Energy Efficient Cooperative Routing in Wireless Networks

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Abstract

In this paper, we explore physical layer *cooperative communication* in order to design network layer *routing* algorithms that are energy efficient. We assume each node in the network is equipped with a single omnidirectional antenna and that multiple nodes are able to coordinate their transmissions in order to take advantage of spatial diversity to save energy. Specifically, we consider *cooperative MIMO* at physical layer and *multi-hop routing* at network layer, and formulate *minimum energy routing* as a *joint* optimization of the transmission power at the physical layer and the link selection at the network layer. Using dynamic programming, we compute the energy consumption of the optimal cooperative routing in different network scenarios, which shows energy savings of up to 55%, compared with the optimal non-cooperative routing. As the network becomes larger, however, finding optimal routes becomes computationally intractable as the complexity of the dynamic programming approach increases as $O(2^{2n})$, where n is the number of nodes in the network. As such, we develop two *greedy* routing algorithms that have complexity of $O(n^2)$, and yet achieve significant energy savings. Simulation results indicate that the proposed greedy algorithms perform almost as good as the optimal algorithm and achieve energy savings of more than 50% in the simulated scenarios.

Index Terms

Minimum energy routing, cooperative communication, cooperative MIMO, wireless networks.

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I. Introduction

Energy efficiency is a challenging problem in wireless networks, especially in ad hoc and sensor networks, where network nodes are typically battery powered. It is not therefore surprising that energy efficient communication in wireless networks has received significant attention in the past several years [1]–[5]. Most of the work in this area has specifically focused on designing energy efficient network and physical layer mechanisms. At the network layer, the goal is to find energy efficient *routes* that minimize transmission power in an end-to-end setting [3]–[5]. At the physical layer, the goal is to design energy efficient communication schemes for the wireless medium. One such scheme is the so-called *cooperative communication* [6], [7].

Most routing protocols for ad hoc networks consider a network as a graph of point-to-point links, and multiple links are used to transmit data from a source node to a destination node in a multi-hop fashion. Although the notion of a link has been a useful abstraction for wired networks, for wireless networks, the notion of a link is vague [7]. Wireless networks, however, are often constrained by the same notion of link that is inherited from wired networks, namely, concurrent transmissions of multiple nearby transmitters result in interference producing a collision. Cooperative communication is a radically different paradigm in which the conventional notion of a link is abandoned. Specifically, some of the constraints imposed by the conventional definition of a link are violated, *e.g.*, a link can originate from multiple transmitters, and concurrent transmissions, when coordinated, do not result in collision. In cooperative communication, nodes equipped with a single antenna can achieve diversity and coding gains similar to those of multi-antenna systems by cooperatively coding and transmitting data (interested readers are referred to [7] for an excellent overview of cooperative communication and its impact on higher layer network protocols). To this end, we note that multi-hop communication in wireless networks is a special case of cooperative communication.

Although there has been considerable research on energy efficient routing [3]–[5], and cooperative communication [8]–[12] in isolation, only recently a few works have addressed network layer routing and physical layer cooperation problems *jointly*. This is surprising as cooperative communication is inherently a network solution; hence, it is essential to investigate routing and cooperation jointly. This is the problem we address in this paper for cooperative Multiple-Input Multiple-Output (MIMO) networks.

Khandani *et al.* [13] present one of the early works in this area, where they formulate the energy consumption in a static cooperative wireless network. They quantify the energy savings achieved through cooperation, and design heuristic algorithms to find energy efficient routes from a single source to a single destination. In their work, Khandani *et al.* consider cooperative Multiple-Input Single-Output (MISO) technique for data transmission at physical layer, and show that considerable energy savings can be achieved using cooperative routing techniques. Zhang *et al.* [14] extend Khandani's work to a multi-source multi-destination network, where multiple flows traverse the network simultaneously. Similarly, they also consider the MISO cooperative technique *only*. Since the simple cooperative routing strategies (such as those proposed by Khandani *et al.*) do not work efficiently without considering link contention among different flows, Zhang *et al.* suggest a joint routing and scheduling algorithm to find energy efficient routes. Their work is rather *orthogonal* to our work as we mainly focus on joint routing and cooperation regardless of the number of flows in the network.

It is well known that Multiple-Input Multiple-Output (MIMO) transmission (*i.e.*, the use of multiple antennas at both the transmitter and receiver) improves the network performance in terms of data throughput and transmission range without using additional bandwidth or transmit power. Through cooperation, spatially separated nodes in a wireless network can form cooperative MIMO links that can achieve diversity and coding gains similar to those of multi-antenna MIMO systems [6]–[8], [10]. In this paper, we study *the problem of minimum energy routing with cooperative MIMO communication* in a static wireless network (such as a wireless ad hoc network).

We apply cooperative MIMO in a restrictive form, in which there is no communication among the receivers, *i.e.*, no coding gain from MIMO. The reason is that distributed decoding significantly increases the complexity of the physical layer communication, and incurs substantial signalling overhead. Instead, in this paper, we focus on power gain of cooperative MIMO in a setting resembling multiple concurrent MISO transmissions. Our intuition is that the optimal routing algorithm is multi-hop in nature, where at each hop a decision has to be made about the *set* of transmitting and receiving nodes that form a cooperative link. This means that the receiving set is not necessarily a *single* node as in MISO techniques considered by Khandani *et al.* [13] and Zhang *et al.* [14], rather *multiple* nodes can be appropriately chosen by the routing algorithm. It is obvious that the cooperative MIMO we consider in this paper includes cooperative MISO as a special case, where the receiving set consists of only a single node. Hence, the algorithms we develop in this work are superior to those proposed in [13], as we will show using simulations.

