Distributed Link Scheduling, Power Control and Routing for Multi-hop Wireless MIMO Networks

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***Abstract*— In this paper, we develop a cross-layer, yet distributed, resource allocation mechanism in multi-hop wireless MIMO networks over time varying channels. The objective is to design a scalable scheduler which uses minimum total power to transfer the information bits for all the end-to-end connections at the requested rates. To this end, we decompose the system into multiple isolated MIMO broadcast subsystems. In each time slot, each subsystem independently decides the transmit power, the antenna weights, the transmission rates and the forwarding rules of information bits based on the channel state information and previous decisions of other neighboring subsystems. The proposed algorithm converges asymptotically to the optimal solution under the decomposition.**

I. Introduction

In wireless communications, to minimize average transmit power, the scheduled transmission rates at lower layers should not exceed the demand from the upper layers. This requires a cross-layer design in multi-hop wireless networks.

The cross-layer optimization problem considered in this work is motivated by the developments and discoveries in the following three research themes.

The first subject, called the *interfering link scheduling problem*, is concerned with how to coordinate the transmissions within a wireless network to fulfill the requested point-to-point transmission rates using a minimal allocation of power. It stemmed from the power control problem in cellular networks [1], and was studied afterward in the context of ad-hoc networks [2] [3].

The second research trend is the *minimum cost flow problem*, which is concerned with how to use the least amount of resources to move the information bits from the source node to the destination node at the requested rate. This problem was first investigated by Ford and Fulkerson under a fixed link capacity constraint [4], and later on was extended to a cross-layer context. The minimum cost flow problem in wireless communications, accounting for the interference using omni-antennas, was investigated in [5]. The result was later extended to include the time varying behavior of channel variations in [6].

The third motivating factor for our work is the recognition of the significant improvements offered by multi-user communication techniques [7]. In particular, we are interested in multi-user techniques, such as dirty paper coding or successive interference cancelation that allow for simultaneous transmission of data to many users while minimizing the impact of interference.

Integration of above three problems and techniques requires the integrated design of link scheduling, routing and power control. However, due to the interference, the feasible resource allocations at nodes are coupled with each other. Consequently, the complexity of the optimal cross-layer scheduling algorithm grows exponentially with the system size [2] [5]. This makes scalability a significant problem in implementing the cross-layer scheduler.

To cope with the growing complexity, we adopt the divide-and-conquer approach. Specifically, we divide the system into multiple isolated MIMO broadcast subsystems using the directionality of the antenna arrays and an interference avoidance mechanism. This decomposition approach is a lossy process, which sacrifices both resources and system performance, but gains scalability in return. In light of this, the contribution of our work is three fold: 1) we extend previous work in cross-layer optimization using omni-antennas to a MIMO system; 2) we integrate the enhanced MIMO multi-user capacity of MIMO braodcast channel with higher layer schemes; 3) we devise a locally centralized scheduling algorithm to coordinate the working of MIMO broadcast subsystems such that the best performance under the decomposition is achieved.

II. Notation and System Models

A. Notation

We use bold face to denote matrices and vectors, where an uppercase refers to a matrix and a lowercase refers to a vector. The Hermitian of a general matrix $\mathbf{M}$ is denoted by $\mathbf{M}^*$. If $\mathbf{M}$ is a square matrix, $|\mathbf{M}|$ denotes the determinant and $\mathrm{Tr}(\mathbf{M})$ the trace. A matrix that is conjugate symmetric and positive semidefinite is denoted by $\mathbf{M} \succeq 0$. For a sequence of general matrices $\mathbf{M}^{(k)}$, the long-term average of the sequence is defined as

$$\overline{\mathbf{M}} = \lim_{K\to\infty} \frac{1}{K} \sum_{k=0}^{K-1} \mathbf{M}^{(k)}. \tag{1}$$

Let $\{\mathcal{A}(k);\, k\}$ be a sequence of sets, where $\mathcal{A}(k)$ is a set of random matrices (or vectors) for each k. We define the time average of the set sequence $\mathcal{A}(k)$ as

$$\overline{\mathcal{A}} = \Big\{\chi \,\Big|\, \chi = \overline{\mathbf{X}},\ \text{for some process } \mathbf{X}^{(k)} \text{ such that } \mathbf{X}^{(k)} \in \mathcal{A}(k)\ \forall k.\Big\} \quad (2)$$

B. Network Description

The system consists of N nodes, all equipped with n_t transmit antennas and n_r receive antennas. We denote a MIMO link as a logical connection from one node to another over the matrix channel established by the multiple antennas at the transmitter and the receiver. The MIMO link from node u to node v is identified by the ordered pair (u, v). For simplicity, the terms "MIMO link" and "link", are used interchangeably in sequel.

