taken into account in these existing works. Most recently, we applied a market-based approach for increasing the fairness and efficiency of ad-hoc wireless networks using cooperative beamforming [19]. In particular, a practical protocol was presented in [19] to significantly increase the lifetime and throughput of energy-constrained cooperative networks.

In this paper, our main objective is to develop an effective way to optimize the overall performance of cooperative networks across multiple layers simultaneously. Specifically, we consider energy-constrained networks where cooperative transmission is adopted. A unified cross-layer framework for resource allocation among multiple nodes is presented, where fairness and efficiency are taken into consideration. Our objective is to guarantee that the lifetime of each node can be equal to a target lifetime and that the energy used in transmitting and/or relaying each node's signal is equal to its total energy. Moreover, each node can efficiently use the available energy to optimize its performance such as throughput or outage probability. To achieve this, we propose an energy allocation method consisting of multiple cooperation states, where the relay set of each node is not fixed. In particular, each state corresponds to a set of nodes which run out of energy during the previous states and will not cooperate anymore. In practice, the state of a node corresponds to a particular relay set of this node. In particular, a base station or a head node will announce the set of nodes which do not have energy to serve as relays in each state. A node will then ignore these nodes when it searches its relays in a given state. We shall show that at least one node will run out of its energy in each state. Thus, the total number of states will not be greater than the number of nodes. Based on the energy allocation results, we allocate the node lifetime among the multiple states to determine how long a particular set of relays can serve a node. The proposed multi-state cooperation in which the heavily-used nodes are not always forced to serve as relays is a natural extension of the conventional cooperation protocols with fixed sets of relays. The proposed framework will be applied into cooperative beamforming and selection relaying. Numerical results show that without an appropriate resource allocation, unfair cooperation will result in a significant decrease in the lifetime of heavily-used nodes. In contrast, the proposed framework cannot only guarantee fairness, but also provide significant throughput or diversity gain over the conventional cooperation schemes.

The remainder of the paper is organized as follows. Section II presents the system model. In Section III, a multi-state cooperation methodology with its energy allocation scheme is presented. Section IV investigates the efficient time allocation over multiple states. Numerical results and some implementation issues will be discussed in Section V and VI, respectively. Finally, concluding remarks are presented in Sections VII.

Throughout this paper, the following notations will be used. The superscript ^{T} shall stand for the transpose of a matrix $\mathbf{X}$ or a vector $\mathbf{x}$. The inequality $\mathbf{x} \preccurlyeq \mathbf{y}$ implies that $x_i \leqslant y_i$ for any i. The geometric multiplicity of an eigenvalue $\lambda(\mathbf{X})$ is denoted by $geomult_{\mathbf{X}}(\lambda(\mathbf{X}))$[20]. For a set $\mathcal{X}$, the operator $|\mathcal{X}|$ denotes the number of elements in the set. The operator $\backslash$ denotes the difference of two sets. For an event ω, the indicator function shall be denoted by $\mathcal{I}(\omega)$, where $\mathcal{I}(\omega) = 1$ is ω is true. Otherwise, $\mathcal{I}(\omega) = 0$. A vector with all of its elements equal to 1 is denoted by $\mathbf{1}$. Finally, $\mathbf{0}$ shall denote the all zero matrix/vector with the appropriate size.

II. SYSTEM MODEL

Consider a wireless network which consists of N source/relay nodes. The source node set is denoted by $\mathcal{S} = \{1, \ldots, N\}$. Each source node i transmits to its destination node $d(i)$, which may not belong to $\mathcal{S}$. Let h_{ij} denote the channel power gain between node i and j. In our work, both static channels and time-varying channels can be taken into account. For networks with time-varying channels, which we shall refer to as time-varying networks, small-scale fading is assumed to be Rayleigh so that the instantaneous channel gain h_{ij} is a random variable with an exponential distribution with mean value $\overline{h}_{ij}$. For networks with static channels, which we shall refer to as static networks, $h_{ij} = \overline{h}_{ij}$. It is assumed that $\overline{h}_{ij} = \overline{h}_{ji}$ and the noise power at the receivers is denoted by σ^2. All nodes are assumed to be energy-constrained and the total energy of each node is denoted by E^{total}.

With user cooperation, each source node may employ some nodes to serve as relays. Each cooperative transmission will be assumed to occur over two timeslots, where the source transmits to its relays in the first timeslot and relays re-transmit the signal to the destination in the second timeslot. Since for a particular source-destination (s-d) pair, some nodes may be far away from both the source and the destination, only neighbors are selected in order to increase power efficiency and avoid error propagation. An average channel gain threshold $\overline{g}_i$ is assigned to each node i. Then, node i can only choose the nodes j satisfying $\overline{h}_{ij} \geqslant \overline{g}_i$ to serve as its relays. The set of potential relays for node i is denoted by $\mathcal{R}_i$. Intuitively, $\overline{g}_i$ should be an increasing function of node i's average s-d channel gain. This is because the worse an s-d channel is, the more relays the source node will need. In networks where the s-d distances are approximately the same, we can simply assign the same threshold to each node. In this paper, we assume that the source node itself can act as a relay in the second timeslot. That is, $i \in \mathcal{R}_i$. Assume that all relay nodes are chosen from the source node set $\mathcal{S}$. Hence, $\mathcal{R}_i \subseteq \mathcal{S}$ for any $i \in \mathcal{S}$. In the MAC layer, each source node with its relays can employ an orthogonal channel to avoid multi-user interference. Without loss of generality, FDMA is assumed throughout this paper. Furthermore, each node is assumed to have a saturated queue with always packet availability.

In this paper, two typical cooperation schemes are considered: cooperative beamforming and selection relaying. The

TABLE I
COOPERATION MATRIX

Cooperation Matrix	
Cooperative Beamforming	$a_{ij} = \begin{cases} \dfrac{\overline{g}_j \overline{h}_{id(j)} + \left(\sum_{n \in \mathcal{R}_j} \overline{h}_{nd(j)} \right)^2 \mathcal{I}\{i=j\}}{\left(\overline{g}_j + \sum_{n \in \mathcal{R}_j} \overline{h}_{nd(j)} \right) \sum_{n \in \mathcal{R}_j} \overline{h}_{nd(j)}} & i \in \mathcal{R}_j \\ 0 & i \notin \mathcal{R}_j \end{cases}$
Selection relaying	$a_{ij} = \begin{cases} \dfrac{\Pr\{h_{ji} \geq \xi_j\}}{\sum_{n \in \mathcal{R}_j} \Pr\{h_{jn} \geq \xi_j\}} & i \in \mathcal{R}_j \\ 0 & i \notin \mathcal{R}_j \end{cases}$

cooperative beamforming is a rate-optimal cooperation scheme adopted in static networks. In this case, the virtual antenna array formed by the relays will re-transmit the signals with beamforming in order to achieve the highest throughput. Selection relaying, on the other hand, is adopted in time-varying networks [5]. As selection relaying is adopted, only the relays which can decode the source information correctly will retransmit. The set of nodes that decode correctly in a timeslot is often referred to as the decoding set $\mathcal{D}$.

We denote the energy that node j consumed in transmitting/relaying signals of node i to be $E_j^{(i)}$. In wireless networks, all the nodes are expected to have the same lifetime T^*. As a result, each node should consume all of its energy, E^{total}, simultaneously at the end of the target node lifetime interval $[0, T^*]$. No nodes are allowed to have residual energy after T^*. Otherwise, its lifetime can be longer than T^*. On the other hand, the energy utilized in transmitting and/or relaying each node's information should be equal in order to guarantee fairness. In non-cooperative networks where nodes transmit directly without employing relays, this can be easily satisfied since each node's energy consumed is utilized to transmit its own information. In cooperative networks, this is not naturally achieved and hence an appropriate resource allocation is desired.

III. ENERGY ALLOCATION IN COOPERATIVE NETWORKS

In this section, we address the energy allocation problem in cooperative networks. Two basic constraints for energy allocation as well as a linear relationship between the energy allocated and energy consumed are presented. In order to satisfy the two constraints, a multi-state cooperation methodology is proposed. We then provide a geometrical approach to allocate the energy state-by-state via a finite-step iteration algorithm. In each state, the energy allocation is obtained by solving a linear equation.

A. Energy Allocation Vector and Consumption Vector: Constraints and Relationship

Let us denote the energy consumption vector $\mathbf{e}^C = [e_1^C, \ldots, e_N^C]^T$, where the ith element $e_i^C = \sum_{j=1}^n E_i^{(j)}$ is the total energy consumed by node i. Note that the energy allocated to a node is the total energy utilized in transmitting and relaying this node's information. We denote the energy allocation vector $\mathbf{e}^A = [e_1^A, \ldots, e_N^A]^T$, where the ith element $e_i^A = \sum_{j=1}^n E_j^{(i)}$. Since the node is energy-constrained and all

nodes should consume all of their energy within their target lifetime, the energy constraint is written as

$$\mathbf{e}^C = E^{max}\mathbf{1} \qquad (1)$$

Due to the fairness requirements, e_i^A should be equal for each node i. Since the total energy consumed by all nodes is $\sum_{n=1}^N E^{max} = NE^{max}$, the fair allocation constraint should guarantee that $e_i^A = NE^{max}/N$. Therefore, such constraint is given by

$$\mathbf{e}^A = E^{max}\mathbf{1}. \qquad (2)$$

In a non-cooperative network, the two constraints (1)-(2) are naturally satisfied since $E_j^{(i)} = 0$ for $i \neq j$. As cooperative transmission is adopted, $\mathbf{e}^A$ and $\mathbf{e}^C$ will be shown to be linearly related. In order to derive such a relationship, a *cooperation matrix* is defined as follows.

