Optimal Power Schedule for Distributed MIMO Links

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***Abstract*—We present an optimal power scheduling scheme to maximize the throughput of a set of distributed multiple-input multiple-output (MIMO) wireless links. This scheme exploits both spatial and temporal freedoms of the source covariance matrices of all MIMO links. In particular, the source covariance matrix of each MIMO link is allowed to vary within a block of time (and/or frequency) slots. This scheme, also referred to as space-time power scheduling, optimizes an integration of link scheduling and power control for MIMO links. The computational problem involved in this scheme is non-convex. However, a gradient-projection algorithm developed for this scheme consistently yields a higher capacity than all other existing schemes.**

***Index Terms*—Network of MIMO links, medium access control, space-time power scheduling.**

I. Introduction

A MULTIPLE-INPUT multiple-output (MIMO) wireless link is now well known to provide a much higher capacity than a single-input single-output (SISO) wireless link in an environment with rich electromagnetic scattering. Many coding and modulation techniques for point-to-point MIMO links have been developed in the past decade. These advances have now motivated a strong research interest in networking issues of MIMO links. Some efforts for improving the network-wise throughput of multiple MIMO links have been attempted in [1]-[8].

In [1] and [2], iterative beamforming algorithms were proposed to maximize the output signal-to-interference-and-noise ratio (SINR) at all receivers, or minimize the mean-square error (MSE) of the signal waveform estimation. However, for both algorithms, each MIMO link is limited to use only one data stream. These approaches are strongly suboptimal as they do not fully exploit the spatial freedom provided by the multiple antennas at each link. In [3] and [4], the authors investigated the impact of mutual interferences on the network capacity of multiple MIMO links under a scheme where the source covariance matrices of MIMO links are independent of time. In [5], the source covariance matrix of each link is selfishly "optimized". The non-cooperative nature of this scheme leads to a suboptimal solution known as Nash equilibrium [6], [9]. In [7], the source covariance matrices are jointly searched using the projected gradient ascent of the sum capacity of all MIMO links, which yields a much better solution than Nash equilibrium. In [8], the asymptotic capacity of a large wireless networks of MIMO links is investigated.

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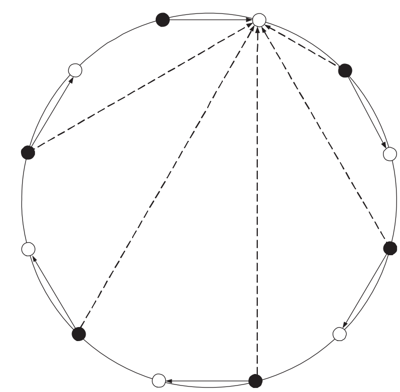

Fig. 1. An example of wireless network. Solid circles are source nodes; Hollow circles are destination nodes. Solid lines are signal streams; Dashed lines are interference streams.

All of the previously developed schemes are space-only schemes where the temporal freedom of source covariance matrices is ignored. In this paper, we propose a space-time power scheduling scheme where the source covariance matrices of MIMO links are allowed to be functions of time and/or frequency. For convenience, we will only refer to "time" although "frequency" (such as in OFDM systems) can obviously play the same role. This new scheme will also be called optimal power schedule (OPS). The utilization of both temporal and spatial freedom makes it possible to achieve a higher averaged capacity of a network of MIMO links. The computational problem involved in the OPS scheme is non-convex, which we solve by following a gradient projection (GP) technique [10]. With the GP algorithm, the OPS scheme consistently yields a higher capacity than all existing schemes in the literature.

The rest of this paper is organized as follows. In the next section, a model of distributed MIMO links is introduced. The proposed OPS scheme and the GP algorithm are developed in Section III. In Section IV, we show some numerical examples. The conclusions are drawn in Section V.

