Cooperative Power Scheduling for Wireless MIMO Networks

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***Abstract*—We examine signaling strategies for wireless MIMO networks with interference. Previous approaches have focused on maximizing either individual or total throughput, resulting in an inefficient or potentially unfair allocation of resources. We propose two methods motivated by game-theoretic results. First, we extend the non-cooperative Nash equilibrium proposed in previous literature. Second, we present a cooperative method based on the Nash bargaining solution which provides an axiomatic arbitration scheme. Simulation results show that the Nash bargaining solution provides a fair allocation of resources without significantly sacrificing total throughput.**

I. Introduction

Managing the mutual interference between multiple-input multiple-output (MIMO) nodes in a wireless network is key to realizing their inherent throughput advantages. Information-theoretic approaches to this problem focus on controlling the mutual information across links by appropriately choosing source covariance matrices. For example, [1] proposes an iterative water-filling algorithm to find a power allocation that is individually optimal for each source node. As noted in [2], this algorithm results in a Nash equilibrium [3], a signaling strategy where no single source node can improve the mutual information across its link by choosing a different covariance matrix. This algorithm is therefore optimal from an individual standpoint.

An alternative algorithm is proposed in [2] that is optimal from the perspective of the entire network. Using a gradient search, the algorithm finds the source covariances that maximize the sum mutual information across all links. In [4], it is pointed out that when interference is high, the optimal source covariances found in [2] perform worse than a simple TDMA schedule. Motivated by this result, [4] presents a framework in which the source covariances can vary in time. This generalized model allows for the simultaneous optimization of both the link schedule and power control. By exploiting this additional degree of freedom, significantly improved network throughput is achieved, and the TDMA solution is obtained as a special case.

The methods described above are primarily concerned with optimizing throughput, and can result in solutions where weaker links are never scheduled. In this paper, we introduce two signaling strategies that incorporate fairness into the time-varying schedule of [4]. First, we develop a time-varying extension of the Nash equilibrium presented in [1]. Second, we propose the application of the Nash bargaining solution [5] to the problem. Our simulation results suggest that the Nash bargaining approach provides an efficient trade-off between overall throughput and individual link performance. When mutual interference is high, the TDMA schedule results from both the Nash bargaining solution and the time-varying Nash equilibrium.

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II. System Model

Consider a wireless network which consists of L point-to-point links; that is, there are L unique source nodes and L unique destination nodes. For simplicity, we will assume that each node has N antennas, although our results are not dependent on this assumption. The source node on the ith link transmits a complex baseband vector $\mathbf{x}_i$. The signal received by the destination node can be written as

$$\mathbf{y}_i = \mathbf{H}_{i,i}\mathbf{x}_i + \sum_{\substack{j=1 \\ j\neq i}}^{L} \mathbf{H}_{i,j}\mathbf{x}_j + \mathbf{n}_i \ , \tag{1}$$

where $\mathbf{H}_{i,j}$ refers to the $N \times N$ channel matrix, which gives the complex gain between the antennas of jth source node and the ith destination node. The $N \times 1$ vector $\mathbf{n}_i$ represents additive complex Gaussian noise normalized to have unit covariance $\mathbf{C}_{\mathbf{n}_i} = \mathbf{I}$.

To discuss the information-theoretic properties of the network, we view each $\mathbf{x}_i$ as a zero-mean complex Gaussian random vector with $E\{\mathbf{x}_i\mathbf{x}_i^H\} = \mathbf{P}_i$, where $(\cdot)^H$ denotes the Hermitian transpose. Each node is power-constrained:

$$\mathrm{tr}\{\mathbf{P}_i\} \leq P_{max,i} \ . \tag{2}$$

As in [4], we define L time slots and allow the source covariances to vary in time, assuming that the channel matrices are static over the time slots. In [4], Rong and Hua constrain the average power, requiring that

$$\frac{1}{L}\sum_{t=1}^{L} \mathrm{tr}\{\mathbf{P}_i(t)\} \leq P_{max,i}. \tag{3}$$

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For each time slot, the interference covariance at the ith receiver is given by

$$\mathbf{R}_i(t) = \sum_{\substack{j=1 \\ j \neq i}}^{L} \mathbf{H}_{i,j}\mathbf{P}_j(t)\mathbf{H}_{i,j}^H. \quad (4)$$

The average mutual information across link i can now be expressed as

$$I_i = \frac{1}{L}\sum_{t=1}^{L} \log_2 \frac{\left|\mathbf{H}_{i,i}\mathbf{P}_i(t)\mathbf{H}_{i,i}^H + \mathbf{I} + \mathbf{R}_i(t)\right|}{|\mathbf{I} + \mathbf{R}_i(t)|}, \quad (5)$$

where $|\cdot|$ represents the matrix determinant.