Definition 1 (Cooperation Matrix): The cooperation matrix is defined to be a matrix $\mathbf{A} = [a_{ij}]_{N \times N}$, where the element a_{ij} denotes the energy ratio that node i contributes to node j. That is,

$$a_{ij} = \frac{E_i^{(j)}}{\sum_{n=1}^N E_n^{(j)}}. \qquad (3)$$

Note that the cooperation matrix $\mathbf{A}$ is determined by the cooperation scheme and the relay sets $\mathcal{R}_i$, for $i = 1, \ldots, N$. Since $\sum_{i=1}^N a_{ij} = 1$, $\mathbf{A}^T$ is a stochastic matrix [20].[1] The cooperation matrices of two cooperation schemes are given in Table I, with the detailed derivation given in Appendix I.

According to (3), the energy that node i consumes for transmitting/relaying the signal of node j can be presented as $E_i^{(j)} = a_{ij}e_j^A$. Hence, the total energy consumption of node i is obtained as $e_i^C = \sum_{j=1}^N a_{ij}e_j^A$. As a result, the energy allocation and consumption can be related by

$$\mathbf{A}\mathbf{e}^A = \mathbf{e}^C. \qquad (4)$$

By substituting (1) and (2) into (4), we have

$$\mathbf{A}E^{max}\mathbf{1} = E^{max}\mathbf{1}. \qquad (5)$$

According to Definition 1 and (5), the cooperation matrix $\mathbf{A}$ should be a doubly-stochastic matrix in order to satisfy both (1) and (2). Unfortunately, $\mathbf{A}$ cannot satisfy (5) in general because it cannot be doubly-stochastic for networks with randomly-located nodes.

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[1] As defined in [20], a stochastic matrix is a nonnegative matrix in which each row sum is equal to 1. In addition, a doubly-stochastic matrix is a nonnegative matrix in which each row sum as well as each column sum is equal to 1.

B. Multi-state Cooperation: To Cooperate or Not to Cooperate

Since the energy constraint (1) and the fairness constraint (2) cannot be satisfied simultaneously as relay sets are fixed, each node should be allowed to use a different relay set in a different cooperation state in order to satisfy (1)-(2). This motivates us to develop a resource allocation framework consisting of multiple cooperation states, which we shall refer to as *multi-state cooperation*. In each state k, the relay set $\mathcal{R}_i(k)$ for any node i is fixed. Therefore, the cooperation state is given by the set of all relay sets. Let $\mathbf{e}^A(k)$ denote the energy allocation vector in state k, where the ith element is the total energy utilized in transmitting and relaying node i's information in state k. Also let $\mathbf{e}^C(k)$ denote the energy consumption vector in state k, where the ith element is the total energy consumed by node i in state k. For a multi-state cooperation, the energy allocation $\mathbf{e}^A(k)$, $k = 1, \ldots, K$, should satisfy the energy and fairness constraints given by

$$\begin{cases} \sum_{k=1}^K \mathbf{e}^C(k) = \sum_{k=1}^K \mathbf{A}(k)\mathbf{e}^A(k) = E^{max}\mathbf{1} \\ \sum_{k=1}^K \mathbf{e}^A(k) = E^{max}\mathbf{1}, \end{cases} \quad (6)$$

where K is the total number of states and $\mathbf{A}(k)$ is the cooperation matrix associated with state k. In order to obtain $\mathbf{e}^A(k)$ that satisfies (6), a state-by-state energy allocation methodology is presented. In each state, the energy allocation should satisfy the constraint

$$\mathbf{e}^A(k) = \mathbf{e}^C(k), \quad (7)$$

which can always be satisfied by the method described next in Section III-C. However, $e_i^C(k)$ may not be equal to $e_j^C(k)$ for any $j \neq i$ in general. Therefore, some nodes will consume all of their energy in state k while others may still have residual energy to be allocated and consume in the following states. In each state, only the nodes that have residual energy can transmit and serve as relay for others. Iteratively, we can allocate the residual or remaining energy state-by-state until all of the energy is allocated in the final state.

Let $\mathbf{e}^{max}(k)$ denote the residual energy vector, where the ith element $e_i^{max}(k)$ is the node i's residual energy in state k. In the initial state 1, $\mathbf{e}^{max}(1) = E^{max}\mathbf{1}$. After energy allocation in state k, the residual energy $\mathbf{e}^{max}(k+1)$ of the next state is given by

$$\mathbf{e}^{max}(k+1) = \mathbf{e}^{max}(k) - \mathbf{e}^A(k). \quad (8)$$

Constrained by $e_i^{max}(k)$, the relay set of node i in state k, $\mathcal{R}_i(k)$, is given by

$$\mathcal{R}_i(k) = \\ \begin{cases} \{i : \overline{h}_{ij} \leq \overline{g}_i, e_j^{max}(k) > 0, j \in \mathcal{S}\} & e_i^{max}(k) > 0 \\ \{i\} & e_i^{max}(k) = 0 \end{cases} \quad (9)$$

In Section III-C, we will present an energy allocation method, where at least one node will run out of energy in each state. Therefore, all of the energy can be allocated within $K < N$ states so that the residual energy vector in the final state K satisfies

$$\mathbf{e}^{max}(k+1) = \mathbf{0}. \quad (10)$$

According to (7), (8), and (10), (6) is satisfied in a K-state cooperation.

C. Energy Allocation in One State

In this part, the analytical result for energy allocation in one state is presented. For a particular state k, the cooperation matrix $\mathbf{A}(k)$ is determined by the relay sets given by (9). Thus, by substituting (4) into (7), it follows that $e^A(k)$ should be a nonnegative solution to the following equation

$$\mathbf{A}(k)\mathbf{e}^A(k) = \mathbf{e}^A(k). \quad (11)$$

and satisfy the residual energy constraint in state k, which is given by

$$\mathbf{e}^A(k) \preccurlyeq \mathbf{e}^{max}(k). \quad (12)$$

Since $\mathbf{A}^T(k)$ is a stochastic matrix, there must be an eigenvalue $\lambda(\mathbf{A}(k)) = \lambda(\mathbf{A}^T(k)) = 1$ [20]. Thus, Eqn. (11) must have nontrivial solutions. The solution space is the eigenspace of $\mathbf{A}(k)$ with respect to $\lambda(\mathbf{A}(k)) = 1$. In order to obtain $\mathbf{e}^A(k)$, a *network decomposition* methodology is first introduced in order to find an orthogonal basis set of the solution space. We shall show that each basis characterizes the fair energy allocation of a sub-network. For convenience, we can ignore the index k in this part since we are considering energy allocation of a particular state.

In each state, the cooperative network can be decomposed into disjoint sub-networks, where the nodes in different sub-networks do not cooperate with each other.[2] Intuitively, the energy allocations in each sub-network are independent. Mathematically, for a given cooperation matrix $\mathbf{A}$, the whole network $\mathcal{S}$ can be decomposed into M disjoint sub-networks $\mathcal{S}^{(m)} = \{n_1^{(m)}, \ldots, n_{|\mathcal{S}^{(m)}|}^{(m)}\}$, for $m = 1, \ldots, M$, which satisfy the following
(1) $\mathcal{S} = \bigcup_{m=1}^M \mathcal{S}^{(m)}$, with $\mathcal{S}^{(m)} \bigcap \mathcal{S}^{(n)} = \emptyset, \forall\ m \neq n$.
(2) $a_{ij} = a_{ji} = 0, \forall\ i \in \mathcal{S}^{(m)}, j \in \mathcal{S}^{(n)}, m \neq n$.
(3) Each sub-network $\mathcal{S}^{(m)}$ cannot be decomposed into multiple disjoint subsets satisfying properties (1) and (2).

For a given $\mathbf{A}$, the whole network $\mathcal{S}$ can be decomposed into $\mathcal{S}(m)$ satisfying the above three properties by using a graph-theoretic algorithm as shown in Appendix II. It is noted that each sub-network $\mathcal{S}(m)$ will have its own cooperation matrix $\mathbf{A}^{(m)}$. Let $\mathbf{P}$ denote the permutation matrix with elements $p_{uv} = \mathcal{I}\{(\ u = n_i^{(m)}, v = i + \sum_{r=1}^{m-1} |\mathcal{S}^{(r)}|)\ \}$. Then, $\mathbf{A}^{(m)}$ is the mth diagonal block in the diagonal block matrix

$$\mathbf{P}^T \mathbf{A} \mathbf{P} = \begin{bmatrix} \mathbf{A}^{(1)} & & \\ & \ddots & \\ & & \mathbf{A}^{(m)} \end{bmatrix}. \quad (13)$$

Having established the network decomposition methodology, we shall present the optimal energy allocation in one state in the following theorem.