II. Network Model

We consider a network of L (desired) links sharing a common time/frequency band. An example of such a network is shown in Fig. 1. Each link consists of a source node (SN) and a destination node (DN). Each node has N antennas. The vector of the received signal $\mathbf{y}_i$ at the ith DN and time t can be written as

$$\mathbf{y}_i(t) = \sqrt{\frac{\rho_i}{N}}\mathbf{H}_{i,i}\mathbf{x}_i(t) + \sum_{j=1,j\neq i}^{L}\sqrt{\frac{\beta_{i,j}}{N}}\mathbf{H}_{i,j}\mathbf{x}_j(t) + \mathbf{n}_i(t) \quad (1)$$

where $\mathbf{H}_{i,j}, i,j = 1,\cdots,L$ is the $N \times N$ channel matrix between the jth SN and the ith DN, ρ_i denotes the signal-to-noise ratio (SNR) of the ith link, $\beta_{i,j}$ $(j \neq i)$ is the nominal interference-to-noise ratio (INR) of the jth SN to the ith DN, $\mathbf{x}_i(t)$ denotes the $N \times 1$ vector of the normalized transmitted signal from the ith SN, and $\mathbf{n}_i(t)$ is the $N \times 1$ vector of the i.i.d. (independent and identically distributed) additive white Gaussian noise (AWGN) with zero mean and unit covariance matrix $\mathbf{C}_{\mathbf{n}_i} = \mathbf{I}_N$. Here $\mathbf{I}_N$ denotes an $N \times N$ identity matrix. The first term in (1) is the signal of interest at the ith DN, while the second term is the sum of interfering signals from all other $L-1$ SNs. We assume that all the normalized transmitted signals are Gaussian distributed with zero mean vector and covariance matrix $\mathbf{P}_i(t) \triangleq \mathrm{E}\left\{\mathbf{x}_i(t)\mathbf{x}_i^H(t)\right\}$, where $\mathrm{E}\{\cdot\}$ is statistical expectation, and $(\cdot)^H$ the Hermitian transpose. Furthermore, $\frac{1}{T}\sum_{t=1}^{T}\mathrm{tr}\{\mathbf{P}_i(t)\} = N$, where $\mathrm{tr}\{\cdot\}$ is the trace of a matrix.

Each $\beta_{i,j}$ measures a nominal INR, which is independent of $\mathbf{P}_i(t)$ but depends on distances between links and the average transmission power of each link. Even with nonzero $\beta_{i,j}$, there may exist $\mathbf{P}_i(t)$ such that the actual INR is zero or equivalently all the interfering signals are orthogonal to the signal of interest over the time window $t = 1, 2, ..., T$. This is possible only if $T > 1$ or $N > 1$. Such a property under $T > 1$ and $N = 1$ is inherent in the classic time division multiple access (TDMA). This property under $T = 1$ and $N > 1$ has been exploited in some of the papers reviewed earlier. But this property under $T > 1$ and $N > 1$ has not been previously utilized. Obviously, if $T = 1$ and $N = 1$, then the nominal INR is always the same as the actual INR.

In the sequel, we make use of the following assumptions. There is no coding cooperation among different SNs and DNs. The interfering signals are unknown to the DNs, and a single-user receiver is used at each DN. The signal power loss is included in SNR ρ_i, and nominal INR $\beta_{i,j}$. The ith DN knows $\mathbf{H}_{i,i}$. The entries of each $\mathbf{H}_{i,j}$ are constant over a window of T time slots and known to a scheduler. This assumption is realistic for static (such as mesh) networks. But for performance evaluation, we assume that over different windows, the entries of $\mathbf{H}_{i,j}$ are i.i.d. complex Gaussian with zero mean and unit variance. The i.i.d. condition is useful for fairness among all links over multiple windows. For static networks, the i.i.d. condition from one window to another can be induced purposely by varying the phase of each transmitting antenna randomly (provided $N > 1$). The capacity issue of distributed MIMO links without the channel knowledge at the SNs (or the scheduler) is addressed in [11].

For given $\mathbf{P}_1(t),\cdots,\mathbf{P}_L(t)$, the sum capacity of all L links at time t can be written as $I_t = \sum_{i=1}^{L}\log_2\left|\mathbf{I}_N + \frac{\rho_i}{N}\mathbf{H}_{i,i}\mathbf{P}_i(t)\mathbf{H}_{i,i}^H\mathbf{R}_i(t)^{-1}\right|$ where $|\cdot|$ denotes the determinant of a matrix, and $\mathbf{R}_i(t) = \sum_{j=1,j\neq i}^{L}\frac{\beta_{i,j}}{N}\mathbf{H}_{i,j}\mathbf{P}_j(t)\mathbf{H}_{i,j}^H + \mathbf{I}_N$.