We assume time is slotted with the slot unit normalized to one. We use the index k $(= 0, 1, 2, \dots)$ to indicate time slots. At a given time k, the state of channel gain matrix of link (u, v) is described by a random matrix $\mathbf{H}^{(k)}_{uv} \in \mathbb{C}^{n_t \times n_r}$. We assume that $\mathbf{H}^{(k)}_{uv}$ and $\mathbf{H}^{(k)}_{u'v'}$ of different links (u, v) and (u', v') are mutually independent. Furthermore, we assume for any given pair of nodes u and v, the sequence of channel matrices $\mathbf{H}^{(1)}_{uv}, \mathbf{H}^{(2)}_{uv}, \dots$ is stationary and ergodic. For simplicity, we define the tuple $\mathbf{\Pi}^{(k)}_u = (\mathbf{H}^{(k)}_{u1}, \dots, \mathbf{H}^{(k)}_{uN})$ to denote the set of channel matrices of the links originated at node u.

In the system, the information bits are transferred from its source node to its destination node through single or multiple paths supported by the links. The abstraction of this end-to-end connection is called a flow. We identify the flow from node a to node b by the ordered pair (a, b). We assume that there are J flows in the system, and the j^{th} flow is identified by (a_j, b_j). The set $\mathcal{F}$ consists of all flows in the system. Let $f^{uv}_{ab}(k)$ be the amount of information belonging to flow (a, b) directly transmitted from node u to node v in time slot k. Note that to guarantee lossless relaying of information and to combat channel variations, nodes are equipped with J queues of infinite size, storing information bits of each flow.

At any given time k, and with the full knowledge of the global channel state $(\mathbf{\Pi}^{(k)}_1, \dots, \mathbf{\Pi}^{(k)}_N)$ a potentially centralized controller is responsible to allocate the following:

1) $\mathbf{\Phi}^{(k)} = (\mathbf{P}^{(k)}_1, \mathbf{P}^{(k)}_2, \dots, \mathbf{P}^{(k)}_N)$,
   Array of covariance matrices $\mathbf{P}^{(k)}_u \succeq 0$ at each node.

2) $\mathbf{r}^{(k)} = (r_{12}(k), \dots, r_{1N}(k), \dots, r_{N1}(k), \dots, r_{NN-1}(k))$
   Array of the transmit link rates $r_{uv}(k) \geq 0$ on link (u, v).

3) $\mathbf{f}^{(k)} = \Big(f^{a_1b_1}_{12}(k), f^{a_2b_2}_{12}(k), \dots, f^{a_Jb_J}_{12}(k), \dots, f^{a_1b_1}_{NN-1}(k), \dots, f^{a_Jb_J}_{NN-1}(k)\Big)$
   Array of transmit rate allocations of flow (a, b) between pairs of nodes (u, v). $f^{uv}_{ab}(k) \geq 0$ and $\sum_{(a,b)\in\mathcal{F}} f^{uv}_{ab}(k) \leq r_{uv}(k)$.

subject to the following constraints:

C1$-$ (**Physical layer constraint I**)
Given channel state $(\mathbf{\Pi}^{(k)}_1, \dots, \mathbf{\Pi}^{(k)}_N)$ and power allocation $\mathbf{\Phi}^{(k)}$, transmission rate vector $\mathbf{r}^{(k)}$ can be achieved with low enough bit error rate.

C2$-$ (**Physical layer constraint II**)
The peak transmit power of each node is limited to $P_{\max}$, that is $\mathrm{Tr}(\mathbf{P}^{(k)}_u) \leq P_{\max}$ and $\mathbf{P}^{(k)}_u \succeq 0$.

C3$-$ (**Queue Stability**)
The queue build-up at each relaying node v is stable, i.e. the long-term average of information bit rate of flow (a, b) entering node v equals the long-term average of information bit rate of flow (a, b) leaving node v. That is $\sum_{u\neq v} \overline{f^{uv}_{ab}} = \sum_{w\neq v} \overline{f^{vw}_{ab}} \quad \forall (a, b) \in \mathcal{F}$.