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[2]In the first state, a network may consist of only one sub-network if its topology is not clustered. Due to the reshaping of the relay sets, some nodes will not cooperate with others and be isolated in the following states. In this case, however, a network must be decomposed into more than one sub-network.
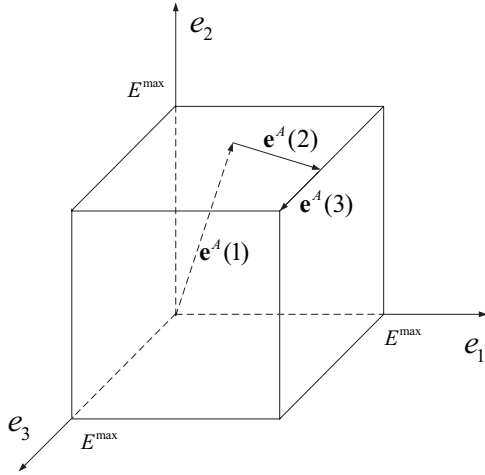
Fig. 1.   Geometrical representation of multi-state energy allocation

Fig. 2.   Multi-State Cooperation in the Time Domain

Theorem 1: The optimum energy allocation vector that satisfies (11)-(12) is obtained by

$$\mathbf{e}^A = \sum_{m=1}^{M} \left[\min_{i \in \mathcal{S}^{(m)}} \left(\frac{e_i^{max}}{b_i^{(m)}} \right) \mathbf{b}^{(m)} \right], \qquad (14)$$

where the orthogonal basis $\mathbf{b}(m) = [b_1^{(m)}, \ldots, b_N^{(m)}]^T$, for $m = 1, \ldots, M$, are non-negative. They are given by

$$\mathbf{b}^{(m)} = \mathbf{P} \times \begin{bmatrix} \mathbf{0}_{\left(\sum_{r=1}^{m-1} |\mathcal{S}^{(r)}|\right) \times 1} \\ \begin{bmatrix} 1 & \cdots & 1 \\ & \mathbf{A}^{(m)} & \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ \mathbf{0}_{\left(|\mathcal{S}^{(m)-1}|\right) \times 1} \end{bmatrix} \\ \mathbf{0}_{\left(\sum_{r=m+1}^{M} |\mathcal{S}^{(r)}|\right) \times 1} \end{bmatrix}.$$
$$(15)$$

where $\mathbf{A}^{(m)}$ is a $|\mathcal{S}^{(m)} - 1|$-by-$|\mathcal{S}^{(m)}|$ matrix obtained by deleting an arbitrary one row of $|\mathbf{A}^{(m)} - \mathbf{I}|$.

D. Energy Allocation in Multiple Cooperation States

Having obtained the energy allocation in one state, our proposed multi-state energy allocation algorithm can be presented as follows.

Multi-state Energy Allocation Algorithm
Step 0: Initialize $k = 1$, and set $\mathbf{e}^{max}(1) = E^{max}\mathbf{1}$;
Step 1: Generate $\mathcal{R}_i(k)$ for $i = 1, \ldots, N$, by (9) and $\mathbf{A}(k)$ by (3);
Step 2: Decompose the network into $\mathcal{S}^{(m)}$, $m = 1, \ldots$, M, using the network decomposition algorithm;
Step 3: Obtain the energy allocation vector $\mathbf{e}^A(k)$ by (13)-(15);
Step 4: Calculate the residual energy vector $\mathbf{e}^{max}(k + 1)$ by (8);
Step 5: $k = k + 1$;
Step 6: If $\mathbf{e}^{max}(k) > 0$, **go to Step 1**;
End

It must be noted here that Theorem 1 shows that the energy allocation is always feasible since the solution is nonnegative. One can easily see that Eqn. (11)'s solution space characterized by $\mathbf{b}^{(m)}$, $m = 1, \ldots, M$, contains infinite number of
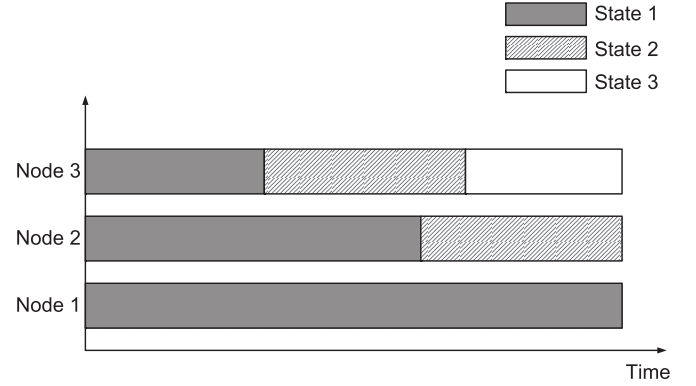
energy allocation vectors satisfying (12). The optimum energy allocation presented in Theorem 1 chooses the solution vector with the maximum 1-norm. The optimality of choosing such an energy allocation vector can be explained as follows. From (9), it can be seen that the number of each node's relays decreases as the state index k increases. Notice that the energy efficiency is higher as more relays are used. Clearly with an increasing state index k the energy efficiency will go down. Therefore, as much as possible energy should be allocated in each state during the iteration. This is why we choose the energy allocation vector with the maximum 1-norm.

From (14) it can be also seen that with the proposed energy allocation, at least one node in each $\mathcal{S}^{(m)}$ satisfies $e_i^A(k) = e_i^{max}(k)$. This implies that at least one node runs out of energy in each state. Therefore, (10) can be satisfied by a K-state ($K \leq N$) energy allocation. From a geometrical perspective, the multi-state energy allocation can be characterized by a K-part curve in $\mathbb{R}^N$ starting from the origin point $\mathbf{0}$ to $E^{max}\mathbf{1}$. The kth part of the curve, $\mathbf{e}^A(k)$, belongs to the eigenspace of $\mathbf{A}(k)$ with respect to $\lambda(\mathbf{A}(k)) = 1$, and the cumulative energy allocation vector is bounded by the super-cube characterized by $E^{max}\mathbf{1}$. For instance, Fig. 1 shows an energy allocation in a three node network. In this case, node 2 is allocated all of its energy in state 1, while nodes 1 and 3 still have residual energy. Next, node 1 is allocated all of its residual energy in state 2. Finally, node 3 runs out of its energy in the last state. Given the above energy allocation outcome, node 2 will always transmit with its state 1's relay set $\mathcal{R}_2(1)=\{1, 2, 3\}$ throughout its entire lifetime. Node 1, however, will use its state 1's relay set, $\mathcal{R}_1(1)=\{1, 2, 3\}$ and state 2's relay set, $\mathcal{R}_1(2)=\{1, 3\}$, in a time sharing manner. Node 3 will have three different relay sets, namely, $\{1, 2, 3\}$, $\{1, 3\}$, and $\{3\}$, which are used in disjoint time durations. Fig. 2 shows how multi-state cooperation evolves in the time domain, where one can see that all nodes will have the same lifetime. How to determine the optimal state duration will be addressed in the next Section.

IV. OPTIMAL STATE DURATION FOR MULTI-STATE COOPERATION

In this section, we investigate how long the set of nodes $\mathcal{R}_i(k)$ can serve as the relay set of node i. Given a target lifetime, we shall allocate the whole lifetime over the multiple

TABLE II
UTILITY FUNCTIONS

Utility Function	
Cooperative Beamforming	$U_{i,k}\left(\frac{e_i^A(k)}{t_i(k)}\right) = \frac{1}{2}\log\left(1 + c_i(k)\frac{e_i^A(k)}{t_i(k)}\right), c_i(k) = \begin{cases} \frac{\overline{g}_i \sum_{j \in \mathcal{R}_i(k)} \overline{h}_{jd(i)}}{(\overline{g}_i + \sum_{j \in \mathcal{R}_i(k)} \overline{h}_{jd(i)})\sigma^2} & |\mathcal{R}_i(k)| \geq 2 \\ 2\overline{h}_{id(i)}/\sigma^2 & |\mathcal{R}_i(k)| = 1 \end{cases}$
Selection Relaying	$U_{i,k}\left(\frac{e_i^A(k)}{t_i(k)}\right) = \sum_{\mathcal{D} \in \mathcal{R}_i(k)} \left\{ \begin{bmatrix} \sum_{j \in \mathcal{D}} \exp\left(-\frac{(2^{2r_i}-1)\sigma^2 \sum_{j \in \mathcal{R}_i(k)} \exp(-\xi_i/\overline{h}_{ij})}{2\overline{h}_{jd(i)} e_i^A(k)/t_i(k)}\right) \prod_{n \neq j} \frac{\overline{h}_{jd(i)}}{\overline{h}_{jd(i)} - \overline{h}_{nd(i)}} \end{bmatrix} \\ \times \prod_{j \in \mathcal{D}} \exp\left(-\frac{\xi_i}{\overline{h}_{ij}}\right) \prod_{j \notin \mathcal{D}} \left[1 - \exp\left(-\frac{\xi_i}{\overline{h}_{ij}}\right)\right] \end{matrix} \right\}$

states of a node. The optimal state duration, which determines the number of time each state would exist or how long $\mathcal{R}_i(k)$ can serve as the relay set of node i, will maximize the node's utility such as throughput or outage probability. A unified utility maximization problem is then formulated for each node.

