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Research Article

Transmission Strategies in MIMO Ad Hoc Networks

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Precoding problem in multiple-input multiple-output (MIMO) ad hoc networks is addressed in this work. Firstly, we consider the problem of maximizing the system mutual information under a power constraint. In this context, we give a brief overview of the nonlinear optimization methods, and systematically we compare their performances. Then, we propose a fast and distributed algorithm based on the quasi-Newton methods to give a lower bound of the system capacity of MIMO ad hoc networks. Our proposed algorithm solves the maximization problem while diminishing the amount of information in the feedback links needed in the cooperative optimization. Secondly, we propose a different problem formulation, which consists in minimizing the total transmit power under a quality of signal constraint. This novel problem design is motivated since the packets are captured in ad hoc networks based on their signal-to-interference-plus-noise ratio (SINR) values. We convert the proposed formulation into semidefinite optimization problem, which can be solved numerically using interior point methods. Finally, an extensive set of simulations validates the proposed algorithms.

1. Introduction

Recently, MIMO ad hoc networks have attracted an increasing interest. The use of multiple antennas at both wireless link sides has shown a promising solution to boost up the spectral efficiency of the point-to-point and cellular communication systems [1, 2]. In ad hoc networks, where the nodes operate without a central administration or underlying infrastructure, the MIMO links play an important role in overcoming some problems such as the lower system throughput and the higher energy consumption. However, a smart optimization signaling algorithm associated with a sophisticated medium access control (MAC) scheme has to be proposed in order to handle these benefits [3]. In this work, we are interested in elaborating smart signaling schemes for MIMO ad hoc networks.

Generally speaking, the transmission strategies with MIMO techniques are addressed in three communication systems: point-to-point MIMO communication, cellular MIMO communication, and MIMO ad hoc networks or more generally MIMO interference channel.

Point-to-point MIMO links are extensively studied in the literature. The great potential of MIMO communications in single link scenario is proven in [1]. The authors in [4] address the joint design of transmit (linear precoding) and receive (linear decoding) beamforming for multi carrier MIMO channels. In [5], the authors show that the optimum linear precoder/decoder diagonalizes the MIMO channel into eigen subchannel.

Besides, extensive research is devoted to MIMO broadcast (MIMO BC) and to MIMO MAC systems. Recall that in these systems, either the transmitter or the receiver is common between the active wireless links. In [6] the authors optimize the mean-square error (MSE) under a power constraint. In [7], the joint optimal downlink beamforming in multicell SDMA system is considered. The author in [8] treats the same problem as before and provides a complete solution by using the virtual uplink equivalence concept.

All the aforementioned works, in both point-to-point and cellular communication systems, concern almost the problem of capacity maximization and prove the fruitfulness of using MIMO techniques. However, evidencing this potentiality in the case of ad hoc networks is not a trivial problem. In these networks, the optimization problem using MIMO techniques needs a more careful study for three reasons. Firstly, we are in fully interfering environment because only one frequency is used. Secondly, the sensitivity of the performance of ad hoc networks depends on the overheads introduced by the feedback link required for any cooperative optimization. Thirdly, the cross layer design which is based on the signal-to-noise ratio of the received packets must be considered.

Mainly, our contributions in this paper are twofold: firstly we propose a fast and efficient cooperative algorithm for the conventional capacity maximization problem, and secondly we devise a novel problem design based on the optimization of the quality of the received signal rather than the system capacity.

In MIMO ad hoc networks, the transmission scheme of each user depends on that of other users since the interferences at each user depend on all the transmit covariance matrices in the network. Thus, the first part of our work which deals with the conventional problem of maximizing the global capacity will be more complicated. The global maximization came usually at the cost of frequently feedback signaling which depends on the convergence rate of the proposed algorithm. In literature and due to the nonconcavity of this problem, only a suboptimum solution is found by using some nonlinear programming methods. The Gradient Projection (GP) algorithm proposed in [9] maximizes the total system capacity subject to constant power constraint at each node in the network. In their work, the authors present centralized and distributed schemes to solve the problem. Although the proposed algorithm converges, its convergence rate slows down as it is approaching the solution. When performing cooperative and distributed optimization, the nodes may share some data along the convergence process. The amount of information to be transmitted in the feedback link will grow with the number of iterations. Thus, reducing this number alleviates the overheads. In this context, Newton method becomes an intuitive candidate for such a problem. However, due to the complexity of computing the inverse of the Hessian matrix, this solution will be excluded. As an intermediate solution, we propose to use the Quasi-Newton (QN) methods which approximate the inverse of the Hessian matrix rather than computing the true one. To summarize, these methods are motivated for two reasons: (i) a provable and super linear convergence can be achieved; (ii) the complexity of this algorithm is far from that of the Newton method and comparable to the gradient one.

In literature, the design of the signaling problem in MIMO ad hoc networks is given usually by the minimization of the total transmit power under a capacity constraint or by the maximization of the capacity under a power constraint. For completeness we propose in the second part of this work a different and efficient problem formulation which consists of minimizing the total power under the quality of the received signal constraints. In cross-layer design for wireless local area network (WLAN) networks the SINR is the common parameter used for acquiring successfully the packets in the network. Thus, we see that improving the quality of the received signal is more beneficial than the direct maximizing of the system capacity. In the fourth section we clarify the motivation and the efficiency for our proposed design in MIMO ad hoc networks.