In the scheme of [5], each link (say link i) measures $\mathbf{R}_i(t)$ based on the previous choice of $\mathbf{P}_1(t),\cdots,\mathbf{P}_L(t)$ and then maximizes the capacity of link i with respect to $\mathbf{P}_i(t)$ alone subject to $\mathrm{tr}(\mathbf{P}_i(t)) = N$. With each new choice of $\mathbf{P}_1(t),\cdots,\mathbf{P}_L(t)$, the same process repeats until convergence. Based on this algorithm, the sum capacity I_t of the network typically converges to a value much smaller than its maximum. The algorithm in [7] searches for the maximum of I_t over $\mathbf{P}_1(t),\cdots,\mathbf{P}_L(t)$ jointly using the GP algorithm, which results in much higher values of I_t.

III. Optimal Power Schedule

We now consider the network capacity averaged over the window of T time slots: $I_A = \frac{1}{T}\sum_{t=1}^{T}I_t$. We will use the following definition for a stacked matrix $\bar{\mathbf{P}}$: $\bar{\mathbf{P}} \triangleq \left[\bar{\mathbf{P}}_1^T,\cdots,\bar{\mathbf{P}}_L^T\right]^T$ with $\bar{\mathbf{P}}_i \triangleq \left[\mathbf{P}_i^T(1),\cdots,\mathbf{P}_i^T(T)\right]^T$ for $i = 1,\cdots,L$. Here $(\cdot)^T$ denotes the matrix transpose. Our new scheme is the following

$$\max_{\bar{\mathbf{P}}} \quad I_A(\bar{\mathbf{P}}) \quad (2)$$

$$\text{s.t.} \quad \frac{1}{T}\sum_{t=1}^{T}\mathrm{tr}\{\mathbf{P}_i(t)\} = N, \qquad i = 1,\cdots,L \quad (3)$$

$$\mathbf{P}_i(t) \geq 0, \qquad t = 1,\cdots,T; i = 1,\cdots,L\,. \quad (4)$$

The scheme in [7] is a special case of the OPS scheme by setting $T = 1$. In this paper, we focus on networks with a symmetric topology such as the circular network in Fig. 1. Hence, no link suffers a fairness problem under the sum capacity criterion. In a similar way as used in [7], the problem (2)-(4) can be shown to be a convex problem when nominal INR $\beta_{i,j}, i,j = 1,\cdots,L,\ j \neq i$ are all sufficiently low.

The choice of T is important. If $T = L$, the TDMA scheme where only one link is scheduled to transmit during any time slot is a feasible (but not necessarily optimal) solution to the above optimization problem. But the complexity of the optimization problem increases rapidly if both T and L increase. For large networks, it is often necessary to choose $T < L$. But for small networks, $T = L$ is recommended as long as the computations required are affordable. In Section IV, we will illustrate the performance of the OPS scheme with respect to T, which suggests that the benefit from $T > L$ is not significant if any. In the sequel, we will set $T = L$ unless mentioned otherwise.

We now develop an algorithm to find a local optimal solution to the problem (2)-(4) by following the GP technique [10]. We have the following constrained optimization problem $\max_{\mathbf{x}} f(\mathbf{x})$ subject to $\mathbf{x} \in \mathcal{X}$ where $f(\cdot)$ is a continuously differentiable scalar function, and $\mathcal{X}$ is a nonempty, closed, and convex set. The GP algorithm starts at an initial point $\mathbf{x}^{(0)}$. At the kth iteration, $\mathbf{x}^{(k)}$ is updated as $\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \delta_k\left(\tilde{\mathbf{x}}^{(k)} - \mathbf{x}^{(k)}\right)$ where $\delta_k \in (0,1]$ is a step size and $\tilde{\mathbf{x}}^{(k)} = \mathrm{proj}\left[\mathbf{x}^{(k)} + s_k\nabla f\left(\mathbf{x}^{(k)}\right)\right]$. Here, $\mathrm{proj}[\cdot]$ denotes the projection onto the feasible set $\mathcal{X}$, and s_k is a positive scalar.