Assume that $\mathcal{R}_i(k)$ serves as a relay set of node i for $t_i(k)$ seconds. Here, $t_i(k)$ denotes the duration of state k. Subject to the target lifetime T^*, the lifetime constraint for each node i is presented by

$$\sum_{k=1}^{K} t_i(k) = T^*. \tag{16}$$

The node i's utility in state k is denoted by $u_i(k)$, which can be represented as a function of the average power in state k. Note that the average power in state k is proportional to the energy allocated to this state and the inverse of the state duration. Thus, we have,

$$u_i(k) = U_{i,k}\left(\frac{e_i^A(k)}{t_i(k)}\right), \tag{17}$$

where the utility function $U_{i,k}(x)$ is an increasing function of x satisfying $U_{i,k}(0) = 0$ and $U'_{i,k}(x) \geq 0$. In static networks, cooperative beamforming is adopted to maximize the s-d throughput. Hence, we shall use the s-d throughput to measure the utility of each node in this case. In time-varying networks, selection relaying is adopted to reduce the outage probability. Therefore, the probability that outage does not occur, $1 - P_{out}$, is adopted to measure the utility of each node. The utility functions are given in Table II with the detailed derivation shown in Appendix IV.

Given the above, the state duration optimization problem for node i can then be formulated as

$$\begin{aligned} \text{Maximize} \quad & \sum_{k=1}^{K} \frac{t_i(k)}{T^*} U_{i,k}\left(\frac{e_i^A(k)}{t_i(k)}\right) \\ \text{Subject to} \quad & \begin{cases} \sum_{k=1}^{K} t_i(k) = T^* \\ t_i(k) \geq 0, \end{cases} \end{aligned} \tag{18}$$

where the objective function is the average utility, which represents the energy efficiency of node i. It is also guaranteed, mathematically, that each node can achieve a target lifetime by the constraints.

From Section III, node i is not allocated any energy in state k if $e_i^A(k) = 0$. Thus, $t_i^*(k) = 0$ as $e_i^A(k) = 0$. In Appendix III, we show that $U_{i,k}(x)$ in Table II is a concave function satisfying $U''_{i,k}(x) \leq 0$. Then, by differentiating the objective function of (18), we get

$$\frac{\partial^2}{\partial t_i(k)^2}\left[\frac{t_i(k)}{T^*} U_{i,k}\left(\frac{e_i^A(k)}{t_i(k)}\right)\right] = \frac{[e_i^A(k)]^2}{T^* t_i^3(k)} U''_{i,k}\left(\frac{e_i^A(k)}{t_i(k)}\right).$$

Clearly (18) is a convex optimization problem and as a result, the Kurash-Kuhn-Tucker (KKT) condition is a necessary and sufficient condition for optimality. By using the KKT condition, the analytical optimal solution for cooperative beamforming is given by

$$t_i^*(k) = \frac{T^* c_i(k) e_i^A(k)}{\sum_{l=1}^{K} c_i(l) e_i^A(l)}. \tag{19}$$

In the case where the KKT condition does not have an analytical solution, with the decomposition principle [pp. 285-288, 21], the optimal solution of (18) will be given by

$$t_i^*(k) = \max\left\{0, f_{i,k}^{-1}(y)\right\}. \tag{20}$$

where $f_{i,k}^{-1}(y)$ denotes the inverse function of $f_{i,k}(x) = \frac{d}{dx}\left[\frac{x}{T^*} U_{i,k}\left(\frac{e_i^A(k)}{x}\right)\right]$, and y is the optimal solution to the following unconstrained problem

$$\text{Maximize } y + \sum_{k=1}^{K} \max\left\{0, \frac{f_{i,k}^{-1}(y)}{T^*} U_{i,k}\frac{e_i^A(k)}{f_{i,k}^{-1}(y)} - y f_{i,k}^{-1}(y)\right\}. \tag{21}$$

By (20)-(21), (18) can be reduced into a one-dimensional optimization problem so that the complexity will be greatly decreased.

V. NUMERICAL RESULTS

In this section, numerical results are presented to compare the performance of cooperative networks with and without resource allocation. Both static networks with cooperative beamforming and time-varying networks with selection relaying are considered. For the sake of fair comparison, direct transmission where nodes do not use any relay is also considered. This provides a baseline reference to compare cooperation gains. As cooperation without resource allocation is adopted, the power consumed for transmitting/relaying each node's signal is equal to the transmission power of direct transmission. This kind of cooperation shall be referred to as full cooperation. The path-loss factor is assumed to be 4 throughout Section V. Let D_{ij} denotes the distance between node i and node j, then $\overline{h}_{ij} = D_{ij}^{-4}$. [3] Finally, the noise power at the receiver is assumed to be $\sigma^2 = 1$. [4]

---

[3]Here, we do not normalize the channel gain since it can be scaled by the transmission power.

[4]Here, we drop the unit in the following text.

TABLE III
SYSTEM PARAMETERS FOR NUMERICAL RESULTS

s-d pair	Node coordinates (Topology)		Relay Selection Threshold
Static Network with Cooperative Beamforming			
	source	destination	
1	(0,1)	(5,0)	
2	(1,0)	(5,0)	0.25
3	(0.8,0)	(5,0)	
4	$(0.5,-\sqrt{3}/2)$	(5,0)	
Time-varying Network with Selection Relaying			
	source	destination	
1	$(-0.5,\sqrt{3}/2)$	$(0.5,\sqrt{3}/2)$	
2	(0,0.1)	(-1,0.1)	0.5
3	(0,-0.1)	(-1,-0.1)	
4	$(-0.5,-\sqrt{3}/2)$	$(0.5,-\sqrt{3}/2)$	

TABLE IV
ENERGY AND TIME ALLOCATION FOR COOPERATIVE BEAMFORMING

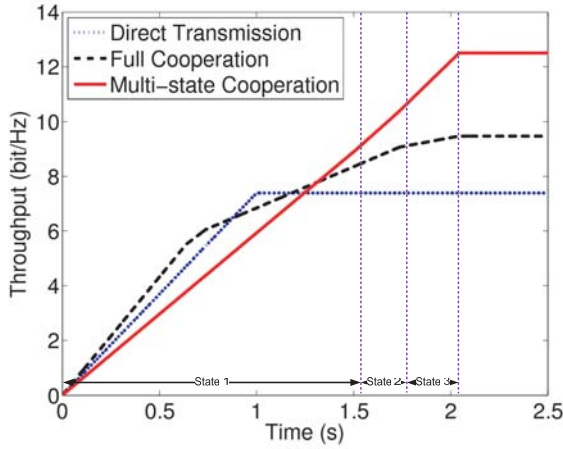|		State 1	State 2	State 3
Node 1	e_1^A	297.1	54.5	648.4
	t_1^*	1.3713	0.1395	0.5326
Node 2	e_2^A	1000	0	0
	t_2^*	2.4034	0	0
Node 3	e_3^A	882.7	177.3	0
	t_3^*	1.7922	0.2512	0
Node 4	e_4^A	498.6	97.9	403.5
	t_4^*	1.5489	0.1804	0.3141

Fig. 3. Throughput curves of direct transmission, cooperative beamforming with full cooperation and multi-sate cooperation. The state durations of node 4, which are also given in Table IV, are presented.

A. Static Network with Cooperative Beamforming

Consider a static network with four source nodes 1-4, randomly located in a unit circle. All the source nodes transmit to a common destination node. The coordinates of all source and destination nodes as well as the relay selection threshold are given in Table III. In static networks, the channel gain is given by $h_{ij} = \overline{h}_{ij}$. Note that $\overline{g}_i = 0.25$ for $i = 1, \ldots, 4$. Thus, nodes 1 and 4 will not serve as relay for each other while nodes 2 and 3 serve all source nodes 1-4. Besides, nodes 2 and 3 will consume more power than others in each cooperative transmission since their links to the destination node are better. Assume that $E^{total} = 1000$. As direct transmission is adopted, the transmission power of each node is 1000 and therefore the lifetime of each node is 1. As full cooperation is adopted, it can be obtained that the maximum node lifetime is 2.0434. For the sake of fair comparison, we set the target lifetime of multi-state cooperation to be 2.0434. By using the multi-state energy allocation algorithm and (19), we obtain the energy and time allocation results shown in Table IV.