In both [2] and [4], the projected gradient method is used to find an optimal set of covariance matrices to maximize the sum (or average) mutual information across the links. Although we do not explicitly seek to maximize the sum mutual information, we state several of their matrix gradient results which will be useful in later sections. For $z = x + jy$, we define $\nabla_z f(z) = \partial f(z)/\partial x + j\partial f(z)/\partial y$. Using this definition, it is shown in [2] that the gradient of a link's mutual information with respect to the source node's covariance at a particular time step is

$$\nabla_{\mathbf{P}_i(t)} I_i = \frac{2}{\ln 2}\mathbf{H}_{i,i}^H\big(\mathbf{H}_{i,i}\mathbf{P}_i(t)\mathbf{H}_{i,i}^H + \mathbf{I} + \mathbf{R}_i(t)\big)^{-1}\mathbf{H}_{i,i}. \quad (6)$$

It is also shown that the gradient with respect to a different source node's covariance is

$$\nabla_{\mathbf{P}_j(t)} I_i = \frac{2}{\ln 2}\mathbf{H}_{i,j}^H\big((\mathbf{H}_{i,i}\mathbf{P}_i(t)\mathbf{H}_{i,i}^H + \mathbf{I} + \mathbf{R}_i(t))^{-1} - (\mathbf{I} + \mathbf{R}_i(t))^{-1}\big)\mathbf{H}_{i,j}, \forall j \neq i. \quad (7)$$

III. Time-Varying Nash Equilibrium

In this section, we extend the algorithm of [1] to the time-varying model described in [4]. Since [1] employs an iterative water-filling scheme, we briefly review the water-filling concept for a single point-to-point link. Let $\mathbf{H}$ be the channel matrix for the link, which is known to both the transmitter and receiver. Let $\mathbf{U\Sigma V}^H = \mathbf{H}$ be the singular value decomposition of the channel matrix and $\mathbf{XDX}^H = \mathbf{P}$ be the eigen-decomposition of the source covariance. Further, let σ_k and d_k denote the N singular values of $\mathbf{H}$ and the N eigenvalues of $\mathbf{P}$, respectively. The column vectors of $\mathbf{V}$ characterize the spatially orthogonal transmit modes of the channel described by $\mathbf{H}$. If the source chooses $\mathbf{X} = \mathbf{V}$, it can distribute its power across the channel modes by selecting the eigenvalues d_k. It is shown in [6] that the optimal choice of eigenvalues is given by

$$d_k = \left[\mu - \frac{1}{\sigma_k^2}\right]^+, \quad (8)$$

where $[\cdot]^+ = \max(\cdot, 0)$, and μ is chosen to satisfy the power constraint in (2):

$$\sum_{k=1}^{N} d_k = P_{max,i}. \quad (9)$$

If, in addition to white noise, there is fixed non-white interference described by the covariance $\mathbf{R}$, we can apply a spatial whitening transform

$$\tilde{\mathbf{H}} = (\mathbf{I} + \mathbf{R})^{-\frac{1}{2}}\mathbf{H}, \quad (10)$$

and use the water-filling algorithm as usual by substituting $\tilde{\mathbf{H}}$ for $\mathbf{H}$.

In [1], each source node iteratively updates its covariance by water-filling across the whitened channel modes. However, in altering its covariance, the source node alters the interference on the other links. The source nodes must therefore continue updating their covariance matrices until a steady-state results.

To extend this algorithm to the time-varying case, we first note that the interference matrices will in general be different at different time steps. Let $\tilde{\mathbf{H}}_{i,i}(t) = (\mathbf{I} + \mathbf{R}_i(t))^{-\frac{1}{2}}\mathbf{H}_{i,i}$ be the whitened channel matrix at time t for the ith link. Even though the channel itself is static across the L time steps, the whitened channel will be different, with different channel modes. Since these different channel modes are temporally—rather than spatially—orthogonal, we can water-fill across the NL channel modes in a similar manner.