The rest of this paper is organized as follows. In Section 2, a review of the pertinent works on the precoding methods in MIMO ad hoc networks is presented. In Section 3, the capacity maximization problem is considered. In this Section, the nonlinear optimization methods are overviewed, and a cooperative and distributed optimization algorithm based on the QN methods is proposed. In Section 4 a new formulation of the signaling problem is proposed, and a solution based on the semidefinite programming (SDP) solver is devised. Finally, a general conclusion is drawn in Section 5.

The notation in this paper will be as follows. The boldface denotes matrices and vectors. For a matrix $\mathbf{R}$: $\mathbf{R}^*$, $\mathbf{R}^T$, and $\mathbf{R}^H$ denote the conjugate, the transpose, and the conjugate-transpose, respectively. $\mathrm{tr}(\mathbf{R})$ is the trace. $\mathbf{I}$ stands for the identity matrix. $\mathbf{R} \succeq 0$ represents a positive semidefinite matrix.

2. Related Work

In the last two years, wireless mobile ad hoc researchers have focused on the MIMO technique to boost up the network spectral efficiency and to improve the achieved quality of service. Interestingly, in this context two fields have received particular emphasis: the first one deals with the cross layer design issues where protocol design is tightly coupled with a deeper understanding of the physical layer and channel behavior [3, 10], and the second addresses the transmit signaling strategies [9, 11, 12].

In [3] some tradeoffs concerning the achievement of the conflicting goals of rate and reliability increases, power savings, and latency reduction are thoroughly discussed. Particular emphasis is placed on the role of the Channel State Information (CSI) at both transmitter and receiver. Moreover, the authors indicate that a solid understanding of channel estimation techniques and on their accuracy and availability are key ingredients of the cross layer design. Winters in [10] discusses the use of smart antenna systems in ad hoc networks and suggests that MAC and routing protocols have to be modified in order to take advantages of the smartness of these antennas.

The optimum signaling problem when employing multiple antenna elements has received less attention. Resolving for optimum signaling for the noninterference and the fixed-interference cases is done with the traditional and generalized waterfilling procedures, respectively, in [1].

The gradient projection algorithm proposed in [9] maximizes the total system capacity subject to constant power constraint at each node in the network. In their work, the authors present centralized and distributed schemes to solve the problem. Although the proposed algorithm outperforms the iterative waterfilling algorithm (IWF), its convergence rate slows down as it is approaching the solution. Recall that, IWF treats the problem as a noncooperative game and aims to reach the Nash equilibrium (NE) which does not provide the best transmission strategy. The optimum signaling in the case where the CSI is assumed only at the receiver, is considered in [13]. The authors demonstrate that putting all power into a single transmitting antenna is optimum in the case of strong interferences. Whereas, dividing the power equally between independent streams from the different antennas is optimum when weak interferences is expected. In [14] the authors show that performing beamforming by all users approaches the optimum signaling when the number of users tends to infinity. More specially, putting the power along the largest eigen value of the channel covariance matrix is shown to be optimal in the sense of achieving system capacity.

The authors in [11] treat the problem of spatial beamforming in MIMO ad hoc networks where each node is equipped with a receive/transmit beamformer pair. They proposed an iterative minimum mean-square error (IMMSE) beamforming algorithm where they enforced the receive beamformer to be equal to the conjugate of the transmit beamformer.

In [15] the authors studied the DSL (Digital Subscriber Line) power control problem as a noncooperative Nash game resulting from the distributed implementation of the iterative waterfilling algorithm (IWFA). They proposed a different problem formulation in order to analyze the convergence behavior of IWFA.

In [16], sufficient conditions for convergence to the equilibrium point are derived under totally asynchronous update. In [17] the authors established the existence of NE of the problem of individual rate maximization in MIMO interference channel. They proved that the Nash equilibrium is unique if the multiuser interference is negligible. In [12] a non-cooperative algorithm is proposed to solve the global problem. The authors perform generalized waterfilling with respect to the transmitting and receiving node covariance matrix. They suggested minimizing an alternative objective function called *TIF* (Total Interference Function) rather than solving the global optimization problem directly. In [18] the authors provide a unified framework for the non-cooperative maximization of mutual information in the Gaussian interference channel. A MIMO asynchronous waterfilling algorithm is provided for systems with square nonsingular channel matrices. A set of conditions is derived to guarantee the convergence of the proposed algorithm and the uniqueness of the NE. In [19] the same authors extend their work for arbitrary channel matrices (rectangular matrices, rank deficient matrices).

In this paper, we consider a scenario of ad hoc network where the nodes aim to increase the system capacity rather than the individual capacity. To this end, they have to exchange some information along the procedure of convergence [9]. Considering this scenario, our contribution can be summarized by two points. First we propose a fast and distributed method to decide the best transmission strategy (which outperforms the Nash equilibrium). We then propose a new problem design more suitable for ad hoc network. This new approach consists in optimizing a quality of service constraint rather than optimizing directly the capacity.