C4$-$ (**Minimum Flow Rate Constraint**)
Each flow (a, b) is guaranteed a long-term average minimum rate λ_{ab}. That is $\forall (a, b) \in \mathcal{F}$ $\sum_{u\neq b} \overline{f^{ub}_{ab}} = \lambda_{ab}$ and $\sum_{v\neq a} \overline{f^{av}_{ab}} = \lambda_{ab}$.

Furthermore, given a set of control policies that satisfy C1-C4, we are interested in the one which also minimizes the long-term average transmit power.

We first note that satisfying condition C1 in this general setting is a non-trivial question as it is closely related to the information theoretic capacity of MIMO ad-hoc networks. Moreover, as N grows, the complexity of any controller will grow and will depend on an ever-growing overhead cost of collecting information about the state of the system.

To cope with the above issues of complexity, we consider a decomposition of the system into multiple isolated MIMO broadcast subsystems. In other words, we make the following assumptions

***Assumption** 1:* Given each node u, there exist a set of nodes $\mathcal{V}(u)$ with whom nodes u forms a MIMO broadcast subsystem in which node u is the transmitter.

***Assumption** 2:* If node $v \notin \mathcal{V}(u)$ then $\mathbf{H}^{(k)}_{uv} = 0$ for all time.

***Assumption** 3:* If $v \in \mathcal{V}(u) \bigcap \mathcal{V}(w)$, then the transmission of signals from u and w have to be orthogonal.

Note that the decomposition together with Assumption 1-3, create a grouping of nodes in the network $\{\mathcal{V}(1), \mathcal{V}(2), \dots, \mathcal{V}(N)\}$, we refer to this decomposition as the network topology and assume it is fixed for all time.

In this work, we are not necessarily concerned with the costs associated with realizing Assumptions 1-3 (one possible way to ensure validity of Assumption 1-3 is via frequency orthogonalization) or loss of optimality due to the proposed decomposition. Philosophically, our decomposition along with Assumptions 1-3 provide a generalization of link-based abstraction of the network [8] [9] with non-interfering links, in which we allow for multi-user techniques to be integrated in the joint link scheduling, routing and power control scheduler. In other words, the contribution of our work remains at the networking layer, we are attempting to modify network mechanisms of link scheduling, power as well as routing to take advantage of broadcast capacity achieving techniques such as dirty paper coding, etc..

Even though we do not consider the realization of Assumption 1-3 as the main focus or contribution of our work, we do discuss some possible candidate schemes in section IV.

Now under Assumptions 1-3, we can simplify constraint C1 as follows.

C1′− (**Physical Layer Constraint I**) $(\mathbf{f}^{(k)}, \mathbf{\Phi}^{(k)})$ is said to be feasible under channel realization $(\mathbf{\Pi}_1^{(k)}, \ldots, \mathbf{\Pi}_N^{(k)})$ if and only if for each node u with the nodes in $\mathcal{V}(u) = \{v_1, \ldots, v_{|\mathcal{V}(u)|}\}$ there exists a link rate schedule $(r_{uv_1}(k), \ldots, r_{uv_{|\mathcal{V}(u)|}}(k))$ such that for any u, $\sum_{(a,b)\in\mathcal{F}} f_{ab}^{uv}(k) = r_{uv}(k) \quad \forall\ v \in \mathcal{V}(u)$ and $(r_{uv_1}(k), \ldots, r_{uv_{|\mathcal{V}(u)|}}(k)) \in \mathcal{C}(\mathbf{P}_u^{(k)}, \mathbf{\Pi}_u^{(k)})$, where $\mathcal{C}(\mathbf{P}_u^{(k)}, \mathbf{\Pi}_u^{(k)})$ is the feasible link rate region of the MIMO broadcast channels formed by node u and its successor nodes $\mathcal{V}(u)$.

We denote all such tuple of $(\mathbf{f}^{(k)}, \mathbf{\Phi}^{(k)})$ with $\mathcal{D}(\mathbf{\Pi}_1^{(k)}, \ldots, \mathbf{\Pi}_N^{(k)})$.