As in [1], the nodes iteratively water-fill until a steady state is reached. Let $\mathbf{U}(t)\mathbf{\Sigma}(t)\mathbf{V}^H(t) = \tilde{\mathbf{H}}_{i,i}(t)$ denote the singular value decomposition of the whitened channel matrix with singular values $\sigma_k(t)$, and let $\mathbf{X}(t)\mathbf{D}(t)\mathbf{X}^H(t) = \mathbf{P}_i(t)$ denote the eigen-decomposition of the source covariance with eigenvalues $d_k(t)$. To water-fill across the NL modes, we set $\mathbf{X}(t) = \mathbf{V}(t)$, and choose the eigenvalues according to

$$d_k(t) = \left[\mu - \frac{1}{\sigma_k^2(t)}\right]^+, \quad (11)$$

and μ such that

$$\frac{1}{L}\sum_{t=1}^{L}\sum_{k=1}^{N} d_k(t) = P_{max,i}, \quad (12)$$

maximizing mutual information while ensuring that that the average power constraint (3) is satisfied. While as in [1] there is no guarantee of convergence, in practice the algorithm works well and converges to a unique point at which no source node can improve the mutual information across its link by altering its power schedule described by the covariance matrices $\mathbf{P}_i(t)$.

IV. Nash Bargaining Solution

To discuss the Nash bargaining solution, we more carefully define the necessary game-theoretic concepts. Let $K = \{1, 2, \cdots, n\}$ be the set of players. Each player i has a *strategy set* S_i, which is the set of actions it may implement. A *strategy profile* $\mathbf{s}$ is an n-dimensional vector over the product strategy space $S = S_1 \times S_2 \times \cdots \times S_n$. Each player has a payoff function $\pi_i(\mathbf{s})$ which quantifies the utility derived by player i from the implementation of the strategy profile $\mathbf{s}_i$. Finally, let R be the set of feasible payoff vectors, that is $R = \{\mathbf{r} : \mathbf{r} = (\pi_1(\mathbf{s}), \pi_2(\mathbf{s}), \cdots, \pi_n(\mathbf{s}))^T, \mathbf{s} \in S\}$. We assume that R is compact, but not necessarily convex.

In a non-cooperative game, players attempt to maximize individual utility without regard for the utility of others.

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They do not communicate and cannot make agreements prior to play, resulting in the Nash equilibrium. In a cooperative game, however, players may communicate, negotiate, and make binding commitments prior to play. While it requires more infrastructure, this framework can result in more efficient strategies implemented by the players.

While there are many cooperative game-theoretic approaches we could discuss, we restrict our attention to a generalization of the n-player Nash bargaining solution [5], which axiomatically selects a set of points in R. Define the *disagreement point* $\boldsymbol{\delta} = (\delta_1, \delta_2, \cdots, \delta_n)^T$. The disagreement point is interpreted as the "status quo" before bargaining or the payoff each player is guaranteed should bargaining fail. It represents a minimum payoff that each player demands in a bargaining scenario.

Define the *negotiation set* $\mathcal{N}$ as the set of all payoff vectors $\mathbf{r}$ for which $r_i > \delta_i$ for all i. The Nash bargaining solution is the set of payoff vectors $\phi(\mathcal{N})$ (which we refer to as the *Nash bargaining set*) defined by

$$\phi(\mathcal{N}) = \left\{ \mathbf{r}^* \in \mathcal{N} : \prod_{i=1}^{n} (r_i^* - \delta_i) \geq \prod_{i=1}^{n} (r_i - \delta_i), \forall \mathbf{r} \in \mathcal{N} \right\}. \tag{13}$$

In other words, the Nash bargaining set is the set of feasible payoff vectors that maximize the product (called the *Nash product*) in (13). In [7], the Nash bargaining solution is shown to satisfy the axioms in the following paragraphs.