Fig. 3 presents the aggregate throughput curves with direct transmission, full cooperation, and multi-state cooperation. It can be seen that full cooperation achieves the highest total rate

of all nodes before node 2 runs out of its energy in $t = 0.6366$. However, nodes 2 and 3 run out of their energy very quickly due to higher power consumption compared to that of direct transmission. After that, nodes 1 and 4 cannot find a relay and have to transmit directly for over 63% of their lifetime. In this scenario, their power efficiency is very poor. With the proposed multi-state cooperation, however, each node i can use all nodes j satisfying $\overline{h}_{ij} = \overline{g}_i$ as relays for at least 67% of their lifetime, as shown in Table IV. Although the transmission power of each node is lower than that of full cooperation at the beginning, all nodes can benefit from the beamforming gain much longer. As a result, the energy efficiency increases. For instance, the aggregate throughput of direct transmission, full cooperation and multi-state cooperation is 7.38 bit/Hz, 9.46 bit/Hz, and 12.50 bit/Hz, respectively. About 69.3% and 32.1% gains are obtained by multi-state cooperation over direct transmission and full cooperation, respectively.

Next, we compare the fairness of the full cooperation and multi-state cooperation. Here, the fairness of cooperation is characterized by two parameters: Increase in lifetime and increase in throughput compared to direct transmission. As shown in Table V, the heavily-used nodes 2 and 3 suffer from a shorter lifetime since their power consumption is increased compared to direct transmission. More seriously, since they run out of energy very soon, their throughput is also reduced compared to direct transmission. Hence, nodes 2 and 3 do not benefit from cooperation indeed. The proposed multi-state cooperation, however, can guarantee that all nodes' lifetime is equal to the target lifetime. Moreover, the increase in throughput of all nodes is approximately equal. In particular, note that node 1 achieves the highest increase in throughput. This is simply due to the fact that node 1's throughput is the smallest without cooperation.

B. Time-varying Networks with Selection Relaying

Consider a time-varying network with four s-d pairs satisfying $\overline{h}_{ij} = 1$ for $i = 1, \ldots, 4$, where the coordinates of the source and destination nodes are given in Table III. The target rate of each s-d pair is 1 bit/s/Hz. Here assume that the thresholds $\overline{h}_i = 0.5$, $i = 1, \ldots, 4$. It can be seen that nodes 1 and 4 are far away from each other so that they will not use each other as a relay. In addition, such a network topology is symmetric with respect to the x-axis. Therefore, the performance of nodes 1 and 4 is the same, as well as that of nodes 2 and 3. We shall use the average Signal-to-Noise

TABLE V
INCREASE IN LIFETIME AND INCREASE IN THROUGHPUT OF COOPERATIVE BEAMFORMING WITH FULL COOPERATION AND MULTI-STATE COOPERATION

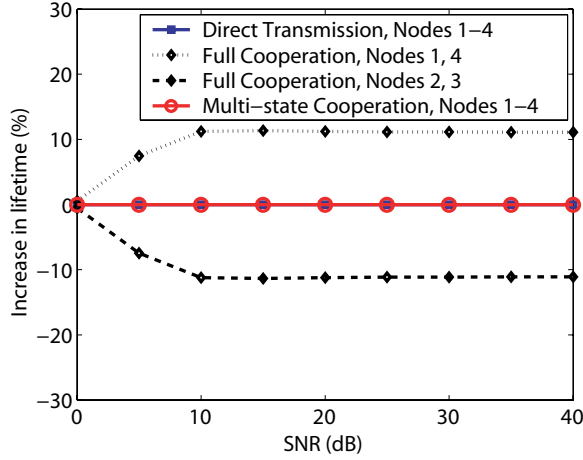|		Node 1	Node 2	Node 3	Node 4
Increase in lifetime	Full cooperation	104%	-36%	-26%	74%
thanks to cooperation	Multi-state cooperation	104%	104%	104%	104%
Increase in throughput	Full cooperation	144%	-38%	-22%	90%
thanks to cooperation	Multi-state cooperation	87%	55%	67%	76%

Fig. 4. Increase in node lifetime with direct transmission, selection relaying with full cooperation and multi-state cooperation
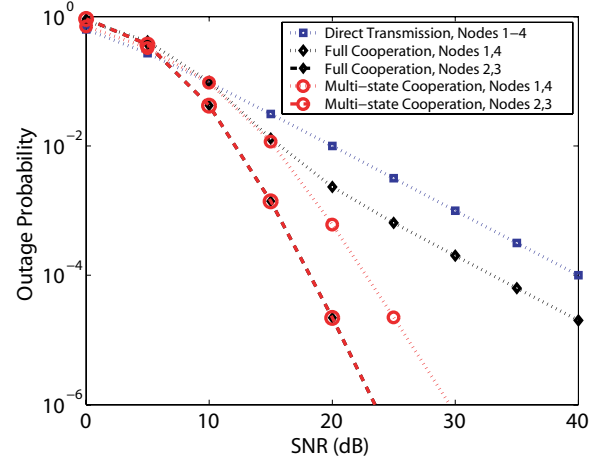

Fig. 5. Outage probability averaged over the lifetime of each node with direct transmission, selection relaying with full cooperation and multi-state cooperation

Ratio (SNR) of direct transmission given by $E^{total}/(T^*\sigma^2)$ to characterize the SNR of the network. The performance will be compared for various SNR values from 0 dB to 40 dB. Without loss of generality, we can normalize lifetime so that $T^* = 1$ and therefore, E^{total} can be determined by the given SNR. As selection relaying is adopted, we assume that the transmission power of the source nodes in the first timeslot is $E^{total}/(2T^*)$. Then, with full cooperation, the average total power of the relays of each node should be $3E^{total}/(2T^*)$. Due to space limitation, we omit the results for energy and time allocation of multi-state cooperation.

Fig. 4 presents the increase in lifetime compared to T^* with direct transmission, full cooperation and multi-state cooperation. With the direct transmission and multi-state cooperation, the lifetime of each node is equal to T^*. With full cooperation, however, the lifetime of nodes 1 and 4 is increased by about 11% T^*, while the lifetime of nodes 2 and 3 is decreased by about 11% T^* in the high SNR region. It can be seen that the gap between the maximum and minimum lifetime increases with SNR. This is because the probability that a relay can decode correctly increases with SNR. By serving more nodes, nodes 2 and 3 will consume a larger number of power in the high SNR region. When SNR is sufficiently high, (e.g. SNR 10 dB), the probability that a relay can decode correctly is approximately equal to 1. Hence, the increase in lifetime will remain constant in the high SNR region.

Fig. 5 presents the outage probability averaged over the lifetime of each node with direct transmission, full cooperation and multi-state cooperation. Since direct transmission cannot achieve diversity gain, the outage probability of all nodes approximately decays as 1/SNR [2]. With full cooperation, the
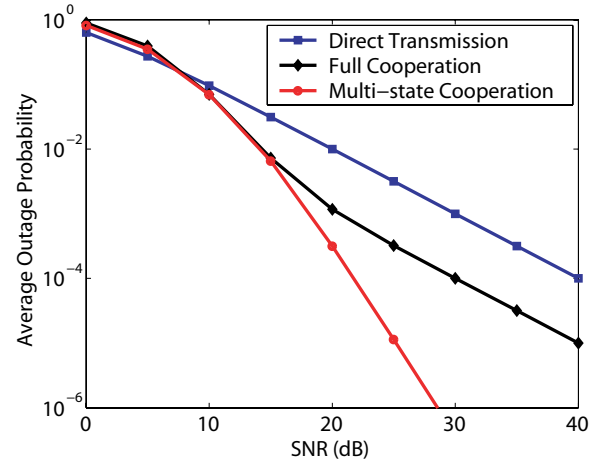

Fig. 6. Outage probability averaged over all nodes of direct transmission, selection relaying with full cooperation and multi-state cooperation

outage probability of nodes 1 and 4 decays as 0.2/SNR. This is because, as shown in Fig. 4, they transmit directly without relay for 20% of their lifetime, when the outage probability is approximately equal to 1/SNR. Since our proposed framework can efficiently allocate time among the states, nodes 1 and 4 can transmit with relays much longer while transmitting directly for only a very short time with much higher transmission power. Although the power of relays is lower compared to full cooperation, multi-state cooperation can benefit from the longer node lifetime when the spatial diversity gain of 3 is achieved. A closer observation shows that node 2 or 3's outage probability with full cooperation is equal to that

with multi-state cooperation. This is simply due to the fact that with multi-state cooperation, the average total power of node 2 or 3' relays is also equal to $3E^{total}/(2T^*)$. Fig. 6 presents the outage probability averaged over all nodes. The average outage probability of full cooperation is approximately equal to 0.1/SNR, while that of our proposed framework is $1/SNR^{2.5}$.

VI. IMPLEMENTATION ISSUES

So far, we have presented, mathematically, a unified framework for fair and efficient resource allocation in cooperative networks. In this Section, we will turn our attention to some implementation issues of the proposed framework.

A. Half-decentralized Implementation

The whole resource allocation scheme proposed in Sections III and IV can be implemented by a half-decentralized protocol, which consists of two steps, namely, centralized multi-state energy allocation and distributed state duration optimization.