III. Problem Formulation

The objective of our work is to develop a locally centralized cross-layer scheduling algorithm which minimizes the average transmit power consumption while maintaining minimum end-to-end throughput requirements under the time varying channels. Mathematically, the above optimization can be formulated as a constrained dynamic program with an expected average cost criterion [10]. Instead, by relaxing condition C1′ to an average constraint, we consider an alternative optimization problem (**P**) whose solution is a lower bound for the solution to our dynamic programming. We then provide a distributed iteration algorithm to solve the optimization (**P**). The important property of this algorithm is that at each instance it satisfies C1′, hence is a solution to the original problem. With this overview, we now proceed with problem (**P**).

Primal problem (P)

$$\begin{aligned} \text{minimize} \quad & \sum_u \mathrm{Tr}(\overline{\mathbf{P}_u}) \qquad (3)\\ \text{subject to} \quad & \text{for each node } v \text{ and flow } (a,b)\\ & \sum_{u\in\mathcal{U}(v)} \overline{f_{ab}^{uv}} + \Delta_{ab}(v) = \sum_{w\in\mathcal{V}(v)} \overline{f_{ab}^{vw}},\\ & (\overline{\mathbf{f}}, \overline{\mathbf{\Phi}}) \in \overline{\mathcal{D}}, \end{aligned}$$

where

$$\Delta_{ab}(v) = \begin{cases} \lambda_{ab} & \text{if } v = a \text{ (source)}\\ -\lambda_{ab} & \text{if } v = b \text{ (sink)}\\ 0 & \text{otherwise,} \end{cases} \qquad (4)$$

$\mathcal{U}(v) = \{u \mid v \in \mathcal{V}(u)\}$, and $\overline{\mathcal{D}}$ is the time average of the set sequence $\mathcal{D}(k) = \mathcal{D}(\mathbf{\Pi}_1^{(k)}, \ldots, \mathbf{\Pi}_N^{(k)})$.

A. Dual problem

Applying the time-sharing argument, one can prove that the constraint set $\overline{\mathcal{D}}$ is convex. Thus, the problem (**P**) is a convex optimization problem. The Lagrangian of the primal problem (**P**) is given below:

$$\begin{aligned} & L(\overline{\mathbf{f}}, \overline{\mathbf{\Phi}}, \vec{\beta}) = \qquad (5)\\ & \sum_v \mathrm{Tr}(\overline{\mathbf{\Phi}}_v) + \sum_v \sum_{ab} \beta_{v,ab} \Bigg[\sum_{u\in\mathcal{U}(v)} \overline{f_{ab}^{uv}} \\ & \qquad - \sum_{w\in\mathcal{V}(v)} \overline{f_{ab}^{vw}} + \Delta_{ab}(v) \Bigg], \end{aligned}$$

where $\beta_{v,ab} \in \mathbb{R}$ is the dual variable for the corresponding equality linear constraint. The dual function is defined as

$$q(\vec{\beta}) = \min_{(\overline{\mathbf{f}}, \overline{\mathbf{\Phi}})\in\overline{\mathcal{D}}} L(\overline{\mathbf{f}}, \overline{\mathbf{\Phi}}, \vec{\beta}). \qquad (6)$$

In optimization theory, the maximization below is called the dual problem.

Dual Problem

$$\max_{\vec{\beta}} q(\vec{\beta}). \qquad (7)$$

Since the primal problem (**P**) is convex, the strong duality theorem ([11] p.p. 504 Prop. 5.2.1) assures that the optimal values of the primal problem and the dual problem are equal. Exploiting this equivalence, we proceed to find the optimal scheduling policy from the dual problem.

We begin with an outline of the procedure. It is known that the dual function is concave ([11], p.p. 592), hence various techniques can be used to solve the maximization (7). Here, we use the common projected subgradient method ([11] p.p. 610). The projected subgradient method consists of an iterative procedure between two steps of dual variable updating and the subgradient evaluation. For clarity, we call the process of dual variable updating the *outer optimization loop*. To update dual variables, one needs to evaluate subgradients at each iteration. However, we cannot causally compute the exact subgradient since the channel realizations are not known in advance. Alternatively, we evaluate an empirical subgradient of $q(\vec{\beta})$ at each iteration, which requires to solve a subsidiary optimization (**P**-1) to be explained later. The empirical subgradient of $q(\vec{\beta})$ is computed via a subsidiary optimization step. To distinguish from the outer optimization, we call the subsidiary optimization the *inner optimization*. It will become clear later that the inner and outer optimizations can be solved in a locally centralized manner. Furthermore, the inner optimization is set up such that at each time k, it satisfies conditions C1′.