First, each $\mathbf{r}^* \in \phi(\mathcal{N})$ is *Pareto efficient*, which means that there is no payoff vector $\mathbf{r} \in R$ which gives *each* player higher payoff than $\mathbf{r}^*$. If there is an i for which $r_i > r_i^*$, there must be at least one j for which $r_j < r_j^*$. Pareto efficiency ensures that we do not overlook any payoff vectors for which each player is better off.

Second, the solution is independent of positive affine transformations in the players' payoff functions.

Third, symmetry among the players is maintained. Let g be a permutation of K. If $g(\mathbf{r}) = (r_{g(1)}, \ldots, r_{g(L)})^T \in \mathcal{N}$ for all $\mathbf{r} \in \mathcal{N}$, then $g(\mathbf{r}^*) \in \phi(\mathcal{N})$ for all $\mathbf{r}^* \in \phi(\mathcal{N})$.

Fourth, the solution is independent of irrelevant alternatives. Consider another set of payoffs $\mathcal{M}$ such that $\mathcal{M} \subset \mathcal{N}$. If $\phi(\mathcal{N}) \cap \mathcal{M}$ is nonempty, then $\phi(\mathcal{M}) = \phi(\mathcal{N}) \cap \mathcal{M}$.

Finally, the solution satisfies a continuity condition which we do not detail here. For a complete explanation, see [7].

When R is convex, only the first four axioms are necessary and the solution contains a unique payoff vector. Otherwise, the five axioms define a set of payoff vectors. With the possible exception of the fourth, these axioms appear to be simple and necessary criteria for a fair arbitration scheme. The axiom of Pareto efficiency guarantees an efficient solution, while the axiom of symmetry guarantees, at least in one sense, a fair solution. We may therefore anticipate that the Nash bargaining solution will effectively trade-off between network throughput and individual links. In [8] it is noted that when $\boldsymbol{\delta} = \mathbf{0}$, the Nash bargaining solution is identical to the proportional fairness criterion proposed in [9].

A. Implementation

To apply the Nash bargaining solution to the MIMO power schedule, we define $K = \{1, 2, \cdots, L\}$, the set of source nodes for each link. We denote player i's strategy set as $\mathcal{P}_i$, the set of feasible collections of matrices that the ith source node can implement. Each element $\mathbf{p}_i \in \mathcal{P}_i$ contains L matrices—one for each time step. The product strategy space is $\mathcal{P} = \mathcal{P}_1 \times \cdots \times \mathcal{P}_L$, where each element $\mathbf{p}$ contains L^2 matrices. The payoff function $\pi_i(\mathbf{p})$ for player i is simply the average mutual information across the ith link given in (5).

Finally, we must define the disagreement point $\boldsymbol{\delta}$ for the MIMO network, which represents the status quo prior to bargaining. A common choice for the status quo is the maximin payoff to each player. The maximin payoff is a worst-case scenario: if all other players agree to devote their efforts to reducing player i's payoff, how much payoff can player i guarantee for itself? For our problem, the maximin payoff can be expressed as

$$\delta_i = \max_{\mathbf{p}_i \in \mathcal{P}_i} \min_{\mathbf{p}_j \in \mathcal{P}_j, j \neq i} I_i(\mathbf{p}). \tag{14}$$

The Nash product, which is denoted by $\Psi(\mathbf{p})$, is now

$$\Psi(\mathbf{p}) = \prod_{i=1}^{L} (I_i(\mathbf{p}) - \delta_i). \tag{15}$$

Unfortunately, we cannot solve in closed-form for the covariance matrices that maximize $\Psi(\mathbf{p})$. Therefore, as in [2] and [4] we will use the gradient projection method to optimize $\Psi(\mathbf{p})$. Although we maximize a different objective function, whose maximum has different theoretical properties, our brief development will largely parallel the discussion in [2]. Gradient projection is used to optimize a scalar function $f(\mathbf{x})$, where $\mathbf{x}$ is constrained to be an element of some convex set. Since the matrices that form the elements of $\mathcal{P}$ are positive semi-definite and subject to a trace constraint, the convexity of $\mathcal{P}$ is easily established. Properly implemented, the procedure is guaranteed to converge to a local optimum.