3. Capacity Maximization Problem

We consider an ad hoc network formed by N links, each of which employs M antenna-elements. The links in the network are assumed to be unicast predefined links [9]. The nodes perform independent decoding with single user detection. We assume also that the CSI is available at both the transmitter and the receiver. This can be done by a smart channel tracking algorithm associated with enhanced MAC design [20]. We assume a frequency nonselective fading MIMO channel between the nodes. Let $\mathbf{H}_{i,j}$ ($M \times M$ complex matrix) denote the channel from node i to node j, and let also $\mathbf{n}_j$ ($M \times 1$) be the noise vector seen by the node j. In this section, the channel matrix and the noise vector are assumed to be *iid* complex Gaussian variables with zero mean and unit variance. For such a receiver the interfering signals are unknown. Thus we model them as Gaussian distributed and it has been shown that many interferences whiten this distribution [1, 13].

The received signal can be seen as the multiplication of the normalized weighted transmitted signal x by the-Signal to-Noise Ratio (SNR) of this signal, namely ρ, and also multiplied by the correspondent channel. By focusing our attention on the node i, the baseband signal received by this node is given by

$$\mathbf{y}_i = \sqrt{\rho_i}\mathbf{H}_{i,i}\mathbf{x}_i + \sum_{j=1, j\neq i}^{N} \sqrt{\gamma_{i,j}}\mathbf{H}_{i,j}\mathbf{x}_j + \mathbf{n}_i, \tag{1}$$

where γ is the Interference-to-Noise Ratio (INR). Under the assumption that the channel and the noise are independent and that $E(\mathbf{n}_i\mathbf{n}_i^H) = \mathbf{I}$, the covariance matrix of interference plus noise is given by $\mathbf{R}_i = \mathbf{I} + \sum_{j=1, j\neq i}^{N} \gamma_{i,j}\mathbf{H}_{i,j}\mathbf{Q}_j\mathbf{H}_{i,j}^H$, where $\mathbf{Q}_j = E(\mathbf{x}_j\mathbf{x}_j^H)$ represents the transmit covariance matrix. Finally the total system capacity can be written as

$$C = \sum_{i=1}^{N} c_i = \sum_{i=1}^{N} \log_2\Big(\det\Big(\mathbf{I} + \rho_i\mathbf{H}_{i,i}\mathbf{Q}_i\mathbf{H}_{i,i}^H\mathbf{R}_i^{-1}\Big)\Big), \tag{2}$$

where the expectation is taken over all the random channel matrices. The global optimization problem is, then:

$$\begin{aligned} &\text{maximize} \quad C \\ &\text{subject to} \quad \mathbf{Q}_i \in \mathcal{S} \quad i = 1 \cdots N. \end{aligned} \tag{3}$$

where $\mathcal{S}$ is the set of positive semidefinite (PSD) matrices having unit trace.

Due to the nonconcavity of this problem, only a suboptimum solution can be found through nonlinear optimization methods. A brief overview of these methods will be given in the following.

3.1. Mathematical Review. Let f be a multivariable function defined on the convex set E. Without loss of generality, all the iterative descent (ascent) methods are defined as an update of the solution at each iteration. A generic algorithm is given by the following equation:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{S}_k \mathbf{g}_k, \quad (4)$$

where the vector $\mathbf{S}_k\mathbf{g}_k$ represents the step or the search direction, and α_k is the step size. Hereafter we will define the matrix $\mathbf{S}_k$ and the vector $\mathbf{g}_k$.

3.1.1. Determination of the Step. Almost all the methods define $\mathbf{g}_k$ as the gradient of f. The difference is only in the definition of the matrix $\mathbf{S}_k$.

The method of steepest the descent (referred later as the gradient method) defines $\mathbf{S}_k$ as the identity matrix. The idea behind this method is that the function f is approximated locally by a linear function. This method is one of the widely used methods for minimizing a function of several variables. It is extremely motivated since it is very simple to be implemented, and only the first partial derivatives of f are required. However, the convergence rate of this method is very slow and is tightly depending on the initial point. This slowness can be interpreted by the fact that two consecutive search direction vectors are orthogonal. That is, $\mathbf{g}_k^T \mathbf{g}_{k+1} = 0$. More careful examination on the convergence of this method can be found in [21].

The Newton method can achieve a superlinear convergence by defining $\mathbf{S}_k$ as the inverse of the Hessian matrix of f. Let $\mathbf{F}$ denote the inverted matrix. Herein, the function f is approximated locally by a quadratic function, and this approximate function is minimized exactly. Therefore, this method can eliminate efficiently the "jamming" or "zigzagging" phenomenon encountered by the gradient method. The order of convergence of this method is two if the initial point is closed to the solution. Although the Newton method is very attractive in terms of convergence properties, it requires a complex evaluation and inversion of the Hessian matrix at each iteration.

The CG method and the QN methods can be regarded as being somewhat intermediate between the method of the steepest descent and Newton method.

The CG method is motivated to accelerate slow convergence of the steepest descent method while avoiding the evaluation and inversion of the Hessian matrix as required by the Newton method. This method is used in the context of MIMO BC [22], in order to maximize the global capacity under global power constraint.

The QN methods use an approximation of the inverse of the Hessian matrix rather than the true inverse that is required in the Newton method. This approximated matrix can be build up on the base of information gathered along the convergence way. These methods offer the most simple, sophisticated, and fast algorithms for solving the unconstrained problems. The constraint is fulfilled separately by performing a projection onto the constraint space. In our work we focus on these methods, and we investigate particularly the DFP (Davidon-Fletcher-Powell) and the SSQN (Self Scaling Quasi Newton) methods. For completeness, we implement also the CGP (Congugate Gradient Projection) method.