B. Inner Optimization Problem

To explain the algorithm in detail, we start with the inner optimization problem assuming the knowledge of dual variable $\vec{\beta}$. Under the linearity of the summation and the separable structure ([11], p.p. 494) of the problem in time, we can rearrange the terms in the summation in (5) and (6), and rewrite the dual function $q(\cdot)$ as:

$$\begin{aligned} q(\vec{\beta}) &= \lim_{T\to\infty}\frac{1}{T}\sum_{k=0}^{T-1}\sum_{u}\Bigg\{\min_{(\mathbf{f}^{(k)},\mathbf{\Phi}^{(k)})\in\mathcal{D}(k)}\mathrm{Tr}(\mathbf{P}_u^{(k)}) \\ &\quad+\sum_{v\in\mathcal{V}(u)}\sum_{ab}(\beta_{v,ab}-\beta_{u,ab})f_{ab}^{uv}(k)\Bigg\} \\ &\quad+\sum_{v}\sum_{ab}\beta_{v,ab}\Delta_{ab}(v) \end{aligned} \tag{8}$$

The minimization in the braces of (8) can be obtained by solving the N optimization subproblems below at each subsystem.
(**P**-1)

$$\begin{aligned} \text{minimize}\quad & \mathrm{Tr}(\mathbf{P}_u^{(k)})+\sum_{v\in\mathcal{V}(u)}\sum_{(a,b)\in\mathcal{F}}(\beta_{v,ab}-\beta_{u,ab})f_{ab}^{uv}(k) \\ \text{subject to}\quad & \sum_{(a,b)\in\mathcal{F}}f_{ab}^{uv}(k)\le r_{uv}(k),\ 0\le f_{ab}^{uv}(k) \\ & \mathrm{Tr}(\mathbf{P}_u^{(k)})\le P_{\max},\ \mathbf{P}_u^{(k)}\succeq 0 \\ & \mathbf{r}_u^{(k)}\in\mathcal{C}(\mathbf{P}_u^{(k)},\mathbf{\Pi}_u^{(k)}),\quad r_{uv}(k)\ge 0 \end{aligned}$$

This is the "inner optimization problem" we mentioned earlier. Note that (**P**-1) can be solved independently by node u if for all nodes $v\in\mathcal{V}(u)$, $\beta_{v,ab}$ is available at node u. In other words, we assume an overhead mechanism for exchanging $\beta_{v,ab}$ with node $v\in\mathcal{V}(u)$.

If we fix all the variables in (**P**-1) except $f_{ab}^{uv}(k)$, (**P**-1) can be viewed as a linear optimization for $f_{ab}^{uv}(k)$. Applying the vertex solutions ([12], p.p. 40) of the linear optimization on $f_{ab}^{uv}(k)$, the first constraint in (**P**-1) can be replaced by

$$f_{ab}^{uv}(k)=\begin{cases} r_{uv}(k) & \text{if } ab\ =\arg\min\limits_{cd}(\beta_{v,ab}-\beta_{u,ab}). \\ & \text{(if the output of argmin is not} \\ & \text{unique, pick one randomly)} \\ 0 & \text{otherwise.}\end{cases}$$

If $(\beta_{v,ab}-\beta_{u,ab})\ge 0$, the trivial solution of $f_{ab}^{uv}(k)$ is $f_{ab}^{uv}(k)=0$. Therefore, we define

$$\gamma_{uv}=\min\{\min_{(a,b)\in\mathcal{F}}\{\beta_{v,ab}-\beta_{u,ab}\},0\}, \tag{9}$$

and solve the following equivalent problem:
(**P**-2)

$$\begin{aligned} \text{minimize}\quad & \mathrm{Tr}(\mathbf{P}_u^{(k)})+\sum_{v\in\mathcal{V}(u)}\gamma_{uv}r_{uv}(k) \qquad (10) \\ \text{subject to}\quad & \mathrm{Tr}(\mathbf{P}_u^{(k)})\le P_{\max},\ \mathbf{P}_u^{(k)}\succeq 0 \\ & \mathbf{r}_u^{(k)}\in\mathcal{C}(\mathbf{P}_u^{(k)},\mathbf{\Pi}_u^{(k)}). \end{aligned}$$

This is a weighted sum rate and transmit power minimization problem of a MIMO broadcast system. One common method to solve this problem is to use the duality of [13].