Two major parts of the GP algorithm are: the computation of the gradient of the objective function, and the projection of the gradient onto a feasible set. The gradient of the objective function with respect to $\mathbf{P}_i(t)$ with $T = L$ can be shown [16] to be

$$\begin{aligned}\mathbf{G}_i(t) &= 2\left[\frac{\partial I_A(\bar{\mathbf{P}})}{\partial \mathbf{P}_i(t)}\right]^* \\ &= \frac{2}{LN\ln 2}\rho_i \mathbf{H}_{i,i}^H \mathbf{S}_i(t)^{-1}\mathbf{H}_{i,i} \\ &+ \frac{2}{LN\ln 2}\sum_{j=1,j\neq i}^{L}\beta_{j,i}\mathbf{H}_{j,i}^H\left[\mathbf{S}_j(t)^{-1}-\mathbf{R}_j^{-1}(t)\right]\mathbf{H}_{j,i}\end{aligned}$$

where $\mathbf{S}_i(t) = \mathbf{R}_i(t) + \frac{\rho_i}{N}\mathbf{H}_{i,i}\mathbf{P}_i(t)\mathbf{H}_{i,i}^H$ and $(\cdot)^*$ denotes the complex conjugate. Some formula from [12] have been used.

After the gradient is obtained, the covariance matrix $\mathbf{P}_i(t)$ is updated to $\hat{\mathbf{P}}_i(t)$ by $\hat{\mathbf{P}}_i(t) = \mathbf{P}_i(t) + s\mathbf{G}_i(t)$ where s is a scalar. Now we need to project the matrix $\hat{\mathbf{P}}_i(t)$ onto the feasible region defined by (3)-(4). In fact, the projection operation can be seen as searching for a point $\tilde{\mathbf{P}}_i(t)$ in the region of (3)-(4), which has a minimal Euclidean distance to the point $\hat{\mathbf{P}}_i(t)$ [7], [10]. This problem can be further formulated, for each i, as

$$\min_{\tilde{\mathbf{P}}_i(1),\cdots,\tilde{\mathbf{P}}_i(L),\mu} \quad \sum_{t=1}^{L}\left(\left\|\tilde{\mathbf{P}}_i(t)-\hat{\mathbf{P}}_i(t)\right\|^2 + \mu\mathrm{tr}\left\{\tilde{\mathbf{P}}_i(t)\right\}\right) - \mu LN \tag{5}$$

$$\text{s.t.} \quad \tilde{\mathbf{P}}_i(t) \geq 0, \qquad t = 1,\cdots,L \tag{6}$$

where μ is the Lagrangian multiplier. Interestingly, the problem (5)-(6) can be decomposed into L subproblems. As an example, the tth subproblem can be written as

$$\min_{\tilde{\mathbf{P}}_i(t)} \quad \left\|\tilde{\mathbf{P}}_i(t)-\hat{\mathbf{P}}_i(t)\right\|^2 + \mu\mathrm{tr}\left\{\tilde{\mathbf{P}}_i(t)\right\} \tag{7}$$

$$\text{s.t.} \quad \tilde{\mathbf{P}}_i(t) \geq 0\,. \tag{8}$$

Solving (7) with respect to $\tilde{\mathbf{P}}_i(t)$, we obtain that $\tilde{\mathbf{P}}_i(t) = \hat{\mathbf{P}}_i(t) - \mu\mathbf{I}_N$. Now we project the matrix $\tilde{\mathbf{P}}_i(t)$ onto the feasible set (8). Let us denote $\hat{\mathbf{P}}_i(t) = \mathbf{U}_i(t)\mathbf{\Lambda}_i(t)\mathbf{U}_i^H(t)$ as the eigenvalue decomposition of matrix $\hat{\mathbf{P}}_i(t)$, where $\mathbf{U}_i(t)$ is the eigenvectors matrix, while $\mathbf{\Lambda}_i(t) \triangleq \mathrm{diag}\{\lambda_{i,1}(t),\cdots,\lambda_{i,N}(t)\}$ is the diagonal matrix containing all the eigenvalues. Therefore, $\tilde{\mathbf{P}}_i(t) = \mathbf{U}_i(t)\left[\mathbf{\Lambda}_i(t)-\mu\mathbf{I}_N\right]^+\mathbf{U}_i^H(t)$ where for an $N\times N$ diagonal matrix $\mathbf{X}$, $[\mathbf{X}]^+$ is defined as $[\mathbf{X}]^+ = \mathrm{diag}\{\max\{x_{1,1},0\},\cdots,\max\{x_{N,N},0\}\}$. The Lagrangian multiplier μ can be obtained by applying (3) to $\tilde{\mathbf{P}}_i(t)$. We have the following equation $\sum_{n=1}^{N}\sum_{t=1}^{L}\max\{\lambda_{i,n}(t)-\mu,0\} = LN$. The left hand side of this equation is a piecewise linear function and monotonically decreasing with respect to μ. Thus, it can be easily solved by, for example, the bisection method [13].