3.1.2. Determination of the Step Size. Exact lines search is the evident and more accurate method in this context. With this method α_k can be computed as

$$\alpha = \arg\min(\mathbf{x} + \alpha \mathbf{g}') \quad (5)$$

where $\mathbf{g}' = \mathbf{S}\mathbf{g}$.

In practice, the exact line search may be hard to find. Inexact line search methods are more appropriate and easier to be implemented [23]. One of these methods, called back tracking line search, depends on two constants a, b with $0 < a < 0,5$ and $0 < b < 1$, and it consists of iteratively increment the variable t until fulfilling the following condition:

$$f(\mathbf{x}_{k+1}) - f(\mathbf{x}_k) \geq at\mathbf{g}'^T\mathbf{g}'; \quad t = b^m t_0. \quad (6)$$

3.2. Quasi-Newton Method for MIMO Ad Hoc Networks. We propose a fast and efficient algorithm based on the quasi Newton method to solve the global optimization problem (3). Our work is based on the gradient projection method proposed in [9] and detailed in [21]. As we have seen in the mathematical review section, the descent direction in the latter method is based essentially on the gradient of the total capacity C. This gradient is calculated with respect to the transmit signaling matrix $\mathbf{Q}_i$ of the user i. In our proposed algorithm, we deflect this gradient direction in order to achieve the most possible linear convergence rate. The deflection is done by approximating the inverse of the Hessian matrix by using the DFP and the SSQN methods. Along the convergence way, the gradient is calculated, and the inverse of the Hessian is updated accordingly. Note that we retain the projection method from [9] to fulfill the constant power constraint in the problem (3). An extensive set of simulations shows that the performance of the QN methods is close to that of the GP method while the convergence rate of the QN methods is much better.

The detailed procedure is illustrated in Algorithm 1. Note that for convenience we use the symbols *vec* and *mat* to convert the matrices into vectors and to concatenate the vectors into matrices, respectively.

The proposed algorithm is similar to the IWF algorithm (based on the Nash equilibrium) where each user tries to maximize the capacity. However, the difference is that our algorithm tries to maximize the system capacity rather than the individual capacity as done by the IWF algorithm.

According to our algorithm, the suboptimum is reached by a cooperative and distributed way which is the most suitable solution for ad hoc networks. More precisely, each user updates independently his covariance matrix with respect to the other updated and notupdated covariance matrices for other users. That is, when calculating the matrix $\mathbf{Q}_i(k+1)$ at the kth iteration, the user i broadcasts the calculated matrix to other users, so by that they can proceed the calculation of their own matrices $\mathbf{Q}_{j/j\neq i}(k+1)$ successively. Clearly, the amount of information to be sent in the feedback link in order to reach the local optimum is straightforward depending on the rate convergence. Such a case in real ad hoc network may generate unsupportable overheads. Explicitly, the network will be saturated by the feedback information.

```
Distributed optimization (at the user i)
Initialization
  Q_i(0), F_i(0);
  k = 0;
  g_i(0) = ∇_{Q_i} C(Q_1(0), ..., Q_i(0), ..., Q_N(0))
Main
While max [abs(Q_i(k) − Q_i(k − 1))] > ϵ
  d = F_i(k) · vec(g_i(k));
  Q′ = Q_i(k) + mat(d);
  Q′′ = projection(Q′) onto S;
  find α_k;
  p_i(k) = α_k d;
  Q_i(k + 1) = Q_i(k) + α_k(Q′′ − Q_i(k));
  broadcasting of Q_i(k + 1);
  g_i(k + 1) = ∇_{Q_i} C(Q_1(k + 1), ..., Q_i(k + 1);
  Q_{i+1}(k), ..., Q_N(k));
  q = vec(g_i(k + 1) + g_i(k));
  find (F_i(k + 1));
  k = k + 1;
end
```

Algorithm 1: Capacity maximization algorithm.

Thus, we can see the utility to optimize the global capacity while keeping limited the amount of information to be transmitted in the feedback link. The direct solution of this problem is to minimize the number of iterations. Our proposed algorithm by using the quasi-Newton methods represents the most appropriate solution in this context. As we will see, it represents a tradeoff between the capacity maximization, the convergence rate, and the complexity.

Nevertheless, the proposed algorithm contains three embedded functions that need to be shown in explicit mathematical forms: (1) find α_k, (2) projection ($\mathbf{Q}'$), and (3) find ($\mathbf{F}_i(k+1)$). In the following, we examine these three functions in details.

3.2.1. Projection($\mathbf{Q}'$). From the subject function of (3), we know that the space of feasible solutions can be defined by the set S of *PSD* matrices having unit trace. Then, the problem is how to project the matrix $\mathbf{Q}'$ onto S. For the sake of simplicity, we first introduce the concept of Hermitian vector. Assume now that $\mathbf{b} = \text{vec}(\mathbf{A})$ where $\mathbf{A}$ is a Hermitian matrix, then $\mathbf{b}$ is called a Hermitian vector. From this definition we have the following property:

$$\forall m, n \in [1, M] \quad \mathbf{b}_{(m-1)M+n} = \mathbf{b}^*_{(n-1)M+m}. \tag{7}$$

For notation simplicity, we will refer to $\mathbf{b}_{(m-1)M+n}$ by $\mathbf{b}_{mn}$.