C. Outer Optimization Loop

Now we discuss the outer optimization loop in maximizing the dual function. The outer optimization loop update the dual variables $\vec{\beta}$ as follows:

$$\begin{aligned} \beta_{u,ab}^{(k+1)}=\beta_{u,ab}^{(k)}\ +\ \epsilon\Bigg(&\sum_{w\in\mathcal{U}(u)}f_{ab}^{wu\#}(k)- \\ &\sum_{v\in\mathcal{V}(u)}f_{ab}^{uv\#}(k)+\Delta_{ab}(v)\Bigg), \end{aligned} \tag{11}$$

where the superscript '#' denotes the optimal solution obtained from the inner optimization, and $\epsilon>0$ denotes the step size. The terms in the parentheses of (11) is the empirical subgradient of $q(\cdot)$ at $\vec{\beta}^{(k)}$. Note that the updates can be accomplished locally at each node u by exchanging the values of $f_{ab}^{wu\#}(k)$ and $f_{ab}^{wu\#}(k)$ with its predecessor and successor nodes in the directed graph describing the system topology. For completeness, we summarize the scheduling algorithm as follows:

Algorithm *1:* At the beginning of the time slot k, each node exchanges the values of its dual variables $\beta_{u,ab}^{(k)}\ \forall(a,b)\in\mathcal{F}$ with the nodes in the set $\mathcal{V}(u)$. Based on this information, each node, u, solves the inner optimization problem (**P**-1) through the equivalent problem (**P**-2) independently. The scheduler then takes the solution of (**P**-1) as its decision of the resource allocation. At the end of the time slot k, node u exchanges the solution of (**P**-1) with the nodes $\mathcal{V}(u)$, then updates the dual variables according to (11).

The following theorem states the main result of this work:

Theorem *1:* If each channel in the system forms an stationary and ergodic process which is mixing ([14] p.p. 415), then with probability one, the long-term averages of the scheduled flow rates in Algorithm 1 are feasible, and the long-term average of the power consumption of the system converges to the optimal solution of problem (**P**) under Assumption 1-3 as the step size $\epsilon\to 0$.

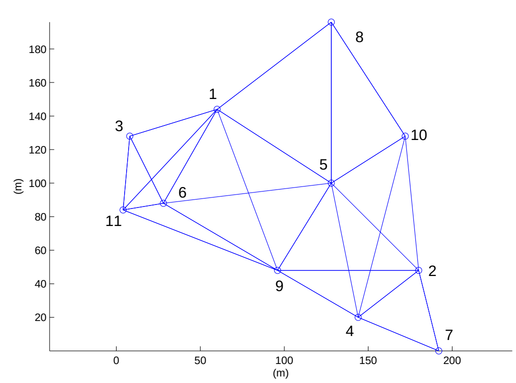

Fig. 1. System Topology

IV. Numerical Example

We consider a MIMO ad-hoc network with 11 nodes, and the network topology is depicted in Fig-1. In all of our simulation settings, each node is equipped with 8 transmit antennas and 8 receive antennas. The antennas are aligned linearly and separated at half carrier wavelength. We have two flows in the system. Flow A transfers information bits from node 11 to node 10, and flow B transfers information bits from node 2 to node 7. Each node is subjected to the peak transmit power of 1Watt. The pathloss exponent of the channel gain is 4, the available bandwidth is 1MHz, and the carrier frequency is 5GHz. In our simulation, we let each node moves locally. This causes variation of the channel, but doesn't alter the system topology. In our example, each link is subjected to three multipaths.

Recall that our framework is valid if Assumption 1-3 are satisfied. The fulfillments of Assumption 1 and Assumption 3 can be rationalized as follows.

First, we group each node u with its neighbors $\mathcal{V}(u)$ in Fig-1 to form a MIMO broadcast subsystem. For example, node 1 along with nodes 3, 5, 6, 8, 9 and 11 form a MIMO broadcast subsystem where node 1 is the transmitter, and node 2 along with node 4, 5, 7, 9 and 10 form another MIMO broadcast subsystem where node 2 is the transmitter, and so on. This provides a decomposition satisfying Assumption 1.

Second, we separate signals from different subsystems at their common receiver using the multiple antennas and interference avoidance algorithm. Note that the antenna arrays provide multiple resolvable antenna beams at the transmitters and receivers. To satisfy Assumption 3. We use the directionality of the antenna array to resolve the inter-subsystem interference to the granularity of the antenna beamwidth. The remaining conflicts within the antenna beams are left to the interference avoidance mechanism. The interference avoidance mechanism will prevent any possible conflict within a receive antenna beam by allowing only one transmitter to send signal in the direction which incurs the conflict. Through this process, the orthogonality requirements in Assumption 3 can be satisfied.