Our contributions can be summarized as follows:

1) We consider cooperative MIMO in a wireless network, and formulate the cooperative link cost (in terms of transmission power) between a set of transmitting and receiving nodes as an optimization problem, which we solve using quadratic programming. The optimal solution does not have a simple form; hence, we derive a sub-optimal solution for the power allocation problem.
2) We formulate energy optimal routing as an optimization problem, and show the optimal route can be found using dynamic programming. However, the optimal solution has exponential complexity; hence, we develop two heuristic algorithms of polynomial complexity, namely, *Greedy Limited Cooperative* (GLC) and *Greedy Progressive Cooperative* (GPC), to find energy efficient routes.
3) We provide simulation results to evaluate the performance of our routing algorithms, and compare them against those proposed by Khnadani *et al.* [13]. In particular, we show that: (a) energy savings of up to 50% can be achieved with our heuristic algorithms, (b) optimal routing based on cooperative MIMO outperforms optimal routing based on cooperative MISO (by more than 10% in terms of energy savings in our simulations), and, (c) our heuristic algorithms result in energy savings of 20% more than heuristic algorithms proposed in [13].

The rest of this paper is organized as follows. In Section II, we describe the system model considered in this paper, and formulate the MIMO link cost in terms of transmission power. Our proposed optimal and heuristic cooperative routing algorithms are presented in Section III. Simulation results are presented in Section IV, where we compare energy savings achieved by different cooperative techniques as well as performance of different heuristic algorithms. Finally, our conclusions as well as future research directions are discussed in Section V.

II. System Model

We consider a wireless network consisting of a set of nodes distributed randomly in an area, where each node has a single omnidirectional antenna. We assume that each node can adjust its transmission power in order to control its transmission radius. We also assume that multiple nodes can coordinate their transmissions at the physical layer to form a cooperative MIMO link. It is well known that cooperative MIMO results in improved network reliability, coverage, and energy consumption [8], [10]. We model a MIMO transmission between a set of transmitting and receiving nodes as multiple MISO transmissions (similar to [15], [16]), and use concepts from MISO systems to formulate energy consumption in a cooperative MIMO transmission.

A. Channel Model

We consider a time-slotted wireless channel between each pair of transmitting and receiving nodes, and assume that the channel is fully characterized by the channel gain h. The channel gain captures the mixed effects of symbol asynchronism, multipath fading, shadowing and path-loss between the two nodes. In our model, we assume that channel gain is inversely proportional to the distance between the communicating nodes.

The model for the discrete-time received signal at each non-transmitting node j is as follows

$$y_j[t] = \sum_{i=1}^{N} h_{ij}\, x_i[t] + \eta_j[t] \tag{1}$$

where, $y_j[t]$ is the received signal at node j in time-slot t, N is the number of transmitters, h_{ij} is the channel gain between the transmitting node i and the receiving node j, $x_i[t]$ is the signal transmitted by node i, and $\eta_j[t]$ models the noise and other interferences received at node j. If transmitter i uses transmission power P_{t_i} during this time-slot, the received power level at node j is given by $P_{r_j} = h_{ij}^2 P_{t_i}$. However, every node has a limit on its maximum transmit power denoted by $\mathrm{P_{max}}$. The channel gain is assumed to be fixed over time. For notational simplicity, we omit the time-slot index t in the following discussion.

We assume that the transmitted data can be decoded without error if the received Signal-to-Noise Ratio (SNR) is above a minimum threshold $\mathrm{SNR_{min}}$, and that no data is received otherwise. Without loss of generality, we also assume that the information is encoded in a signal that has unit power and that we can adjust magnitude of the signal by multiplying a scaling factor w_i, so that the transmitted power by node i would be w_i^2. The noise at receiver j is assumed to be additive and the noise power is denoted by P_{η_j}.

B. Link Cost Formulation

In this subsection, our objective is to find the optimal power allocation required for a successful transmission from a set of m transmitting nodes $T = \{t_1, t_2, \ldots, t_m\}$ to a set of n receiving nodes $R = \{r_1, r_2, \ldots, r_n\}$[1]. We define the *link cost* (LC) as the summation of the transmission power over all nodes in the transmitting set T, that is

$$\mathrm{LC} = \sum_{t_i \in T} w_i^2 \, . \tag{2}$$

We build vector $\mathbf{h_j}$ as the vector of channel gains between transmitting nodes in T and a receiver $r_j \in R$, and vector $\mathbf{w}$ as the power scaling factor for nodes in T, as follows (recall that h_{ij} is the channel gain between a transmitter t_i and a receiver r_j):

$$\mathbf{h_j} = \begin{bmatrix} h_{1j} \\ h_{2j} \\ \vdots \\ h_{mj} \end{bmatrix} ,$$

and,

$$\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_m \end{bmatrix} .$$

Considering the two vectors $\mathbf{h_j}$ and $\mathbf{w}$, the received signal at receiver r_j can be written as

$$y_j = \mathbf{h_j}^{\mathrm{T}} \mathbf{w} + \eta_j \, . \tag{3}$$

In order to have a successful transmission, the received SNR should be greater than $\mathrm{SNR}_{\min}$ for all the nodes in R. Consequently, the following inequality should be satisfied:

$$\mathbf{h_j}^{\mathrm{T}} \mathbf{w} \geq \sqrt{\mathrm{SNR}_{\min} P_{\eta_j}}, \qquad \text{for all } r_j \in R \, , \tag{4}$$

[1]When there is no ambiguity, we use node index j (or i) to refer to node $r_j \in R$ (or $t_i \in T$)

where, P_{η_j} is the noise power at receiver r_j. There is also a constraint on the maximum power transmitted by each node, which can be written as:

$$w_i \leq \sqrt{\mathrm{P_{max}}}, \qquad \text{for all } t_i \in T \ . \tag{5}$$

We are interested in minimizing the transmission power for a successful transmission from T to R, where the total transmitted power is expressed as:

$$\|\mathbf{w}\|^2 = \sum_{t_i \in T} w_i^2 \,. \tag{6}$$

The power allocation problem is now an optimization problem with $(m+n)$ constraints given by (4) and (5).

Equivalently, this problem can be written in a matrix form as follows:

$$\mathbf{y} = \mathbf{H}^{\mathrm{T}}\mathbf{w} + \mathbf{n}, \tag{7}$$

where,

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \qquad \mathbf{n} = \begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_n \end{bmatrix},$$

and,

$$\mathbf{H} = [\mathbf{h_1}, \mathbf{h_2}, \ldots, \mathbf{h_n}] \ .$$

Recall that y_j and η_j are the received signal and the additive noise at receiver r_j, respectively.