To simplify our algorithm, we find the covariances that maximize $\ln(\Psi(\mathbf{p}))$, which is given by

$$\Psi'(\mathbf{p}) = \ln(\Psi(\mathbf{p})) = \sum_{i=1}^{L} \ln(I_i(\mathbf{p}) - \delta_i). \tag{16}$$

First, we must compute the gradient of Ψ' with respect to each covariance matrix in $\mathbf{p}$. Applying the chain rule to the logarithm, we get

$$\nabla_{\mathbf{P}_i(t)} \Psi'(\mathbf{p}) = \sum_{j=1}^{L} \frac{1}{I_j(\mathbf{p}) - \delta_j} \nabla_{\mathbf{P}_i(t)} I_j(\mathbf{p}). \tag{17}$$

This equation exposes an important feature of the Nash bargaining solution. Finding the Nash bargaining solution is similar to finding the global optimum from [4], except that each term in the gradient is scaled by a variable weight. If a link's mutual information is comparatively close to the disagreement point, it gets a higher weight in computing the gradient.

At iteration k, we take a step in the direction of the gradient for each source node and each time block, forming a new collection of matrices $\hat{\mathbf{p}}^k$:

$$\hat{\mathbf{P}}_i^k(t) = \mathbf{P}_i^k(t) + s\nabla_{\mathbf{P}_i^k(t)}\Psi'(\mathbf{p}^k), \tag{18}$$

where s is a fixed step size. However, simply following the gradient may lead us outside our feasible region $\mathcal{P}$. We therefore project $\hat{\mathbf{p}}^k$ onto $\mathcal{P}$. Using the usual matrix inner product $\langle \mathbf{A},\ \mathbf{B}\rangle = \mathrm{tr}(\mathbf{A}^H\mathbf{B})$, the induced norm is $\|\mathbf{A}\|_F = \sqrt{\mathrm{tr}(\mathbf{A}^H\mathbf{A})}$, the Frobenius norm. Therefore, we project onto $\mathcal{P}$ by choosing the element $\tilde{\mathbf{p}}^k \in \mathcal{P}$ that minimizes the sum of the squared Frobenius norm of the matrices in $\tilde{\mathbf{p}}^k - \hat{\mathbf{p}}^k$:

$$\tilde{\mathbf{p}}^k = \arg\min_{\mathbf{p}\in\mathcal{P}} \sum_{i=1}^{L}\sum_{t=1}^{L} \left\|\mathbf{P}_i(t) - \hat{\mathbf{P}}_i^k(t)\right\|_F^2. \tag{19}$$

Since the source nodes' constraints are independent of each other, the constrained optimization can be decoupled into L independent problems. We omit the details here, but it is straightforward to show that the projected matrices are given by

$$\tilde{\mathbf{P}}_i^k(t) = \mathbf{X}_i^k(t)[\mathbf{D}_i^k(t) - \nu_i^k\mathbf{I}]^+(\mathbf{X}_i^k(t))^H, \tag{20}$$

where $\mathbf{X}_i^k(t)\mathbf{D}_i^k(t)(\mathbf{X}_i^k(t))^H = \hat{\mathbf{P}}_i^k(t)$ is the eigen-decomposition of $\hat{\mathbf{P}}_i^k(t)$, $[\mathbf{A}]^+$ zeros out any negative entries in the matrix $\mathbf{A}$, and ν_i^k is chosen to satisfy the constraints in (3). For each source node, the projection operator equally scales down the eigenvalues of the L matrices until the average trace constraint is satisfied.

We complete the iteration by stepping in the feasible direction defined by $\tilde{\mathbf{p}}^k$:

$$\mathbf{p}^{k+1} = \mathbf{p}^k + a_k(\tilde{\mathbf{p}}^k - \mathbf{p}^k), \tag{21}$$

where $a_k \in [0, 1]$ is a variable step size. Since (21) defines a convex combination of two elements of the convex set $\mathcal{P}$, $\mathbf{p}^{k+1} \in \mathcal{P}$. As in [2] and [4], we choose a_k using Armijo's rule along the feasible direction $\tilde{\mathbf{p}}^k - \mathbf{p}^k$. This rule requires that $a_k = \gamma^{m_k}$, where $\gamma \in [0, 1]$ and m_k is the smallest nonnegative integer such that