With the above computations of gradient and projection, a general form of the GP algorithm for the OPS scheme is as follows, for $i = 1,\cdots,L$ and $t = 1,\cdots,L$,

$$\mathbf{P}_i^{(k+1)}(t) = \mathbf{P}_i^{(k)}(t) + \delta_k\left(\tilde{\mathbf{P}}_i^{(k)}(t) - \mathbf{P}_i^{(k)}(t)\right) \tag{9}$$

$$\tilde{\mathbf{P}}_i^{(k)}(t) = \mathrm{proj}\left[\mathbf{P}_i^{(k)}(t) + s_k\mathbf{G}_i^{(k)}(t)\right] \tag{10}$$

$$\mathbf{G}_i^{(k)}(t) = \nabla_{\mathbf{P}_i^{(k)}(t)} I_A\left(\bar{\mathbf{P}}^{(k)}\right) \tag{11}$$

where δ_k and s_k denote the step size parameters at the kth iteration. We choose the step size parameters δ_k and s_k by the Armijo rule, i.e., s_k is a constant through all iterations, i.e., $s_k = s$, while at the kth iteration, δ_k is set to be γ^{m_k}. Here m_k is the minimal nonnegative integer that satisfies the following inequality

$$I_A(\bar{\mathbf{P}}^{(k+1)}) - I_A(\bar{\mathbf{P}}^{(k)}) \geq \sigma\gamma^{m_k}\mathrm{tr}\left\{\left(\bar{\mathbf{G}}^{(k)}\right)^H\left(\bar{\tilde{\mathbf{P}}}^{(k)} - \bar{\mathbf{P}}^{(k)}\right)\right\} \tag{12}$$

where σ and γ are constants. According to [10], usually σ is chosen close to 0, for example $\sigma \in [10^{-5}, 10^{-1}]$. A proper choice of γ is usually from 0.1 to 0.5. The convergence criterion of the GP algorithm can be chosen as $\mathrm{maxabs}\left\{\bar{\mathbf{P}}^{(k+1)} - \bar{\mathbf{P}}^{(k)}\right\} \leq \varepsilon$ where $\mathrm{maxabs}\{\cdot\}$ denotes the maximal absolute value of each element of a matrix, and ε is a positive constant close to 0.

The above algorithm can be implemented in a distributed fashion where each link searches for its optimal source covariance matrix (concurrently with other links) based on the previous source covariance matrices obtained by other links. This algorithm requires additional communications among links for each update. But at convergence, the result is very close to that of the above centralized algorithm [16].

IV. Numerical Examples

In this section, we present simulation results to compare the proposed OPS scheme with the following schemes: the scheme in [5] referred to as the DI scheme, the scheme in [7] referred to as the YB scheme, the classic TDMA scheme, the half spectrum reuse scheme in [15] referred to as the BEH scheme, and a zero interference (ZI) scheme. The DI, YB and TDMA schemes have been mentioned before. The BEH scheme first divides the network into two sets of $L/2$ links where each set has the maximum spacing between links. The BEH scheme then applies the DI scheme to each of the two sets within half of the total available spectrum. The ZI scheme is the same as the OPS scheme except in addition that all links are forced to be active in each slot and the actual interference between links within each time slot is forced to be zero. We will only consider the ZI scheme for two links, two slots and two antennas on each node. In this case, the additional constraint on the source covariance matrices for the ZI scheme is that $\mathbf{P}_i(t) = p_i(t)\mathbf{v}_i(t)\mathbf{v}_i^H(t), i = 1,2$, where $\|\mathbf{v}_1(t)\| = \|\mathbf{v}_2(t)\| = 1$, $\mathbf{v}_1^H(t)\mathbf{H}_{1,1}^H\mathbf{H}_{1,2}\mathbf{v}_2(t) = 0$, and $\mathbf{v}_2^H(t)\mathbf{H}_{2,2}^H\mathbf{H}_{2,1}\mathbf{v}_1(t) = 0$. The above two equations ensure zero actual interference between the two links in each time slot.