Next, we define our transmit power minimization problem as the following optimization problem (we note that this formulation is a quadratic program):

$$\min_{\mathbf{w}} f(\mathbf{w}) = \frac{1}{2}\mathbf{w}^{\mathrm{T}}\mathbf{Q}\mathbf{w}, \tag{8}$$

subject to the constraints on the received signal powers at the receivers, and the maximum power limit on every transmitter:

$$\mathbf{H}^{\mathrm{T}}\mathbf{w} \geq \mathbf{b}, \tag{9}$$

and,

$$\mathbf{w} \leq \mathbf{p}, \tag{10}$$

where,

$$\mathbf{Q} = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix},$$

$$\mathbf{b} = \begin{bmatrix} \sqrt{\mathrm{SNR}_{\min} P_{\eta_1}} \\ \sqrt{\mathrm{SNR}_{\min} P_{\eta_2}} \\ \vdots \\ \sqrt{\mathrm{SNR}_{\min} P_{\eta_n}} \end{bmatrix},$$

and,

$$\mathbf{p} = \begin{bmatrix} \sqrt{\mathrm{P}_{\max}} \\ \sqrt{\mathrm{P}_{\max}} \\ \vdots \\ \sqrt{\mathrm{P}_{\max}} \end{bmatrix}.$$

Different techniques such as the simplex method, active set method or lagrangian multipliers can be used to solve the optimization problem defined in (8). The optimal solution, however, may not exist as there may not be any feasible solution to the power allocation problem.

C. Approximate Link Cost Formulation

Although, the optimization problem (8) can be numerically solved to find the optimal solution, it is useful to derive a solution which can be written in a closed form. Such a closed-form solution provides some insight into the power allocation problem, as we will see later in Section III, where we use it to prove a property of MIMO links (namely, as the transmitting set becomes larger the link cost becomes smaller).

To derive a closed-form approximation, we consider the set of receiving nodes as a *super node*. Hence, the problem of allocating power to transmitting nodes in our MIMO transmission scenario will be reduced to the problem of power allocation in a *single* MISO transmission scenario. In our MIMO formulation in the previous subsection, each receiving node was able to decode as long as it received sufficient power *collectively* from all the transmitting nodes.

In order to solve the power allocation problem for MISO, we need to compute the channel gains between the transmitters and the super node. To compute channel gains, consider a typical transmitter $t_i \in T$. Node t_i has to transmit at sufficiently high power so that the total power from t_i and other transmitters received at any node $r_j \in R$ is above the minimum SNR level. Intuitively, a receiver with larger channel gain requires less transmit power in order to decode the received signal successfully. We, however, approximate this by assuming that the transmitter t_i sees all receivers $r_j \in R$ as equally bad in terms of transmit power requirement. In other words, node t_i assumes that all nodes $r_j \in R$ have the same channel gain that is equal to the smallest channel gain among all h_{ij}'s for all $r_j \in R$. Let r_{j^*} denote the node with the smallest channel gain. That is

$$j^* = \arg\min_{j:\, r_j \in R} h_{ij} \, .$$

Transmitter t_i uses h_{ij^*} as its channel gain to the super node when computing its transmit power. Let $\mathbf{h}^*$ denote the channel gain vector between transmitters and the super node, where the super node consists of nodes $R = \{r_1, r_2, \ldots, r_n\}$. Based on the above discussion, the i-th entry of the channel gain vector is given by

$$h_i^* = h_{ij^*} = \min_{r_j \in R} h_{ij},$$

and the resulting vector $\mathbf{h}^*$ is expressed as:

$$\mathbf{h}^* = \begin{bmatrix} \min\limits_{r_j \in R} h_{1j} \\ \min\limits_{r_j \in R} h_{2j} \\ \vdots \\ \min\limits_{r_j \in R} h_m j \end{bmatrix} . \tag{11}$$

Next, we rewrite the optimization problem (8) using channel gain vector $\mathbf{h}^*$. The new optimization problem is expressed as:

$$\begin{aligned} &\min \sum_{t_i \in T} w_i^2 \\ \text{w.r.t.} \quad & \mathbf{w}^{\mathrm{T}}\mathbf{h}^* \geq \sqrt{\mathrm{SNR}_{\min} P'_\eta}, \\ \text{and,} \quad & w_i \leq \sqrt{\mathrm{P}_{\max}}, \qquad \text{for all } t_i \in T, \end{aligned} \tag{12}$$

where, P'_η denotes the largest noise component of the super node. P'_η is defined in a way that the node with the highest noise level will also be able to decode the received signal with no errors:

$$P'_\eta = \max_{r_j \in R} P_{\eta_j} \, .$$

Optimization problem (12) can be solved to find the approximate power allocation. Using Lagrangian multipliers technique, the solution to this optimization problem is expressed as:

$$w_i = \frac{h_i^*}{\|\mathbf{h}^*\|^2}\sqrt{\mathrm{SNR}_{\min} P'_\eta}, \tag{13}$$

where, h_i^* is the i-th entry of the channel gain vector $\mathbf{h}^*$. The link cost, as defined in (2), is then given by:

$$\mathrm{LC} = \sum_{t_i \in T} w_i^2 = \frac{\mathrm{SNR}_{\min} P'_\eta}{\sum_{t_i \in T} (h_i^*)^2}\,. \tag{14}$$

Clearly, all of the above equations can be equally applied to Single-Input Single-Output (SISO), Single-Input Multiple-Output (SIMO), and Multiple-Input Single-Output (MISO) communication schemes. It means that we can use a single approach (as described in this section) to compute the transmission cost between any transmitting set T and any receiving set R, with m ($m \geq 1$), and n ($n \geq 1$) nodes, respectively.

III. Cooperative Route Selection

In Section II, we formulated the transmission cost for cooperative communication between two sets of nodes. In this section, we develop optimal and heuristic algorithms to find the least cost route in an arbitrary wireless network.