In the following, we give a theorem in order to demonstrate that $\mathbf{Q}'$ is a Hermitian matrix, and therefore the projection problem can be reduced to how to project a Hermitian matrix onto the set S.

Theorem 1. *The inverse of the Hessian matrix has the conjugacy property when interchanging the index of the column and the line simultaneously. That is* $\mathbf{F}$ *has the following property:*

$$\mathbf{F}_{mn,m'n'} = \mathbf{F}^*_{nm,n'm'} \quad \forall m, n, m', n' \in [1, M]. \tag{8}$$

Proof. The demonstration will be conducted recursively. Assume that this theorem is true for $\mathbf{F}_i(k) = \mathbf{A}$ and demonstrate it for $\mathbf{F}_i(k+1) = \mathbf{B}$. Now we have $\mathbf{A}_{mn,m'n'} = \mathbf{A}^*_{nm,n'm'}$. Note that $\mathbf{F}_i(0)$ can be initialized appropriately, in order to verify the current theorem.

Mainly, the updating formula for the inverse of the Hessian considered in the previous section is based on three matrices: $\mathbf{A}$, $\mathbf{T} = \mathbf{p}\mathbf{p}^H$, and $\mathbf{R} = \mathbf{A}\mathbf{q}\mathbf{q}^H\mathbf{A}$. Now, if we prove that the last two matrices have the conjugacy property, then so for $\mathbf{B}$.

First we demonstrate that if $\mathbf{b} = \text{vec}(\mathbf{g}_i(k))$, then $\mathbf{c} = \mathbf{A}\mathbf{b}$ is a Hermitian vector. Herein, we have to demonstrate that $\mathbf{c}_{mn} = \mathbf{c}^*_{nm}$ for all $m, n \in [1, M]$. Starting from the left side, we know that $\mathbf{c}_{mn} = \mathbf{A}_{mn}\mathbf{b}$ where $\mathbf{A}_{mn}$ is the $(m-1)M+n$ line of the matrix $\mathbf{A}$. It follows directly that $\mathbf{c}_{mn} = \sum_{m'=1}^{M}\sum_{n'=1}^{M}\mathbf{A}_{mn,m'n'}\mathbf{b}_{m'n'} = \sum_{m'=1}^{M}\sum_{n'=1}^{M}\mathbf{A}^*_{nm,n'm'}\mathbf{b}^*_{n'm'} = \mathbf{c}^*_{nm}$ where we used the fact that $\mathbf{A}$ has the conjugacy property as assumed before, and $\mathbf{b}$ is a Hermitian vector. This latter property can be induced directly from the analytical form of the gradient matrix given in [9, 22].

From Algorithm 1, we have that $\mathbf{p} = \alpha_k\mathbf{A} \cdot \text{vec}(\mathbf{g})$, then $\mathbf{p}$ is a Hermitian vector (as shown above). That is, $\mathbf{p}_{mn} = \mathbf{p}^*_{nm}$. Thus, $T_{mn,m'n'} = (\mathbf{p}\mathbf{p}^H)_{mn,m'n'} = \mathbf{p}_{mn}\mathbf{p}^*_{m'n'} = \mathbf{p}^*_{nm}\mathbf{p}_{n'm'} = (\mathbf{p}_{nm}\mathbf{p}^*_{n'm'})^* = ((\mathbf{p}\mathbf{p}^H)_{nm,n'm'})^* = \mathbf{T}^*_{nm,n'm'}$.

From [24], we recognize that $\mathbf{A}$ is a positive semidefinite matrix. Then we have $\mathbf{A} = \mathbf{A}^H$, and $\mathbf{R}$ can be written as $\mathbf{u}\mathbf{u}^H$ where $\mathbf{u} = \mathbf{A}\mathbf{q}$, which has exactly the same form as $\mathbf{T}$, and therefore the demonstration will be the same.

Therefore, by summing the three components of $\mathbf{B}$, we have

$$\mathbf{B}_{mn,m'n'} = \mathbf{B}^*_{nm,n'm'} \quad \forall m, n, m', n' \in [1, M]. \tag{9}$$

□

Consequently, $\mathbf{d} = \mathbf{F} \cdot \text{vec}(\mathbf{g})$ is a Hermitian vector (same demonstration as $\mathbf{c}$), and finally $\mathbf{Q}'$ is a Hermitian matrix.

As mentioned before, the problem now is how to project the Hermitian matrix $\mathbf{Q}'$ onto the set S. By using the Frobenius norm as the matrix distance criterion, it was shown that adjusting the eigenvalues appropriately and keeping the same eigenvectors solves for the projection problem. To be clearer, let $\mathbf{Q}' = \mathbf{V}\Lambda\mathbf{V}^H$ be the eigenvalue decomposition of $\mathbf{Q}'$. Therefore, to satisfy the constant power constraint we need to find μ such that $\text{tr}(\Lambda - \mu\mathbf{I})^+ = 1$. Once μ is found. $\mathbf{Q}''$can be constructed as follows: $\mathbf{Q}'' = \mathbf{V}(\Lambda - \mu\mathbf{I})\mathbf{V}^H$.