Before the simulation results are presented, it is useful to mention the following expectations based on the principles of each scheme: 1) The proposed OPS scheme should yield the highest capacity in all situations. 2) The YB scheme should yield the same capacity as the OPS scheme if the nominal INR are very small. For example, when all links are far apart from each other, all links can be treated as independent of each other. 3) The DI scheme should also yield the same capacity as the OPS scheme if the nominal INR are very small. Without interference, the DI scheme is also optimal. 4) The TDMA scheme should yield a higher capacity than the YB and DI schemes when the nominal INR are very high because TDMA causes zero actual interference among links. 5) The

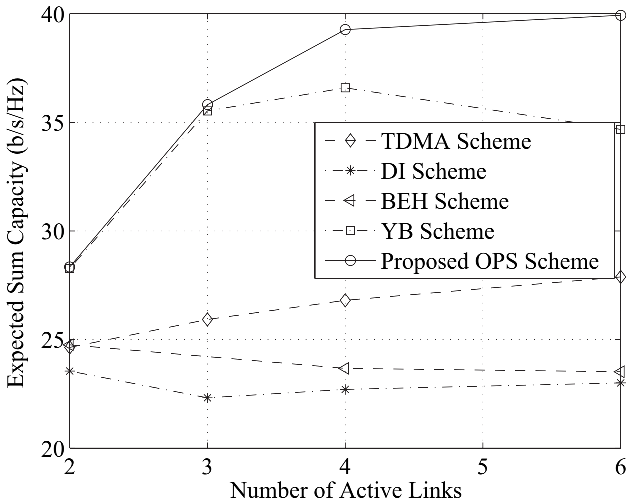

Fig. 2. Expected sum capacity versus L the number of active links. $N = 2$ and $T = L$.

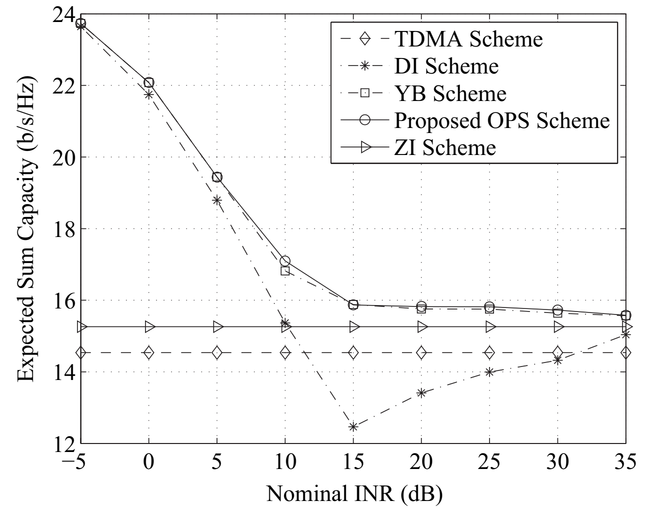

Fig. 3. Expected sum capacity versus nominal INR. $N = 2$ and $T = L = 2$. In this case ($L = 2$), the BEH scheme is equivalent to TDMA.

BEH scheme is a mixture of the TDMA and DI schemes, and so should be its performance. 6) The ZI scheme may or may not be better than the TDMA scheme although both yield zero actual interference in each slot.

We define an expected sum capacity as $C_{\text{mean}} = \mathrm{E}_{\mathcal{H}}\{I_A(\bar{\mathbf{P}})\}$ where $\mathcal{H}$ denotes the set of all realizations of the matrices $\mathbf{H}_{i,j}, i, j = 1, \cdots, L$. To compute the expectation or distribution of the sum capacity of all active links under each scheme, we use 1000 independent channel realizations. For each channel realization (corresponding to each window of T time slots), a random initial condition for the source covariance matrices was used to start the computation of the OPS, DI, YB schemes. For the OPS and YB schemes, the following parameters are applied in the GP algorithms: $s = 1, \sigma = 0.1, \gamma = 0.5$, and $\varepsilon = 0.01$.