A. Optimal Route Selection

In this subsection, we consider finding the optimal cooperative route from a source node s to a destination node d in an arbitrary network. The optimal routing algorithm is multi-hop in nature and selects a cooperative link in every time-slot (recall that our system is slotted). The transmitting and receiving sets, in every time-slot k, are denoted by T_k and R_k, respectively. Starting from the source node, the initial transmitting set, T_0, is simply $\{s\}$, and a route is found as soon as the receiving set at some time-slot k contains the destination node d. Considering the transmitting and receiving sets in previous time-slots, the transmitting set in time slot $k+1$ can be defined in three different ways:

1) **Progressive Cooperative:** All nodes that have the data from previous transmissions cooperate in the next transmission. In this case, the transmitting set in time-slot $k+1$ is given by

$$T_{k+1} = T_k \cup R_k, \qquad k = 0, 1, \ldots\,.$$

2) **Selective Cooperative:** Only a non-empty subset of all nodes that already have the data participate in the transmission. In this case, the transmitting set in time-slot $k+1$ is expressed as

$$T_{k+1} \subseteq T_0 \cup R_0 \cup R_1 \cup \ldots \cup R_k, \qquad T_{k+1} \neq \emptyset\,.$$

3) **Limited Cooperative:** Only the receiving nodes in previous time-slot cooperate in the next transmission. In this case, the transmitting set in time-slot $k+1$ is given by

$$T_{k+1} = R_k, \qquad k = 0, 1, \ldots\,.$$

We now use the link cost $\mathrm{LC}(T_k, R_k)$ (between a transmitting set T_k and a receiving set R_k) defined in Section II to formulate the total cost of a cooperative route. A *cooperative route* is essentially a sequence $T = \langle (T_0, R_0), (T_1, R_1), \ldots, (T_l, R_l) \rangle$ of pairs of corresponding transmitting and receiving sets, where $T_0 = \{s\}$ and $d \in R_l$. Our goal is to find a route T that minimizes the total transmission power P_T given by

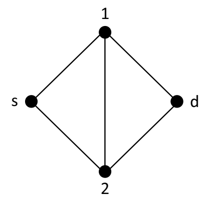
$$P_T = \sum_{k=0}^{l} \mathrm{LC}(T_k, R_k)\,. \tag{15}$$

The solution to this problem specifies an optimal transmission policy at every time slot, and determines the least cost route in the network. We use dynamic programming to find the optimal cooperative route in our simulations.

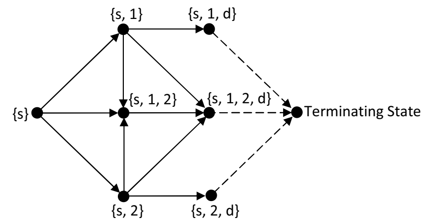
We next discuss some properties of the optimal algorithm with respect to its algorithmic complexity.

1) Algorithmic Complexity of Cooperative Routing: A *cooperation graph* [13] can be used to show the state space of the optimal routing problem, where a *state* is defined as the set of nodes that have so far received the data. Fig. 1 shows a network and its corresponding cooperation graph with *progressive cooperative* as the transmission scheme. Arches between the nodes in the cooperation graph represent possible transitions between the states (each transition represents a potential transmission). The cost for an arch is the link cost defined in Section II, and the cost for the dashed arches is zero (they all go to the *Terminating State*). The optimal cooperative route is the *shortest path* between node $\{s\}$ and the Terminating State in the cooperation graph.

Fig. 2 shows a network with 4×4 grid topology. For this network, we have specified the least cost routes taken by non-cooperative and limited cooperative algorithms. For non-cooperative routing, the sequence of nodes traversed from source s to destination d is $\langle s, 1, 5, 6, 10, 11, d \rangle$.



(a) A sample network.



(b) Cooperative graph with 8 states.

Fig. 1. Cooperative graph of *progressive cooperative* routing algorithm. The graph in (b) is the cooperation graph corresponding to sample network in (a).

For limited cooperative routing algorithm, starting from $\{s\}$ as T_0, the sequence of R_k's is $\langle\{1,4\},\{5,8,9\},\{10,13,14\},\{d\}\rangle$.

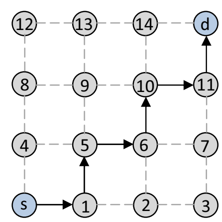


Fig. 2. A regular grid topology with 16 nodes. A least cost non-cooperative route from s to d is the sequence $\langle s,1,5,6,10,11,d\rangle$. The least cost route with *limited cooperative* algorithm from s to d, on the other hand, is the sequence $\langle\{s\},\{1,4\},\{5,8,9\},\{10,13,14\},\{d\}\rangle$.

In a network with $n+1$ nodes, there are $O(2^n)$ nodes in the cooperation graph. Since there are $O(2^{2n})$ edges in a graph with 2^n nodes, a standard shortest path algorithm (such as the Dijkstra's algorithm) will have complexity of $O(2^{2n})$. Unfortunately, this indicates that finding the optimal cooperative route in an arbitrary network has exponential computational complexity in the number of nodes, which becomes computationally intractable for large networks. In the next subsection, we will develop suboptimal cooperative routing algorithms that have polynomial complexity and perform reasonably efficient compared with the optimal cooperative routing algorithm discussed here.

2) Progressive versus Selective Cooperative Routing: Earlier, we described three mechanisms for selecting the set of transmitting nodes in a cooperative routing algorithm. It can be shown that both *selective cooperative* approach and *progressive cooperative* find exactly the same route.

We first prove a property of MIMO links.