$$\Psi'(\mathbf{p}^{k+1}) - \Psi'(\mathbf{p}^k) \geq \sigma\gamma^{m_k}\left\langle \nabla\Psi'(\mathbf{p}^k),\ \tilde{\mathbf{p}}^k - \mathbf{p}^k\right\rangle \tag{22}$$

$$= \sigma\gamma^{m_k}\sum_{i=1}^{L}\sum_{t=1}^{L}\mathrm{tr}\big((\nabla_{\mathbf{P}_i(t)}\Psi'(\mathbf{p}^k))^H(\tilde{\mathbf{P}}_i(t) - \mathbf{P}_i(t))\big) \tag{23}$$

for a small constant σ. After each iteration, we check to see whether or not the convergence criterion is met, which is

$$\max\left|\mathbf{p}^{k+1} - \mathbf{p}^k\right| < \epsilon \tag{24}$$

for a small constant ϵ. If (24) is met, iterations stop and $\mathbf{p}^{k+1}$ is chosen as a fair power schedule.

To compute the disagreement point $\boldsymbol{\delta}$, we modify the gradient projection method to search for the maxi-min point for each link. The ith source node steps in the direction of steepest ascent, while the other nodes step in the direction of steepest descent. When the algorithm converges, the ith source cannot improve the mutual information across its link, and the other sources cannot further damage it. The algorithm is repeated for each of the L links.

V. Results

To evaluate the performance of the Nash bargaining solution, we simulate using MIMO channels with independent Rayleigh fading and variable signal- and interference-to-noise ratios (SNR and INR). We set $P_{max,i} = N, \forall i$ and choose

$$\mathbf{H}_{i,i} = \sqrt{\frac{\rho_i}{N}}\bar{\mathbf{H}}_{i,i}, \mathbf{H}_{i,j} = \sqrt{\frac{\beta_{i,j}}{N}}\bar{\mathbf{H}}_{i,j}, \tag{25}$$

where the entries of $\bar{\mathbf{H}}_{i,i}$ and $\bar{\mathbf{H}}_{i,j}$ are independent complex Gaussian distributed with zero mean and unit variance. The parameter ρ_i is the expected received signal-to-noise ratio (SNR) across the ith channel when the ith source transmits at full power, and $\beta_{i,j}$ is the expected received interference-to-noise ratio (INR) between the jth transmitter and the ith receiver when the ith source transmits at full power.

We show two measures of system performance: average mutual information per link and minimum mutual information per link. The average mutual information per link quantifies the effectiveness of the algorithm in terms of total throughput, while the minimum mutual information quantifies the "fairness" of the solution. For our simulations, we let the number of links be $L = 6$ and the number of antennas be $N = 2$. In the gradient projection algorithm, we set $s = 1$, $\gamma = 0.5$, $\sigma = 10^{-3}$, and $\epsilon = 10^{-3}$.

First, we examine system performance as we vary INR. In this simulation, each link has an SNR of 20dB and the INR is the same among all links. While this scenario is somewhat artificial, it allows us to easily examine how each algorithm handles increased interference. In Figure 1, we show the average mutual information per link as a function of INR. For comparison, we show results for the Nash bargaining solution (NBS) alongside those for the time-varying Nash equilibrium, the optimal power schedule (OPS) of [4], the Nash equilibrium of [1], and a TDMA power schedule. Each data point represents the average of 100 independent simulations.

Since the SNR and INR are the same for all of the links, the Nash bargaining solution and the global OPS are similar. This intuitively pleasing result stems from the fact that, when players' feasible utilities are symmetric, the Nash bargaining solution equally allocates utility. The instances where the NBS yields a higher throughput than the OPS are a likely an artifact of the local, rather than global, optimality of the gradient projection approach. We also note that the time-varying and standard Nash equilibrium solutions perform almost identically unless the INR is high, in which case the time-varying approach converges to the TDMA schedule.