First, we consider four possible sets of symmetric MIMO links on the circular network shown in Fig. 1, i.e., $L = 2, 3, 4, 6$. Let r denote the radius of the circle. It can be easily calculated that the distance between the SN and the DN of each MIMO link is $d_0 = 2r \sin(\pi/M)$, and the distances between a DN and an interfering SN is $d_k = 2r \sin(\theta_k/2), k = 1, \cdots, L-1$, where θ_k is the angle corresponding to the arc between one DN and its kth interfering SN. We assume that all SNs transmit with the same power P_T. Then, the SNR of each MIMO link can be written as $\rho_i = \frac{P_T}{d_0^\alpha} = \frac{P_T}{(2r)^\alpha (\sin \pi/M)^\alpha} = \frac{\tilde{P}_T}{(\sin \pi/M)^\alpha}$ for $i = 1, \cdots, L$ where $\tilde{P}_T \triangleq P_T/(2r)^\alpha$ is a normalized transmission power (also a normalized SNR), and α denotes the path loss exponent and is set to be $\alpha = 3$. Similarly, the nominal INR of each MIMO link can be calculated as $\beta_{i,j} = \tilde{P}_T/\tilde{d}_k^\alpha$ with $\tilde{d}_k = \sin(\theta_k/2)$ for $k = (j-i)_{mod_L}$, $i, j = 1, \cdots, L$, and $j \neq i$.

Fig. 2 shows the expected sum capacity C_{mean} for all schemes versus the number L $(= T)$ of active links at $\tilde{P}_T = 20$dB and $N = 2$. The BEH scheme is not included at $L = 3$ due to the half spectrum reuse constraint. C_{mean} using the DI and BEH schemes are almost independent of L. For the YB scheme, C_{mean} drops when L becomes relatively large. This is because the transmission power of each link in the YB scheme is fixed in a single time slot. And when L become large, so does the actual interference among all links. For the TDMA and OPS schemes, C_{mean} is monotonically increasing with L. As expected, the proposed OPS scheme has the largest C_{mean} for all values of L.

For the rest of the simulation examples, we assume that $\rho_i = 20$dB, $i = 1, \cdots, L$, and $\beta_{i,j} = INR, i, j = 1, \cdots, L, j \neq i$. This assumption does not necessarily correspond to the circular network. By INR, we will mean nominal INR unless specified otherwise.

Fig. 3 shows C_{mean} versus INR for $T = L = 2$ and $N = 2$. Since $L = 2$, the BEH scheme (not shown) is equivalent to the TDMA scheme. Shown in this figure, the OPS scheme and the YB scheme yield similar C_{mean} for all values of INR. This is because under $T = L = N = 2$, there is not enough freedom for the OPS scheme to be significantly different from the YB scheme. It is shown in [16] that as INR becomes infinity, the optimal power schedule can be achieved only if each of concurrent links in a slot transmits no more than $N - 1$ data streams. Under $T = L = N = 2$, for almost all channel realizations, each of the two schemes activates two links in each time slot at any INR. And at high INR, each link for both schemes transmits effectively one data stream. Comparing the TDMA and ZI schemes which both cause zero actual interference between links in each time slot, the latter has a higher C_{mean} than the former. However, both TDMA and ZI schemes have smaller C_{mean} than the OPS scheme. The curve for the DI scheme is unusual, which decreases first and then increases later as INR increases. This is a strange phenomenon of the Nash equilibrium reached by the DI scheme.

Fig. 4 shows C_{mean} versus INR for $T = L = 6$ and $N = 2$. Due to half spectrum reuse, the BEH method yields a much smaller C_{mean} than the DI, YB, and OPS schemes at low INR. For all schemes except TDMA, C_{mean} decreases as INR increases. When INR is very high, the DI, BEH, and YB schemes have smaller C_{mean} than TDMA. Due to a larger L (unlike $L = 2$ in Fig. 3), the OPS scheme now yields a much higher capacity than the YB scheme.

The cumulative distribution of the sum capacity of each of the tested schemes is plotted in Fig. 5 where SNR=20dB,

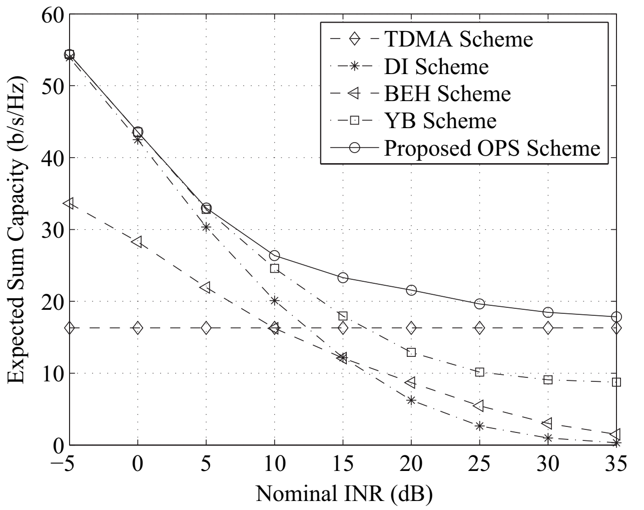

Fig. 4. Expected sum capacity versus nominal INR. $N = 2$ and $T = L = 6$.