Property 1. *The cost of a MIMO link decreases by increasing the number of transmitting nodes.*

Proof: In Section II, we derived the transmission cost of a MIMO link based on the channel gain vector $\mathbf{h}^*$, where each element h_i^* is the minimum channel gain between transmitter t_i and all the nodes in the receiving set (see (11)). Consider a cooperative MIMO link with n transmitting nodes. As shown in (14), the MIMO link cost is given by

$$\mathrm{LC} = \frac{\mathrm{SNR}_{\min} P'_\eta}{\sum_{i=1}^{n} (h_i^*)^2} .$$

Clearly, increasing the number of transmitting nodes only adds more positive numbers to the denominator, decreasing the link cost. ■

Now, consider path P_s chosen by the selective cooperative algorithm, which is a sequence:

$$P_s = \langle (T_0, R_0), (T_1, R_1), \ldots, (T_l, R_l) \rangle,$$

where, T_k and R_k ($k = 0, \ldots, l$) represent the transmitting and receiving sets in time-slot k, respectively. We can now construct a progressive path P_p based on P_s, as the sequence

$$P_p = \langle (T_0, R_0), (T'_1, R_1), \ldots, (T'_l, R_l) \rangle,$$

where,

$$T'_k = T_0 \cup R_0 \cup R_1 \cup \ldots \cup R_{k-1}, \qquad \text{for } k \geq 1 .$$

Hence, in every time-slot k, we have[2] $T_k \subseteq T'_k$, and consequently, $|T_k| \leq |T'_k|$. Using Property 1, it is obtained that

$$\mathrm{LC}(T'_k, R_k) \leq \mathrm{LC}(T_k, R_k).$$

By summing link costs over l time-slots, we obtain that

$$\sum_{k=0}^{l} (T'_k, R_k) \leq \sum_{k=0}^{l} \mathrm{LC}(T_k, R_k),$$

which, indicates the end-to-end cost of the progressive route P_p is smaller than or equal to the end-to-end cost of the selective route P_s. Hence, an optimal selective cooperative algorithm will necessarily choose the same route as the progressive cooperative algorithm. In summary,

[2]This follows from the definition of the selective cooperative routing algorithm.

selective cooperative behaves the same as progressive cooperative algorithm, but with higher computational complexity. Therefore, we will not consider selective cooperative in the rest of this paper.

B. Suboptimal Route Selection

As mentioned in the previous subsection, the complexity of finding the optimal cooperative route is exponential in the number of nodes. Thus, finding the optimal route in an arbitrary network becomes computationally intractable even for networks with relatively small sizes.

In this subsection, we develop heuristic algorithms for the problem of finding an efficient route between a source and a destination in a cooperative network. In optimal cooperative routing described in the previous subsection, we were looking for a sequence of R_k's that minimize the total transmission power. To develop heuristic routing algorithms, we consider the largest set of nodes that the transmitting set T_k can reach (in an error-free transmission) to be the receiving set R_k, at time-slot k. In other words, a transmitting cluster is considered as a *super node* trying to broadcast data as far as possible. We call this approach *the greedy approach* because the transmitting set greedily selects receiving nodes in order to construct the largest feasible receiving set. In every time-slot k, the largest receiving set R_k is selected for a transmitting set T_k so that the power constraints described in Section II for a successful cooperative transmission are satisfied. That is, we choose R_k for a set T_k so that the following constraints are satisfied:

$$w_i \leq \sqrt{\mathrm{P}_{\max}}, \qquad \text{for all } t_i \in T_k,$$

and,

$$\sum_{t_i \in T_k} w_i h_{ij} \geq \sqrt{\mathrm{SNR}_{\min} P_{\eta_j}}, \qquad \text{for all } r_j \in R_k\,.$$

In the previous subsection, two cooperative routing algorithms were developed: *Limited Cooperative* algorithm and *Progressive Cooperative* algorithm. The proposed greedy approach can be applied to both of these algorithms resulting in *Greedy Limited Cooperative* and *Greedy Progressive Cooperative* algorithms. We will evaluate the performance of these greedy algorithms through simulations in Section IV. The simulation results indicate that the greedy algorithms perform relatively efficient compared to the optimal algorithms albeit with significantly lower complexity. For the network shown in Fig. 2, we have computed the least cost route taken by the greedy limited cooperative algorithm. Starting from $\{s\}$ as T_0, the sequence of R_k's is $\langle\{1,4\},\{2,5,6,8,9\},\{3,7,10,11,13,14,d\}\rangle$.

Probing all potential nodes for inclusion in the receiving set R_k, in time-slot k, takes $O(n)$ time. Since the maximum length of a route is[3] $O(n)$, the complexity of finding a route with the greedy algorithms is $O(n^2)$. Thus, greedy routing algorithms are significantly faster than the optimal ones, which have complexity of $O(2^{2n})$ for a network with n nodes.

Besides significantly reducing the complexity of cooperative route selection, while performing almost the same as the optimal route selection algorithms, the greedy algorithms are actually more suitable for wireless ad hoc networks. The reason is that the greedy schemes are more amenable to a distributed implementation, which is desired in ad hoc networks. Designing distributed cooperative routing algorithms is beyond the scope of this paper, and is the topic of a future work.

IV. Performance Evaluation

We have simulated the routing algorithms discussed in previous sections to evaluate their performance numerically in some sample networks. In the following subsections, we present our simulation results and compare the performance of different algorithms in terms of energy consumption. We first present simulation results when there is only a single flow in the network. This scenario serves as a basis for comparison and is useful in isolating the effect of cooperation from other factors that arise in a multi-flow scenario. Next, we present simulation results for the case of having multiple flows in the network to study the impact of cooperation on network throughput, which is an important performance measure in multi-flow networks.

A. Simulation Parameters

For the simulations, we consider a wireless network with n^2 nodes placed on an $n \times n$ grid. We chose two nodes s and d located at the lower left and the upper right corners of the grid, respectively, and find cooperative and non-cooperative routes from s to d. We then compute the total amount of energy consumed on each route using different routing algorithms. A regular 4×4 grid topology with the optimal non-cooperative route from s to d is depicted in Fig. 2.

[3] If the network nodes are distributed over a two-dimensional area then the average path length will be $O(\sqrt{n})$. Here, we consider the worst case scenario when path length is $O(n)$ to avoid making any specific assumptions about the network coverage.