3.2.2. Find α_k. In order to determine α_k, we adopt the back tracking line search due to its simplicity in implementation. Herein, we do not suggest that this method is very accurate compared to the exact line search method. However, we believe that the value of α_k will affect all the compared algorithms, similarly. According to this method, we choose fixed values of $a \in [0, 0.1]$, $b \in [0, 1]$, and $t_0 \in [0, 1]$ and

$C_{(k+1)} = C(\ldots, \mathbf{Q}_{i-1}(k+1), \mathbf{Q}_i(k+1), \ldots)$
$C_{(k)} = C(\ldots, \mathbf{Q}_{i-1}(k+1), \mathbf{Q}_i(k), \ldots);$
while $C_{(k+1)} - C_{(k)} \leq at \sum_{i=1}^{N} \mathrm{tr}(\mathbf{g}_i^H(k)(\mathbf{Q}'' - \mathbf{Q}_i(k)))$
$t = bt;$
end;
$\alpha_k = t;$

Algorithm 2: Back tracking line search.

we find t according to the incremental procedure presented in Algorithm 2.

3.2.3. Find $(\mathbf{F_i}(\mathbf{k}+1))$. In this work, we investigate the DFP and the SSQN Quasi-Newton methods. According to these methods, the inverse of the Hessian matrix can be computed iteratively according to (10):

$$\mathbf{F}_i^{\mathrm{DFP}}(k+1) = \mathbf{F}_i(k) + v1 - v2,$$
$$\mathbf{F}_i^{\mathrm{SSQN}}(k+1) = (\mathbf{F}_i(k) - v2)\frac{c_1}{c_2} + v1, \tag{10}$$

In which, $c_1 = \mathbf{p}_i^H(k)\mathbf{q} > 0$ when α_k is chosen appropriately, $c_2 = \mathbf{q}^H \mathbf{F}_i(k)\mathbf{q}$, $v1 = \mathbf{p}_i(k)\mathbf{p}_i^H(k)/c_1$, and $v2 = \mathbf{F}_i(k)\mathbf{q}\mathbf{q}^H\mathbf{F}_i(k)/c_2$.

3.3. Simulation Results. An extensive set of simulations is carried out in order to compare the performance of the four aforementioned algorithms: GP, CGP, and our proposed algorithms, namely, DFP and SSQN.

For fairness in our comparison, we plot in each figure (1) the achievable per-user capacity, which stands for the local optimum in our problem and (2) the convergence rate represented by the number of iterations to reach this local optimum. Moreover and for the sake of comparison fairness, we use the same common parameter used in [9] such as the symmetric case where the *SNR* and the *INR* values are the same for all users. We note that our results are averaged on high number of randomly generated channel matrices. For more simplicity, we use fixed number of antenna elements at each node ($M = 2$).

As a first result, we show in Figure 1, the performance with respect to the number of users. From the per-user capacity point of view, we notice that the four compared algorithms achieve almost the same performances. However, the DFP and SSQN algorithms perform much better than the others in term of convergence rate. In this figure, we set the *SNR* at 0 dB and the *INR* at 0 dB. We examine the case of two, three, four, and five users. In the results, we exclude the scarce cases where the algorithms do not converge. To interpret the results, we focus firstly on the GP algorithm curves. We can see that our results concerning this algorithm match very well with the results given in [9] in terms of capacity and number of iterations. Recall that the number of iterations of the GP method is less than 30 almost the time when the symmetric configuration is adopted (as suggested

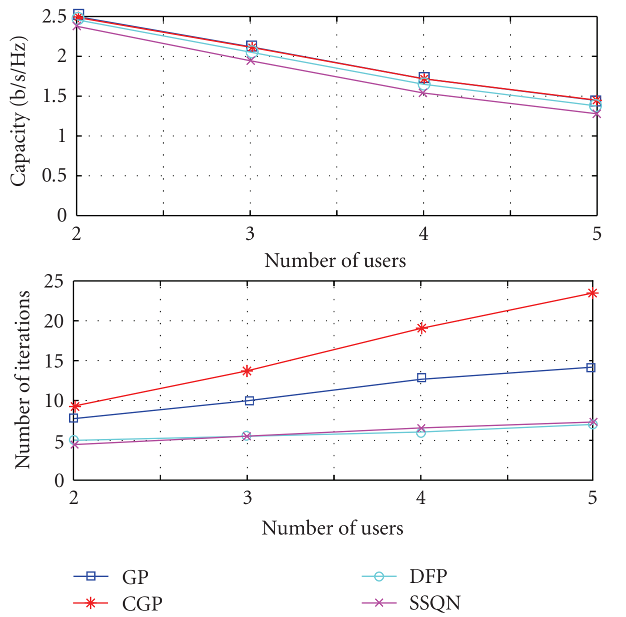

Figure 1: Per-user capacity and convergence rate versus number of users for $M = 2$, SNR = 0 dB, and INR = 0 dB.