To perform multi-state energy allocation, a control node, which can be a base station, an access point or simply an elected head node, needs to collect each node's local information of the average source-relay (s-r) and/or relay-destination (r-d) channel gains, which can be obtained locally via 1) the average power gain estimation based on pilot energy; or 2) Global Positioning System (GPS). By using the multi-state energy allocation algorithm, the control node will determine the energy allocation vectors, and then broadcast them over the whole network.

Based on the energy allocation results, each node can locally formulate and solve its own state duration optimization problem (18), which only requires local parameters information such as the s-r and r-d channel information. No information exchange is needed among nodes in this stage.

Note that many wireless systems, such as cellular networks or WLANs, have centralized controllers. The control node only needs to collect the average channel gain information and broadcast the energy allocation results during the initial network configuration. As such, the proposed framework will not induce much overhead in practice.

B. Distributed Implementation

In some networks, having a centralized controller might be impractical. Thus, a fully distributed implementation will be highly desired in this case. A market-based distributed protocol is presented in this part to achieve an approximately fair cooperation.

By jointly considering (1) and (2), we have

$$\sum_{j=1,\ j\neq i}^{N} E_i^{(j)} = \sum_{j=1,\ j\neq j}^{N} E_j^{(i)}, \qquad i = 1, \ldots, N. \quad (22)$$

The above equality implies a market rule, namely, that the energy a node contributes to others should be equal to what others contribute to this node. Based on this market rule, a local parameter referred to as the *energy reward* is introduced for each node. In the distributed protocol, the energy reward

of a node increases when the node helps others and decreases when the node uses others as relays. When a given node requires cooperation, the relays' energy that it can use will depend on its current energy reward. In this way, fairness is guaranteed and over-using the heavily-loaded nodes is avoided, both in distributed manners. A similar method has been proposed in [19] to engineer a distributed fair cooperation protocol in practice.

Finally, it should be pointed out that distributed fair cooperation is still an open problem. The proposed framework, however, provides a performance upper-bound for the distributed solutions.

VII. CONCLUSION

In this paper, we presented a unified cross-layer framework for fair and efficient resource allocation in cooperative networks. Using the proposed framework, all nodes can run out of energy simultaneously and each node is allocated an equal number of energy so that fairness is guaranteed. The proposed approach is based on the use of a multi-state cooperation methodology where the total energy is allocated among the nodes state-by-state via a geometric and network decomposition approach. Given the energy allocation results, the optimal state duration of each node is found so as to maximize each node's utility such as throughput or outage probability. By deriving the cooperation matrices and utility functions, we applied the proposed framework into cooperative beamforming and selection relaying. The performance of cooperation networks with and without resource allocation was also compared. It was demonstrated that the proposed framework guarantees an equal lifetime of all nodes. This is in contrast to the unfair cooperation which will result in a significant decrease in the lifetime of heavily-used nodes. For instance, the decrease in lifetime of heavily-used nodes is 36% for cooperative beamforming and 11% for selection relaying with full cooperation. Furthermore, the proposed framework can achieve 32% throughput gain over full cooperative beamforming. For selection relaying, the proposed framework can guarantee a diversity gain greater than 2 on average compared to full cooperation, which achieves only a diversity gain of 1 on average. In particular, due to the lack of fairness, full cooperation will result in a short lifetime of those heavily-loaded nodes. As a result, other nodes have to transmit directly without relay assistance. Thus, the diversity gain of full cooperation is lower than that of multi-state cooperation.

APPENDIX A
ENERGY CONSTRAINTS AND COOPERATION MATRICES DERIVATION

A. Cooperative beamforming

Note that $\overline{h}_{jn} \geq \overline{g}_j$ for any $n \in \mathcal{R}_j$. As cooperative beamforming is adopted, a source node can transmit to its relays in the first timeslot, with reliable transmission rate given by

$$C_j^{s\rightarrow r} = \log\left(1 + \overline{g}_j P_j^s/\sigma^2\right), \quad (23)$$

where P_j^s denotes the power of node j in the first timeslot. In the second timeslot, the source as well as its relays transmit

to the destination node in a beamforming manner. From the beamforming capacity formula for MISO channel [1], the capacity of the r-d channel can be obtained by

$$C_j^{r \to d} = \log\left(1 + P_j^\Sigma \sum_{n \in \mathcal{R}_j} \overline{h}_{nd(j)}/\sigma^2\right), \qquad (24)$$

where P_j^Σ denotes the total power of relays in the second timeslot. According to the max-flow-min-cut theorem, the reliable transmission rate should be the minimum of the s-r and r-d channel capacities. By taking two timeslots per transmission, the capacity of cooperative beamforming is given by

$$C_j^{CB} = \tfrac{1}{2} \min\left\{ \log\left(1 + \overline{g}_j P_j^s/\sigma^2\right), \\ \log\left(1 + P_j^\Sigma \sum_{n \in \mathcal{R}_j} \overline{h}_{nd(j)}/\sigma^2\right)\right\}, \qquad (25)$$

Hence, we have $P_j^s \overline{g}_j = P_j^\Sigma \sum_{n \in \mathcal{R}_j} \overline{h}_{nd(j)}$ in order to maximize the power efficiency. Since the energy consumption in both timeslots are constrained, the resource allocation takes both timeslots into account so that the total energy constraint is $E^{max} = E^{total}$.

Consider node j using the relay set $\mathcal{R}_j$ for time duration t_j. With beamforming, the power that node $i \in \mathcal{R}_j$ consumes in relaying node j's signal is $P_i^{r \to d(j)} = P_j^\Sigma \overline{h}_{id(j)} / \sum_{n \in \mathcal{R}_j} \overline{h}_{nd(j)}$. Note that the energy consumed by a node is the result of multiplying this node's transmission power and its transmission time. Since the relays only transmit in the second timeslot, we have $E_i^{(j)} = P_i^{r \to d(j)} t_i/2 = t_j P_j^\Sigma \overline{h}_{id(j)} / \left(2 \sum_{n \in \mathcal{R}_j} \overline{h}_{nd(j)}\right)$. The source node j itself transmits in both timeslots, with power P_j^s in the first timeslot and power $P_i^{r \to d(j)}$ in the second timeslot. Therefore, we have $E_j^{(j)} = t_j P_j^\Sigma \left(\overline{h}_{jd(j)} / \sum_{n \in \mathcal{R}_j} \overline{h}_{nd(i)} + \sum_{n \in \mathcal{R}_j} \overline{h}_{nd(i)}/\overline{g}_j\right)/2$. One can easily see that $E_i^{(j)} = 0$, if $i \notin \mathcal{R}_j$ for any cooperation schemes. By substituting into (3), the results in Table I can be obtained accordingly.

B. Selection Relaying

As selection relaying is adopted, the power that a source node transmits to relays is fixed to be P^s so that the relays may know the decoding threshold of the s-r channel gain [5], $\xi_j = (2^{2r_j} - 1)\sigma^2/P^s$, where r_j is the target rate of node j. As a result, only the even timeslot is considered by the resource allocation and the energy constraint is $E^{max} = E^{total} - P^s T^*/2$. Similar to Appendix I-A, the energy consumed by a node is determined by multiplying this node's transmission power and its transmission time. With selection relaying, the total time that node $i \in \mathcal{R}_j$ serves as relay for node j is $t_j \Pr\{i \in \mathcal{D}\} = t_j \Pr\{h_{ji} \geq \xi_j\}/2$.[5] Since the nodes in $\mathcal{D}$ transmit with equal power $P^{r \to d(j)}$, it follows that $E_i^{(j)} = P^{r \to d(j)} \Pr\{h_{ji} \geq \xi_j\}/2$. By substituting into (3), the results in Table I can be obtained accordingly.

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[5]Note that $\Pr\{h_{jj} \geq \xi_i\} = 1$. With selection relaying, a node can always retransmit its own message in the second timeslot.

Network Decomposition Algorithm

Step 0: Initialize $M = 1$, and $\mathcal{S}^{(1)} = \emptyset$;
Step 1: If $\bigcup_{m=1}^{M} \mathcal{S}^{(m)} = \mathcal{S}$, **go to End**;
Step 2: Choose one node s such that $s \notin \bigcup_{m=1}^{M} \mathcal{S}^{(m)}$. Let $\mathcal{T} = \{s\}$ and $\mathcal{S}^{(M+1)} = \{s\}$;
Step 3: If $\mathcal{T} = \emptyset$, **go to Step 6**;
Step 4: $\mathcal{T} = \{n : a_{np} + a_{pn} > 0, \ p \in \mathcal{S}^{(M+1)}, \ n \notin \mathcal{S}^{(M+1)}\}$;
Step 5: $\mathcal{S}^{(M+1)} = \mathcal{S}^{(M+1)} \cup \mathcal{T}$, **go to Step 3**;
Step 6: $M = M + 1$, **go to Step 1**.
End

APPENDIX C
PROOF OF THEOREM 1

We begin by providing the following lemma.

Lemma 1: The dimension of the solution space to $\mathbf{A}(m)\mathbf{e}(m) = \mathbf{e}(m)$ is 1 with the solution particularly being a nonnegative vector.