We assume that the channel gain h_{ij} between transmitter i and receiver j is inversely proportional to the geometric distance between nodes i and j. Without loss of generality, we assume that the maximum transmission power at every node is 1, *i.e.*, $\mathrm{P}_{\max} = 1$. We consider a homogeneous network, where all nodes experience the same level of noise denoted by P_η. We also set channel gains h_{ij} so that for every two nodes i and j that are directly connected on the grid $h_{ij} = \sqrt{\mathrm{SNR}_{\min} P_\eta}$. With these assumptions, the transmission power consumed over a non-cooperative Single-Input Single-Output (SISO) link is 1.

B. Single-Flow Energy Efficiency

Our goal is to design energy efficient routing algorithms. Hence, the performance measure of interest in comparing different routing algorithms is the total energy consumed to transmit data from a source to a destination. We choose the optimal non-cooperative (ONC) routing algorithm, *i.e.*, Dijkstra's algorithm, as the baseline for comparing cooperative algorithms. We define the *energy savings* of a cooperative routing algorithm π as follows:

$$\text{Energy Savings}(\pi) = \frac{\text{Energy}_{\text{Non-cooperative}} - \text{Energy}_\pi}{\text{Energy}_{\text{Non-cooperative}}} \times 100, \tag{16}$$

where Energy_π denotes the total transmission energy consumed by cooperative algorithm π.

We compare the efficiency of the optimal MIMO algorithms described in Subsection III-A with the MISO algorithm proposed in [13]. We also compare the performance of our suboptimal algorithms described in Subsection III-B with the optimal as well as the suboptimal algorithms proposed in [13]. Specifically, we compare our proposed algorithms against the following algorithms proposed in [13]:

- **MISO Cooperation Along Non-cooperative Path (CAN):** This is a MISO cooperative routing algorithm, where in every time-slot, the next node along the optimal non-cooperative route toward the destination is selected as the MISO receiver. The transmitting set contains all the nodes that have already received data.
- **CAN-3:** CAN-l is a suboptimal algorithm and is similar to CAN except that the transmitting set only consists of the last l nodes on the non-cooperative route from the source to the destination. We implement CAN-3 because it was shown in [13] that $l = 3$ nodes are sufficient to realize most of the benefits of CAN-l.

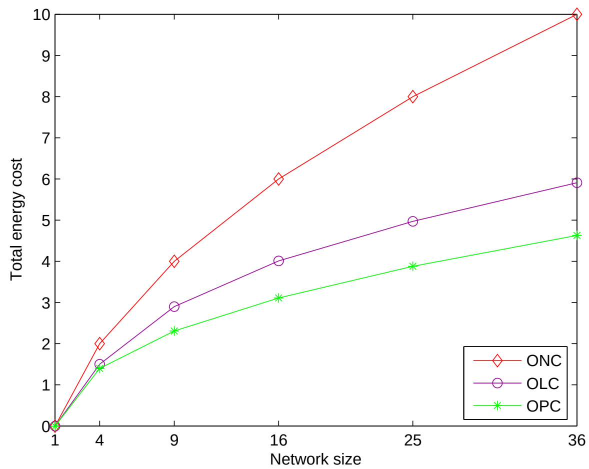


Fig. 3. Energy cost of optimal MIMO cooperative routing algorithms.

- **PC-**3**:** PC-l is another suboptimal algorithm. In this algorithm, all transmitting nodes are combined into a super node and then the optimal non-cooperative route is computed between the super node and the destination node. The super node includes all last l nodes along the current best route toward the destination. It was shown in [13] that most of the benefits of this algorithm are achieved using $l = 3$, thus we implement PC-3 for simulation purposes.

Table I summarizes different algorithms that are implemented in our simulations. For clarity purposes, the table also shows the abbreviations used on the figures.

1) Optimal Routing: Fig. 3 shows the total energy cost for the two optimal cooperative MIMO algorithms OLC and OPC (refer to Table I for details), and the optimal non-cooperative routing ONC (which is just a shortest path algorithm). The total energy cost is the end-to-end link cost for a routing algorithm as defined in (15). As shown in the figure, the total energy cost is reduced by using the MIMO schemes. Specifically, it shows that the larger the network is, the higher the reduction in energy cost. As expected, OPC consumes less energy than OLC due to the growing number of transmitters in the progressive algorithm, *i.e.*, OPC, as the data progresses over the path to the destination.

Fig. 4 shows the energy savings of different cooperative routing algorithms for different network sizes. We observe that OPC (a MIMO technique) significantly outperforms CAN (a MISO technique), and achieves energy savings of close to 55% for a network with 36 nodes (a

TABLE I

SIMULATED ALGORITHMS.

Algorithm	**Description and key features**
ONC	Optimal Non-Cooperative Routing.
OLC	Optimal MIMO Limited Cooperative Routing: The set of receivers in the previous time-slot becomes the transmitting set in the current time-slot. This algorithm is based on the *limited cooperative* technique described in Subsection III-A.
OPC	Optimal MIMO Progressive Cooperative Routing: Transmitting set contains all the nodes that have received data in previous time-slots. This algorithm is based on the *progressive cooperative* technique described in Subsection III-A.
GLC	Greedy MIMO Limited Cooperative Routing: This algorithm is the heuristic version of OLC, where the receiving set contains all possible receivers as described in Subsection III-B.
GPC	Greedy MIMO Progressive Cooperative Routing: This algorithm is the heuristic version of OPC, where the receiving set contains all possible receivers as described in Subsection III-B.
CAN	MISO Cooperation Along Non-cooperative Path: The algorithm progresses along the shortest non-cooperative path. The transmitting set is determined using dynamic programming.
CAN-3	The transmitting set in CAN consists of only the last 3 nodes on the non-cooperative path.
PC-3	Last 3 nodes along the current best route are combined into a super node. The optimal non-cooperative route is found between the super node and the destination.