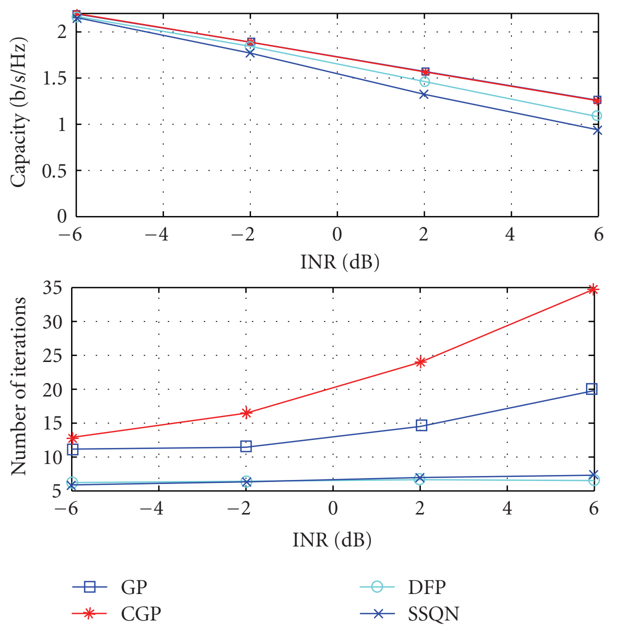

Figure 2: Per-user capacity and convergence rate versus interference-to-noise ratio for $M = 2$, $N = 4$, SNR = 0 dB.

by the authors). However the DFP and the SSQN achieve a superlinear convergence rate by reaching the local optimum in no more than 7 iterations, alleviating by that the amount of feedback information fourfold.

In the Figure 2, the performances versus the *INR* values for fixed *SNR* value are depicted. As shown in this figure, the convergence rate of the DFP and the SSQN methods is the best among the others. Basically, we observe that the convergence rate is independent from the interference level. Both the DFP and the SSQN reach the local optimum with less than 6 iterations. However, the GP and the CGP algorithms converge more quickly when low interference level is presented. Whereas, they show a poor convergence rate when the interferences become strong. By comparing the proposed method and the old methods, we can obtain an improvement on the convergence rate up to 400%.

From the per-user capacity perspective, the simulations show that a small gap is presented between the proposed method and the old method. This gap is negligible in low and moderate interference environment. Whereas, when strong interferences are presented, a small degradation on the DFP and the SSQN can be noticed. However, this degradation comes at the cost of the significant gain in the convergence rate.

Generally speaking, the performances of DFP and SSQN are much better than that of GP and CGP. In low interference environment, the proposed algorithms enjoy a provable and fast convergence. However, in strong interference environments where the old algorithms show a poorer convergence rate, a slight sacrifice on the capacity leads to higher convergence rate, which is an appropriate solution for MIMO ad hoc networks.

4. Novel Optimized Signaling Scheme

In the previous section, we dealt with the conventional problem of capacity maximization under a power constraint.

In this section we attack the signaling problem from a different angle. We propose a different and efficient problem formulation which consists in minimizing the total power under Quality of Signal (QS) constraints. To the best of our knowledge, this formulation is not addressed before in the context of precoding in MIMO ad hoc networks.

This novel problem design is motivated, since in WLAN networks the successful reception of the packets is based on their SINR values. Thus, maintaining a minimum SINR threshold would be more efficient in boosting up the system throughput. Our proposition does not deal directly with the SINR of each stream. Instead, it deals with another entity which is related to the SINR by an increasing function.

Explicitly, our proposition consists in minimizing the total power while maintaining the quality of the received signal above a certain predefined threshold. This quality of signal is interpreted as the ratio of the power of the total desired signal received across the antenna array over the power of the interuser interference signals received by the same antenna array.

4.1. System Model. For notation simplicity, we introduce a slight modification on the system model given in the previous section. We use the operator $l(\cdot)$ to denote explicitly that the destination of the source i is $l(i)$. The channel matrix denoted by $\widetilde{\mathbf{H}}$ and the noise vector are assumed to be *iid* complex Gaussian variables. For each node let $\mathbf{G}$ represent the transmit precoder in which the transmit power is embedded. By focusing our attention on the node $l(i)$, the baseband signal received by this node is given by

$$\mathbf{y}_{l(i)} = \underbrace{\widetilde{\mathbf{H}}_{l(i),i}\mathbf{G}_i\mathbf{x}_i}_{\text{desired signal}} + \underbrace{\sum_{j=1,j\neq i,l(i)}^{N} \widetilde{\mathbf{H}}_{l(i),j}\mathbf{G}_j\mathbf{x}_j}_{\text{inter ferences}} + \underbrace{\mathbf{n}_{l(i)}}_{\text{noise}}, \tag{11}$$

where $\mathbf{x}_i$ represents the normalized information to be sent ($E(\mathbf{x}_i^H\mathbf{x}_i) = 1$). The first term in (11) represents the desired signal intended to node $l(i)$ while the second regroups the total interference signal received by node $l(i)$, and the third is the additive white Gaussian noise. Under the assumption that the channels and the noise are independent and that $E(\mathbf{n}\mathbf{n}^H) = \mathbf{I}$, the covariance matrix of the received signal after the decoding by a matrix $\mathbf{D}_{l(i)}$ can be written as

$$E\left(\mathbf{r}_{l(i)}\mathbf{r}_{l(i)}^H\right) = \mathbf{H}_{l(i),i}\mathbf{Q}_i\mathbf{H}_{l(i),i}^H + \sum_{j=1,j\neq i,l(i)}^{N} \mathbf{H}_{l(i),j}\mathbf{Q}_j\mathbf{H}_{l(i),j}^H + \mathbf{I}, \tag{12}$$

and the covariance matrix of interference plus noise is given by

$$\mathbf{R}_{l(i)} = \mathbf{I} + \sum_{j=1,j\neq i,l(i)}^{N} \mathbf{H}_{l(i),j}\mathbf{Q}_j\mathbf{H}_{l(i),j}^H, \tag{13}$$

where $\mathbf{Q} = \mathbf{G}\mathbf{G}^H$ represents the transmit covariance matrix and $\mathbf{H} = \mathbf{D}\widetilde{\mathbf{H}}$ represents the equivalent channel seen by the transmitter.