We outline the interference avoidance mechanism applied in the simulation as follows. We assume that each node sends pilot signals from each of its transmit antenna beams. The pilot signals are assumed to be separable at every receive antenna beam. The transmit antenna beam whose pilot signal is involved in a conflict generates a random number. The conflicted receive antenna beam grants the access right to the transmit antenna beam corresponding to the largest random number in this conflict. Though the pilot signal from a transmit antenna beam might be involved in more than one conflict, only if the transmit antenna beam gets the access rights from all the conflicts it involved, it is blocked. The non-blocked transmit antenna beam causes the drop of other competing transmit antenna beams. If a transmit antenna beam which got the access right of a receiver antenna beam is dropped, the receive antenna beam will transfer the access right to the one with the next largest number in the same conflict. This process can be implemented in the distributed way.

The performance of total power consumption versus the requested throughput is plotted in Fig-2.

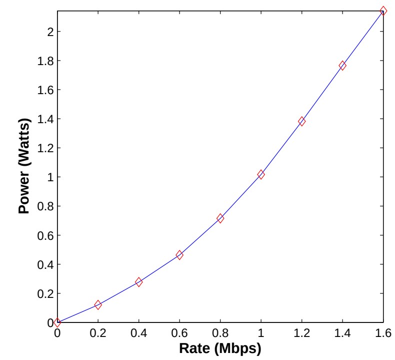

Fig. 2. Power Consumption

V. Discussion

In summary, we have developed a locally centralized algorithm which minimizes the average power consumption of the system, while maintaining the end-to-end throughput, if feasible. Using the same methodology, one could replace the MIMO broadcast subsystem by some other multi-user subsystem structure, such as a MIMO multi-access network. In our setting, the information flows are passed over links in a store-and-forward fashion. One could also try to incorporate network coding and cooperative relays into problem formulation.

References

[1] C. S. Bambos, N.D. and G. Pottie, "Radio link admission algorithms for wireless networks with powercontrol and active link quality protection." *IEEE Proceedings of INFOCOM 1995*.

[2] S. Toumpis and A. Goldsmith, "Capacity regions for wireless ad hoc networks," *IEEE Trans. Wireless Commun.*, vol. 2, no. 4, pp. 736–748, JULY 2003.

[3] Y.-H. Lin and R. Cruz, "Power control and scheduling for interfering links." *IEEE Information Theory Workshop 2004*.

[4] L. Ford and D. Fulkerson, *Flows in Networks*. Princeton University Press, 1962.

[5] A. Cruz, R.L Santhanam, "Optimal routing, link scheduling and power control in multihop wireless networks." *IEEE Proceedings of INFO-COM 2003*.

[6] Y.-H. Lin and R. Cruz, "Opportunistic link scheduling, power control, and routing for multi-hop wireless networks over time varying channels." *Prodeedings of Annual Allerton Conference on Communication, Control, and Computing*, 2005.

[7] D. Tse and P. Viswanath, *Fundamentals of Wireless Communication*. Cambridge University Press, 2005.

[8] N. B. Salem and J. P. Hubaux, "A fair scheduling for wireless mesh networks." *Proceedings of IEEE WiMesh 2005*.

[9] S. B. Gambiroza, V. and E. Knightly, "End-to-end performance and fairness in multihop wireless backhaul networks." *Proceedings of the international conference on Mobile computing and networking* , 2004.

[10] P. Kumar and P. Varaiya, *Stochastic Systems: Identification, Estimation and Adaptive Control*. Prentice Hall, June 1986.

[11] D. Bertsekas, *Nonlinear Programming*. Athena Scientific, 1999.

[12] R. Vanderbei, *Linear Programming-Foundations and Extensions*. Springer, May 2001.

[13] J. N. Vishwanath, S. and A. Goldsmith, "Duality, achievble rates, and sum-rate capacity of gaussian mimo broadcast channels," *IEEE Trans. Inform. Theory*, vol. 49, no. 10, pp. 2658–2668, OCTOBER 2003.

[14] S. Resnick, *A Probability Path*. BIRKHAUSER, 2001.