Next, we examine performance when the links have significantly different quality. We set the INR at 10dB for all links, and we let the SNR (in dB) be a Gaussian random variable with a mean of 20dB and a variable standard deviation. In Figures 2 and 3 we show the average and minimum mutual information per link, respectively, as a function of the standard

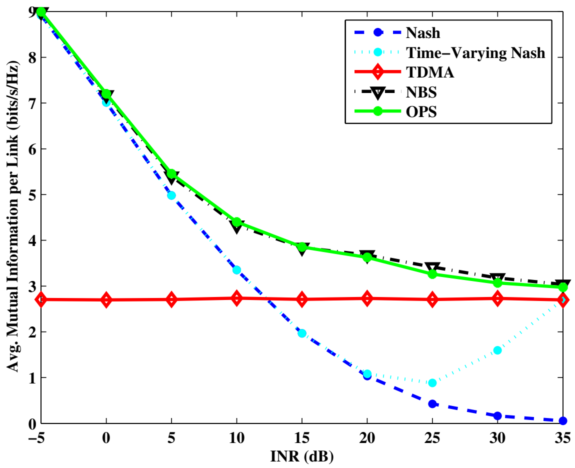

Fig. 1. Average mutual information per link versus INR.

deviation of the SNR. When the standard deviation on the

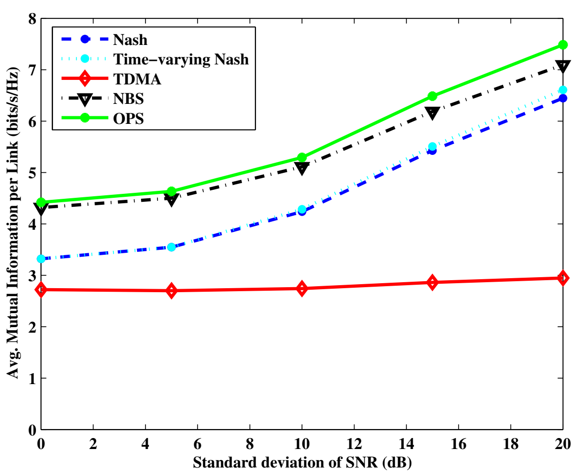

Fig. 2. Average mutual information per link versus SNR standard deviation.

SNR is zero, the links have roughly the same quality and the NBS and OPS solutions are similar. As we increase the SNR standard deviation, however, some links are significantly better than others. Naturally, the OPS approach exploits this asymmetry best in terms of total throughput. The NBS performs just slightly worse, followed by the Nash equilibrium solutions and finally TDMA. The NBS approach, however, enjoys a significantly improved worst-case performance than OPS and the Nash equilibrium solutions and is no worse than TDMA for large link variance. These results support the use of the Nash bargaining approach to provide a useful trade-off between total network throughput and individual link performance.

VI. Conclusion

In this paper we have proposed a MIMO network power scheduling strategy based on the Nash bargaining solution

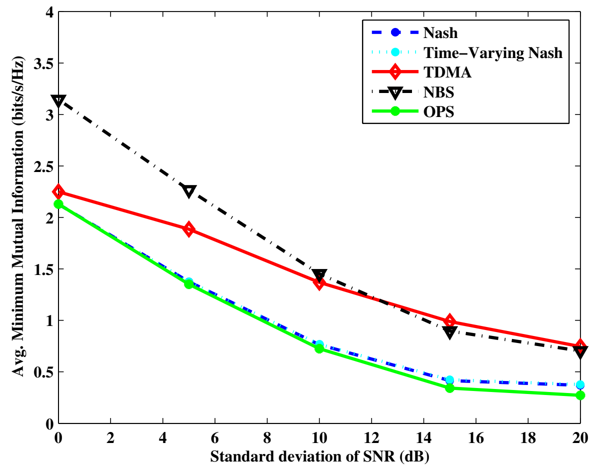

Fig. 3. Minimum mutual information per link versus SNR standard deviation.

from cooperative game theory. Our experimental results indicate that this approach provides a useful trade-off between total network throughput and individual link quality.

There remain several important issues that bear further investigation. First, as in [4], the power constraint limits the time-averaged rather than instantaneous transmitted power. Under this model, source nodes may transmit, for short durations, at higher power than is possible under the models used in [1] and [2]. The impact of per-time-slot and even per-antenna power constraints are an important practical issue that should be addressed.

Also, since the gradient projection method outlined in Section IV-A only guarantees a stationary point, the algorithm does not necessarily result a member of the Nash bargaining set. Fortunately, however, our empirical results are encouraging, suggesting that even in non-ideal situations the spirit of the Nash bargaining approach works well.

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