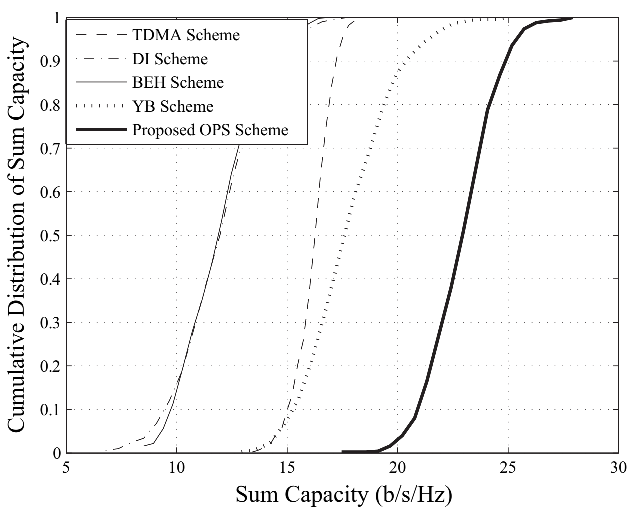

Fig. 5. Cumulative distribution of the sum capacity. $N = 2$ and $T = L = 6$.

INR=15dB, $N = 2$ and $T = L = 6$.

Finally, Fig. 6 shows C_{mean} versus T where $L = 6$, SNR=20dB and INR=20dB, which illustrates the effect of T on the performance of the OPS scheme. We see that when $T = 6$, C_{mean} achieves approximately its peak value. The slight drop from the value for $T = 5$ in Fig. 6 could be due to local minima achieved by the OPS scheme.

V. Conclusions

We have presented a novel scheme for medium access in wireless network of MIMO links where the source covariance matrix of each active MIMO link is treated as a function of time and/or frequency within any given time/frequency band and the network capacity averaged over the time/frequency band is maximized jointly over the source covariance matrices of all active MIMO links. The optimal solution to this scheme is difficult to guarantee because of the non-convex nature of this scheme. However, for all cases that we have considered, the gradient projection (GP) based algorithm developed in this paper has consistently yielded higher capacity than all other schemes considered. The solution provided by the GP algorithm in general depends on the initial condition used for the search. But by using multiple initial conditions and multiple searches, the optimal solution to this scheme can be found with increased probability. Any of the existing schemes such as TDMA can also be used as the initial condition for the search. Further research to reduce the complexity of the search algorithm and to gain a better understanding of the optimal power schedule under this scheme is important.

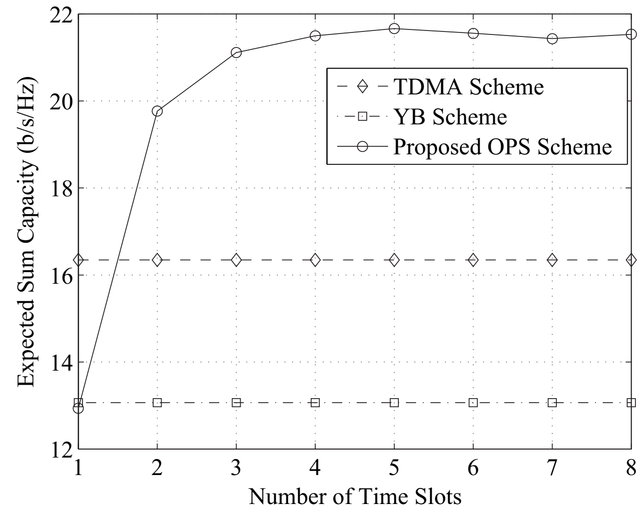

Fig. 6. Expected sum capacity versus T. $N = 2, L = 6$.

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