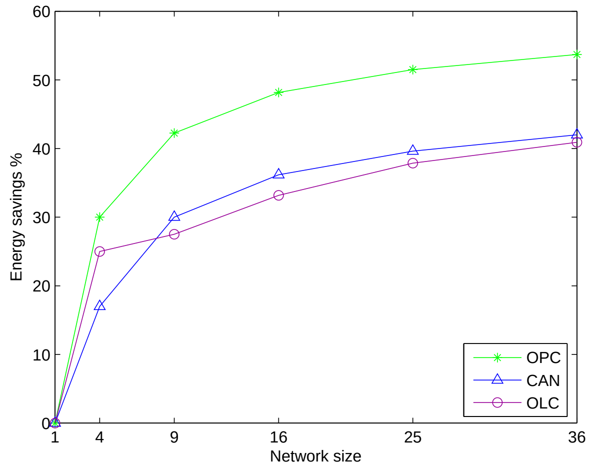


Fig. 4. Energy savings of optimal cooperative routing algorithms.

relatively small network). Interestingly, OLC performs almost the same as CAN although one might expect a better performance. The reason is that CAN is inherently a *progressive* routing algorithm, which achieves low energy consumption by employing a large transmitting set in every step of routing toward the destination.

2) Suboptimal Routing: In Section III-B, we developed two greedy algorithms for finding an energy efficient route between a source and a destination node. We showed that the greedy algorithms have significant advantages in terms of their computational complexity. In this subsection, we conduct simulations to compute energy savings achieved by these algorithms, and compare them with that of optimal routing algorithms.

In Fig. 5, the energy cost of greedy algorithms is compared with the energy cost of the optimal algorithms as well as the energy cost of the optimal non-cooperative algorithm. We observe that the proposed greedy schemes, namely, GLC and GPC, achieve significant energy savings, close to optimal algorithms. Furthermore, GPC (Greedy Progressive Cooperative) algorithm performs slightly better than OLC and MISO CAN algorithms.

Next, we compare the efficiency of GLC and GPC with two suboptimal algorithms CAN-3 and PC-3 (see Table I). In Fig. 6, energy savings of different suboptimal routing algorithms are compared. It is observed that GPC significantly outperforms the other three methods (GLC, CAN-3, PC-3). Interestingly, even the simpler algorithm GLC performs better than MISO schemes as

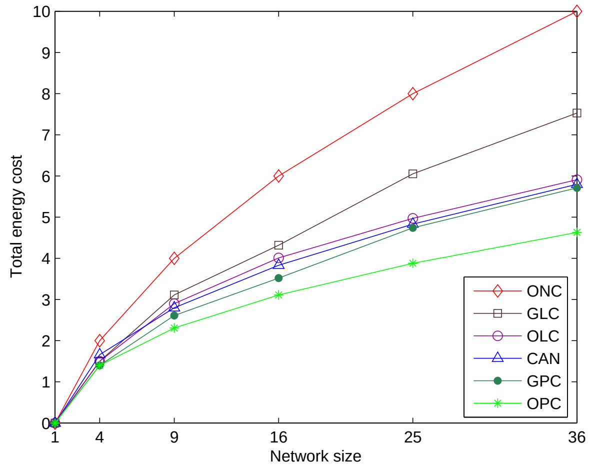


Fig. 5. Energy cost of cooperative routing algorithms.

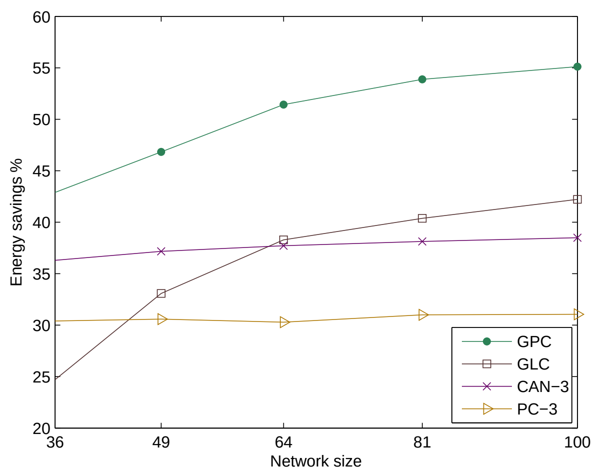


Fig. 6. Energy savings of suboptimal cooperative routing algorithms.

the network becomes larger.

Finally, Table II summarizes our results for the complexity and energy efficiency of different algorithms discussed in this paper.

TABLE II
COMPLEXITY AND EFFICIENCY OF ROUTING ALGORITHMS.

Algorithm	**Complexity**	**Energy Savings**	**Network Size**
MIMO Progressive Cooperative (OPC)	$O(2^{2n})$	55%	36
MISO Progressive Cooperative (CAN)	$O(n^2)$	43%	36
MIMO Limited Cooperative (OLC)	$O(2^{2n})$	42%	36
Greedy Progressive Cooperative (GPC)	$O(n^2)$	55%	100
Greedy Limited Cooperative (GLC)	$O(n^2)$	42%	100
CAN-3	$O(n^2)$	38%	100
PC-3	$O(n^3)$	31%	100

C. Multi-Flow Throughput

So far, we have shown that cooperative routing techniques achieve significant energy savings compared to traditional non-cooperative algorithms. However, we only considered transmission energy and ignored network throughput in the preceding discussions. Clearly, when several nodes cooperatively transmit, network throughput may adversely be affected as cooperation increases the interference when multiple flows exist in the network. The impact on throughput is expected to be even worse when using progressive cooperative algorithms (such as CAN and OPC), where the number of transmitting nodes grows as the routing progresses. In this subsection, using simulations, we investigate the effect of cooperative routing on network throughput, and contrast energy savings of cooperative routing with the loss in network throughput.

We simulate a network consisting of 100 nodes arranged on a 10×10 grid, and consider multiple concurrent flows in the network. For each flow, the source and destination nodes are chosen randomly. Unfortunately, finding the optimal cooperative routes even for this network (which has only 100 nodes) is prohibitively time consuming. Therefore, we instead implement a greedy cooperative routing algorithm, namely, GPC, in our simulations. Similar to the previous subsection, optimal non-cooperative routing (ONC), is used as the basis for performance comparisons. We compute the *mean energy cost* as the average transmission power consumed over all routes for all the flows. Moreover, we use the *mean number of scheduled links* for transmission at each time-slot as the measure of throughput. We note that a *link* here refers to either a cooperative or a non-cooperative link. Since we assume a fixed SNR at every receiver ($\mathrm{SNR}_{\min}$), the rate at which nodes receive data is fixed in the network. Therefore, the network throughput in a time-slot is directly proportional to the number of scheduled links in that time-slot.