Proof: Since $a_{ij} = 0$ for $j \in \mathcal{S}^{(n)}$ and $i \notin \mathcal{S}^{(m)}$, it follows that $\sum_{i \in \mathcal{S}^{(m)}} a_{ij}^{(m)} = \sum_{i=1}^{N} a_{ij} = 1$. Therefore, $\mathbf{A}^{(m)T}$ is a stochastic matrix. Thus, there exists an eigenvalue $\lambda(\mathbf{A}^{(m)}) = 1$. By the Gersgorin disk theorem [20], the spectral radius of $\mathbf{A}^{(m)}$ is $\rho(\mathbf{A}^{(m)}) = 1$. Let $\mathcal{U}$ denote the set satisfying $\mathcal{U} \subset \mathcal{S}^{(m)}$ and $a_{ij} = 0$ for $i \in \mathcal{U}$, $j \in \mathcal{S}^{(m)}/\mathcal{U}$. If $\mathcal{U} = \emptyset$, the matrix $\mathbf{A}^{(m)}$ is irreducible. Since $a_{ii}^{(m)} > 0$ for any i, $\mathbf{A}^{(m)}$ is a primitive matrix. By the Perron-Frobenius theorem [20], $geomult_{\mathbf{A}^{(m)}}(1) = 1$ and there must exist a positive vector $\mathbf{e}^{(m)}$ satisfying $\mathbf{A}^{(m)}\mathbf{e}^{(m)} = \mathbf{e}^{(m)}$. If $\mathcal{U} \neq \emptyset$, there must be a permutation matrix $\mathbf{Q}$ satisfying

$$\mathbf{Q}^T \mathbf{A}^{(m)} \mathbf{Q} = \\ \left[\begin{array}{c|c} \mathbf{B}_{(|\mathcal{S}^{(m)}|-|\mathcal{U}|)\times(|\mathcal{S}^{(m)}|-|\mathcal{U}|)} & \mathbf{C}_{(|\mathcal{S}^{(m)}|-|\mathcal{U}|)\times|\mathcal{U}|} \\ \hline \mathbf{0}_{|\mathcal{U}|\times(|\mathcal{S}^{(m)}|-|\mathcal{U}|)} & \mathbf{D}_{|\mathcal{U}|\times|\mathcal{U}|} \end{array}\right] \qquad (26)$$

where $\mathbf{B}$, $\mathbf{C}$, and $\mathbf{D}$ are matrix blocks with the appropriate size. Since $\mathbf{Q}^{-1} = \mathbf{Q}^T$, it follows that $\mathbf{A}^{(m)}\mathbf{Q}\mathbf{x} = \mathbf{Q}\mathbf{Q}^T \mathbf{A}^{(m)}\mathbf{Q}\mathbf{x} = \mathbf{Q}\mathbf{x}$. Therefore, the solution to $\mathbf{A}^{(m)}\mathbf{e}^{(m)} = \mathbf{e}^{(m)}$ can be obtained by , where $\mathbf{x}$ is the solution to $\mathbf{Q}^T \mathbf{A}^{(m)}\mathbf{Q}\mathbf{x} = \mathbf{x}$. In the partitioned form, this equation is presented by

$$\left[\begin{array}{c|c} \mathbf{B} & \mathbf{C} \\ \hline \mathbf{0} & \mathbf{D} \end{array}\right] \left[\begin{array}{c} \mathbf{x}_1 \\ \hline \mathbf{x}_2 \end{array}\right] = \left[\begin{array}{c} \mathbf{x}_1 \\ \hline \mathbf{x}_2 \end{array}\right]. \qquad (27)$$

According to condition (3) of the network decomposition properties, the matrix $\mathbf{C}$ cannot contain the all-zero column. Otherwise, the sub-network $\mathcal{S}^{(m)}$ can be decomposed. By the Gersgorin disk theorem, the spectral radius of $\mathbf{D}$ is bounded by $\rho(\mathbf{D}) \leq \max \sum_{i=1}^{|\mathcal{U}|} D_{ij} = \max\left(1 - \sum_{i=1}^{|\mathcal{S}^{(m)}|-|\mathcal{U}|} C_{ij}\right) < 1$. As a result, the solution to $\mathbf{D}\mathbf{x}_2 = \mathbf{x}_2$ much be $\mathbf{x}_2 = \mathbf{0}$. By substituting $\mathbf{x}_2 = 0$ into (22), we have $\mathbf{B}\mathbf{x}_1 = \mathbf{x}_1$. Since $\mathbf{B}$ is primitive and $\rho(\mathbf{B}) = 1$, it follows that $geomult_{\mathbf{B}}(1) = 1$ and $\mathbf{x}_1$ can be a positive vector. Since $\mathbf{Q}$ is a permutation matrix satisfying (26) amd $\mathbf{e}^{(m)} = \mathbf{Q}\mathbf{x}$, it follows that $e_i^{(m)} = 0$ for $i \in \mathcal{U}$ and $e_i^{(m)} > 0$, for $i \in \mathcal{S}^{(m)}/\mathcal{U}$. ∎

Having established Lemma 1, we now prove Theorem 1.

Proof: From Lemma 1, we know that $geomult_{\mathbf{A}^{(m)}}(1) = 1$ and $rank(\mathbf{A}^{(m)} - \mathbf{I}) = |\mathcal{S}^{(m)}| - 1$. Since $0 \leq a_{ij}^{(m)} \leq 1$,

$\mathbf{1}^T$ does not belong to the space spanned by all the rows of $(\mathbf{A}^{(m)} - \mathbf{I})$. As a result,

$$\begin{cases} \mathbf{1}^T \overline{\mathbf{e}}^{(m)} &= 1 \\ \mathbf{A}^{(m)} \overline{\mathbf{e}}^{(m)} &= \overline{\mathbf{e}}^{(m)} \end{cases}$$

has a unique solution $\overline{\mathbf{e}}^{(m)}$,[6] which is given by

$$\overline{\mathbf{e}}^{(m)} = \begin{bmatrix} 1 & \cdots & 1 \\ & \mathbf{A}^{(m)} & \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ \mathbf{0}_{\left(|\mathcal{S}^{(m)-1}|\right) \times 1} \end{bmatrix}. \quad (28)$$

Since $\mathbf{1}^T \overline{\mathbf{e}}^{(m)} = 1$, $\overline{\mathbf{e}}^{(m)}$ is nonnegative . Next, by noting that a permutation matrix satisfies $\mathbf{P}^{-1} = \mathbf{P}^T$, we have

$$\begin{aligned} \mathbf{A}\mathbf{b}^{(m)} &= \mathbf{P}\mathbf{P}^T \mathbf{A} \mathbf{P} \begin{bmatrix} \mathbf{0}_{\left(\sum_{r=1}^{m-1}|\mathcal{S}^{(r)}|\right) \times 1} \\ \overline{\mathbf{e}}^{(m)} \\ \mathbf{0}_{\left(\sum_{r=m+1}^{M}|\mathcal{S}^{(r)}|\right) \times 1} \end{bmatrix} \\ &= \mathbf{P} \begin{bmatrix} \mathbf{A}^{(1)} & & \\ & \ddots & \\ & & \mathbf{A}^{(M)} \end{bmatrix} \begin{bmatrix} \mathbf{0} \\ \mathbf{A}^{(m)} \overline{\mathbf{e}}^{(m)} \\ \mathbf{0} \end{bmatrix} \\ &= \mathbf{P} \begin{bmatrix} \mathbf{0} \\ \overline{\mathbf{e}}^{(m)} \\ \mathbf{0} \end{bmatrix} = \mathbf{b}^{(m)}. \end{aligned} \quad (29)$$

Hence, $\mathbf{b}^{(m)}$ belongs to the solution space of (11). From (15), we have $b_i^{(m)} b_i^{(n)} = 0$, for $m \neq n$. Therefore, the $\mathbf{b}^{(m)}$ are orthogonal. That is, $\langle \mathbf{b}^{(m)}, \mathbf{b}^{(n)} \rangle = 0$.

Finally, we show that the basis vectors are complete. According to (13) and since $\mathbf{P}^{-1} = \mathbf{P}^T$, we have $\mathbf{A} = \mathbf{P} diag(\mathbf{A}^{(1)}, \ldots, \mathbf{A}^{(M)}) \mathbf{P}^T$. Since

$$\begin{aligned} &\det\left(\mathbf{A} - \lambda \mathbf{I}\right) \\ &= \det(\mathbf{P}) \det\left(diag(\mathbf{A}^{(1)}, \ldots, \mathbf{A}^{(M)})\right) \det(\mathbf{P}^T) \\ &= \prod_{m=1}^{M} \det\left(\mathbf{A}^{(m)} - \lambda \mathbf{I}\right), \end{aligned} \quad (30)$$

it follows that $geomult_{\mathbf{A}}(1) = \sum_{m=1}^{M} geomult_{\mathbf{A}^{(m)}}(1) = M$. Therefore, the dimension of the solution space of (11) is $\mathbf{M}$. Thus, the solution space can be spanned by the basis $\mathbf{b}^{(m)}$, $m = 1, \ldots, M$. The energy allocation vector can be given by

$$\mathbf{e}^A = \sum_{m=1}^{M} \mu^{(m)} \mathbf{b}^{(m)}. \quad (31)$$

In order to increase the energy efficiency, as much as possible energy should be allocated in each state during iteration. Note that $\mathbf{e}^A(k)$ is always a nonnegative vector. The 1-norm of $\mathbf{e}^A(k)$ is given by

$$\|\mathbf{e}^A(k)\|_1 = \sum_{i=1}^{N} |e_i^A(k)| = \sum_{i=1}^{N} e_i^A(k)$$

As a result, maximizing the 1-norm of $\mathbf{e}^A(k)$ is equivalent to maximizing the energy allocated in state k. Constrained

[6]As $\mathcal{U} = \emptyset$, $\overline{\mathbf{e}}^{(m)}$ is the so-called Perron vector of $\mathbf{A}^{(m)}$ [22].

by (12), $\mu^{(m)}$, $m = 1, \ldots, M$, are chosen to maximize the 1-norm of (31), which can be obtained as

$$\mu^{(m)} = \min_{i \in \mathcal{S}^{(m)}} \frac{e_i^{max}}{b_i^{(m)}}. \quad (32)$$

Here, (32) can be proved as follows. Since $b_i^{(m)} b_i^{(n)} = 0$ for $m \neq n$, $\mathbf{b}^{(m)}$ are orthogonal basis for the solution space of (11) and are nonnegative. If there exists a solution $\widetilde{\mathbf{e}}^A$ to (11), satisfying $\|\widetilde{\mathbf{e}}^A\|_1 > \|\mathbf{e}^A\|_1$, then there must be m, satisfying $\widetilde{\mu}_m > \mu_m$. From (32), we have

$$\widetilde{\mu}^{(m)} > \min_{i \in \mathcal{S}^{(m)}} \left(e_i^{max}/b_i^{(m)}\right). \quad (33)$$

Let $j = \arg\min_{i \in \mathcal{S}^{(m)}} \left(e_i^{max}/b_i^{(m)}\right)$. Clearly, we have

$$e_j^A > \widetilde{\mu}_m b_j^{(m)} > e_i^{max}. \quad (34)$$

This contradicts constraint (12). As a result, it follows that μ_m maximize the 1-norm of $\mathbf{e}^A$. ∎

APPENDIX D
DERIVATION OF UTILITY FUNCTIONS

A. Cooperative Beamforming

As $|\mathcal{R}_i(k)| \geq 2$, the capacity is determined by the total power of the virtual array. Since $P_j^s \overline{g}_j = P_j^\Sigma \sum_{n \in \mathcal{R}_j} \overline{h}_{nd(j)}$, the energy used by the virtual array is $e_i^A(k) \overline{g}_i / (\overline{g}_i + \sum_{j \in \mathcal{R}_i(k)} \overline{h}_{jd(i)})$. Since the virtual antenna array only transmits in even timeslots, the capacity of node i in state k is given by

$$\begin{aligned} U_{i,k}\left(\frac{e_i^A(k)}{t_i(k)}\right) &= \frac{1}{2} \times \\ &\log\left(1 + \frac{2\overline{g}_i \sum_{j \in \mathcal{R}_i(k)} \overline{h}_{jd(i)}}{\left(\overline{g}_i + \sum_{j \in \mathcal{R}_i(k)} \overline{h}_{jd(i)}\right) \sigma^2} \frac{e_i^A(k)}{t_i(k)}\right). \end{aligned} \quad (35)$$

As $|\mathcal{R}_i(k)| = 1$, we assume that the source repeats its transmission in the second timeslot.[7] Hence, the capacity is obtained by

$$U_{i,k}\left(\frac{e_i^A(k)}{t_i(k)}\right) = \frac{1}{2} \log\left(1 + \frac{2\overline{h}_{id(i)}}{\sigma^2} \frac{e_i^A(k)}{t_i(k)}\right). \quad (36)$$

By differentiating the utility function twice, we have

$$U_{i,k}''(x) = -\frac{c_i^2(k)}{2[1 + c_i(k)x]^2} \leq 0. \quad (37)$$

Hence, $U(x)$ is a concave function.

B. Selective Relaying

Using the methods in Appendix I-B and the Rayleigh fading assumption, we know that the each relay's transmission power, $P^{r \to d(i)}$, is given by $P^{r \to d(i)} = \frac{2e_i^A(k)}{t_i(k) \sum_{j \in \mathcal{R}_i(k)} \exp(-\xi_i/\overline{h}_{ij})}$. From [5], the outage threshold is $\eta_i = \frac{(2^{2r_i}-1)\sigma^2}{P^{r \to d(i)}}$. By substituting $P^{r \to d(i)}$ into the formula of η_i, we get

$$\eta_i(k) = \frac{(2^{2r_i} - 1)\sigma^2 \sum_{j \in \mathcal{R}_i(k)} \exp(-\xi_i/\overline{h}_{ij})}{2e_i^A(k)/t_i(k)}. \quad (38)$$

[7]In fact, repetition coding is not rate-optimal compared with direct with direct transmission in each timeslot. In low SNR regime, however, it is near optimal.

Using the method of conditional probability, the outage probability can be given by

$$P_{out,i}(k) = \sum_{\mathcal{D} \in \mathcal{R}_i(k)} \Pr \left\{ \sum_{j \in \mathcal{D}} h_{jd(i)} < \eta_i(k) \Big| \mathcal{D} \right\} \Pr\{\mathcal{D}\},$$

(39)

where the probability of a particular $\mathcal{D}$ can be obtained by

$$\Pr\{\mathcal{D}\} = \prod_{j \in \mathcal{D}} \exp\left(-\frac{\xi_i}{\overline{h}_{ij}}\right) \prod_{i \notin \mathcal{D}} \left[1 - \exp\left(\frac{\xi}{\overline{h}_{ij}}\right)\right]. \quad (40)$$

By using the generating function [13], [22], the conditioned outage probability is calculated as[8]

$$\Pr\left\{ \sum_{j \in \mathcal{D}} h_{jd(i)} < \eta_i(k) \Big| \mathcal{D} \right\} = \sum_{j \in \mathcal{D}} \left[1 - \exp\left(-\frac{\eta_i(k)}{\overline{h}_{jd(i)}}\right)\right]$$
$$\times \prod_{n \neq j} \frac{\overline{h}_{jd(i)}}{\overline{h}_{jd(i)} - \overline{h}_{nd(i)}}. \quad (41)$$

By substituting (39)-(41) into $u_i(k) = 1 - P_{out,i}(k)$, the results in Table II can be obtained.

Next, we shall show that the utility function of selection relaying is convex in the high SNR regime, which denotes the regime of interest for outage probability. From [5], the conditional outage probability can be approximated by a power function of $x = \frac{e_i^A(k)}{t_i(k)}$ in the high SNR regime. That is

$$\Pr\left\{ \sum_{j \in \mathcal{D}} h_{jd(i)} < \eta_i(k) \Big| \mathcal{D} \right\} \sim \frac{1}{|\mathcal{D}|!} \left(\frac{s_i}{x}\right)^{|\mathcal{D}|} \prod_{j \in \mathcal{D}} \frac{1}{\overline{h}_{jd(i)}},$$

(42)

where $s_i(k) = \frac{(2^{2r_i}-1)\sigma^2}{2} \sum_{j \in \mathcal{R}_i(k)} \exp\left(-\frac{\xi}{\overline{h}_{ij}}\right)$. It follows that the utility function can be approximately given by

$$U_{i,k}(x) \sim 1 - \sum_{\mathcal{D} \in \mathcal{R}_i(k)} \frac{\Pr\{\mathcal{D}\}}{|\mathcal{D}|!} \left(\frac{s_i}{x}\right)^{|\mathcal{D}|} \prod_{j \in \mathcal{D}} \frac{1}{\overline{h}_{jd(i)}} \quad (43)$$

By differentiating it twice, we have

$$U_{i,k}''(x) \sim -\sum_{\mathcal{D} \in \mathcal{R}_i(k)} \frac{\Pr\{\mathcal{D}\}(|\mathcal{D}|+1)}{(|\mathcal{D}|-1)!} \frac{s_i^{|\mathcal{D}|}}{x^{|\mathcal{D}|+2}} \prod_{j \in \mathcal{D}} \frac{1}{\overline{h}_{jd(i)}}$$
$$\leq 0. \quad (44)$$

Thus, it follows that the utility function of selection relaying is concave in the important high SNR regime.

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[8]Due to the random distribution of nodes, we assume that $\overline{h}_{jd(i)} \neq \overline{h}_{nd(i)}$, for $j \neq n$ here. If $\overline{h}_{jd(i)} = \overline{h}_{nd(i)}$, the results can be found in [22].

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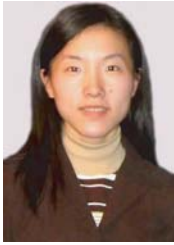
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