We run simulations with number of flows changing from 1 to 10. For each flow count, we repeat the simulations 30 times, each time choosing source destinations randomly. Results are presented in Figs. 7 and 8. Each data point in the figures is computed as the average over 30 simulation runs. We have also plotted the 95% confidence intervals for every data point. We compute each data point as follows:

- To compute the mean number of scheduled links, in every simulation run, we compute the average number of scheduled links per time-slot (by counting the number of scheduled links in every time-slot and dividing by the number of time-slots to find the routes). We then use this average (computed over one run) to compute the mean number of scheduled links over 30 simulation runs.
- To compute the mean energy cost, we compute total energy cost for each flow, and use it to compute the mean energy cost over all the flows in the network.

In the following subsections, we discuss our multi-flow simulation results.

1) Energy Efficiency: Fig. 7 shows the mean energy cost for cooperative algorithms GPC and CAN, and non-cooperative algorithm ONC, for different number of flows. Although, in previous subsection, we reported energy savings of up to 55% for single flow networks, with multiple flows, energy savings are only around 30%. It should be noted that large savings in energy are achieved over long routes, however in this simulation we could have routes consisting of a single hop, where no savings are achieved. Therefore, the observed energy savings here are smaller than the savings reported in Subsection IV-B.

2) Network Throughput: Mean number of scheduled links is shown in Fig. 8. We observe that the mean number of scheduled links, and consequently the network throughput sharply decreases as the number of flows increases in the network. For instance, when there are 10 flows in the network, about 40% savings in mean energy cost is achieved, while more than 50% of the network throughput is lost. A similar behavior can be seen in CAN, where more than 40% of the network throughput is lost to achieve 35% savings in energy, when there are 10 flows in the network.

Reduction in the number of scheduled links in each time-slot is due to the interference caused

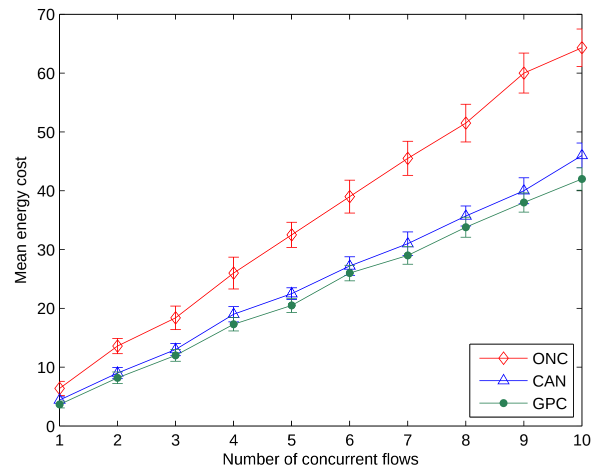


Fig. 7. Mean energy cost over different routes in a 10×10 network.

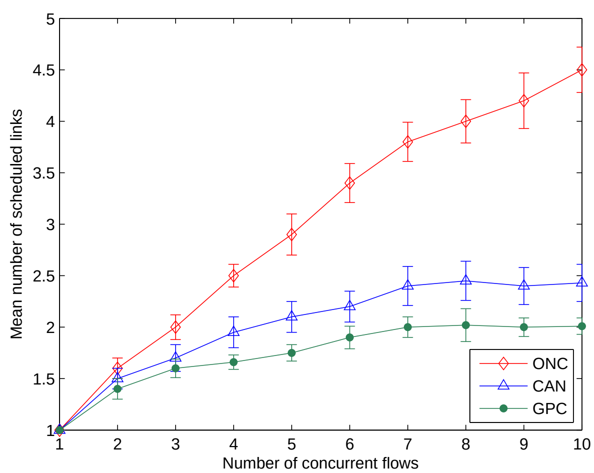


Fig. 8. Mean number of scheduled links per time-slot in a 10×10 network.

by the large transmitting sets formed by these progressive algorithms (both GPC and CAN are progressive cooperative algorithms). Based on this observation, we conclude that there is a trade-off between energy savings and throughput achieved by cooperative routing algorithms. In general, it might be possible to apply interference cancelation techniques [17], [18] in order to reduce the interference between concurrent cooperative links, and hence increase the network throughput.

V. Conclusion

In this paper, we studied the problem of finding the minimum energy cooperative route in an arbitrary wireless network. We considered a cooperative MIMO technique for transmission at physical layer, and formulated the cost of a cooperative link between a set of transmitters and a set of receivers as the minimum transmission power required for successful decoding at every node in the receiving set. This is a general formulation of a cooperative link, which subsumes single-input-single-output, single-input-multiple-output, and multiple-input-single-output transmission techniques considered by other researchers [13], [14]. We showed that the minimum energy cooperative route (with general link cost formulation) can be found using dynamic programming, and that such a cooperative routing achieves significant energy savings (up to 55% in our simulations) compared to the minimum energy non-cooperative routing.

Unfortunately, finding the optimal cooperative route is computationally intensive, requiring $O(2^{2n})$ time for a network that has n nodes. To avoid the exponential complexity of the optimal algorithm, we developed two greedy algorithms that find energy efficient cooperative routes in $O(n^2)$ time. Our simulation results indicate that the proposed greedy algorithms perform almost as efficient as the optimal algorithm, and achieve close to 50% energy savings compared to the optimal non-cooperative routing.

Although significant savings in energy can be achieved by employing cooperative MIMO at physical layer, our simulation results showed that the network throughput drastically decreases when there are multiple flows in the network. A future work is to study the trade-off between energy and throughout in cooperative networks with multiple flows. Zhang *et al.* [14] considered multi-flow routing and scheduling in a MISO cooperative network. However, we are not aware of any work in MIMO cooperative networks beyond the asymptotic capacity results [19], [20]. Interference cancelation techniques [17], [18] can also be used to reduce the interference between concurrent cooperative links, and hence increase the network throughput. We hope to study multi-flow MIMO cooperative networks in the future.

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