4.2. Problem Formulation. In literature, the research issues concern the problem of capacity maximization. In ad hoc networks, the optimization problem needs a more careful study. In fact, as suggested in [3, 10], the quality of the received signal measured by the signal-to-interference-plus-noise ratio is the criterion adopted for connectivity in cross layer design (also by the IEEE standardization comity), and it is commonly used by the WLAN devices manufacturers. As follows, a packet is successfully received if this criterion is above a prespecified threshold. Moreover, maximizing the overall system capacity may not lead always to the high throughput obtained under a quality of signal (QS) constraint due to critical links that fall below the packet capture threshold.

In this section, we focus on the optimality of the transmission strategy in the sense of minimizing the total transmit power under a QS constraint at each user. The global optimization problem is given in (14). Since the system capacity is an increasing function of the QS values of each user, boosting up these values can achieve a desired capacity. This fact will be examined later by simulation. On the other hand, the SINR of each stream is related to the QS by an increasing function. If we set a bigger QS threshold, then we obtain a better SINR values:

$$\begin{aligned} &\text{minimize} \quad \sum_{i=1}^{N} \operatorname{tr}(\mathbf{Q}_i) \\ &\text{subject to} \quad \frac{\operatorname{tr}\left(\mathbf{H}_{l(i),i}\mathbf{Q}_i\mathbf{H}_{l(i),i}^H\right)}{\operatorname{tr}\left(\mathbf{I}+\sum_{j=1\, j\neq i,l(i)}^{N}\mathbf{H}_{l(i),j}\mathbf{Q}_j\mathbf{H}_{l(i),j}^H\right)} \geq \delta_i \\ &\qquad\qquad i = 1\cdots N. \end{aligned} \tag{14}$$

However, to be more concise about this formulation, some points have to be recalled and clarified.

(i) We perform this study under the assumption that the decoder is independent.

(ii) In this work, we focus only on the precoder design, and we aim to alleviate the interuser interferences as this factor is the major limit in ad hoc networks.

(iii) The intrauser interference (the mutual interference between streams) is not addressed in our formulation. An optimal decoder can reduce this kind of interferences.

(iv) The signal quality is measured as the ratio between the power of the total desired signal to the power of the total interuser-interferences-plus-noise power.

(v) This transmission strategy can be seen as a step in an iterative joint precoder/decoder design for MIMO ad hoc networks. Although we do not address the decoder design in this work, we believe that a receiving scheme optimizing the SINR for each stream would be complementary to our transmit scheme.

(vi) The improvement due to utilizing the designed precoder represents the minimum gain that can be obtained (i.e., in the case where the decoder is not optimized). If we use an optimized decoder in parallel with the designed precoder, the gain will be boosted up.

This problem is not convex, and the solution cannot be obtained directly. In the next section we show that, by using matrix theory and semidefinite programming, we can solve this problem efficiently.

4.3. Semidefinite Optimization. Semidefinite programming (SDP) or semidefinite optimization (SDO) deals with convex optimization problems over symmetric positive semidefinite matrices [23]. Although this latter constraint is nonlinear, but convex, so by using such interior point methods we can still solve these problems with polynomial complexity and practical efficiency. A general formulation of a semidefinite optimization problem can be written as

$$\begin{aligned} &\text{minimize} \quad \operatorname{tr}(\mathbf{AX}) \\ &\text{subject to} \quad \operatorname{tr}(\mathbf{B}_i\mathbf{X}) = b_i \quad i = 1\cdots N. \\ &\qquad X \succeq 0 \end{aligned} \tag{15}$$

Note that $\mathbf{X} \succeq 0$ denotes that the matrix $\mathbf{X}$ is positive semidefinite.

From practical point of view, many problems can be casted into the form of convex optimization. The utility to convert a problem into convex one is that even if an analytical form of the solution may not exist, the problem can still be solved efficiently using numerical methods. Convex optimization can be solved iteratively using recently developed high-efficient interior point methods by converting the constrained problem into a sequence of unconstrained ones, which can be solved with Newton methods. Some program packages are developed to solve such kind of optimization problem, that is, SeDuMi [25]. This tool is encouraged for our problem since it can handle efficiently complex number manipulation.

4.4. Global Algorithm. The primal problem (14) turns out to be non-convex. However, by using some matrix manipulation tools we can convert it to a general SDP problem. Assuming that $\mathbf{F}_{i,j} = \mathbf{H}_{l(i),j}^H\mathbf{H}_{l(i),j}$ and knowing that $\operatorname{tr}(\mathbf{XY}) = \operatorname{tr}(\mathbf{YX})$, the constraint in (14) can be written as:

$$\operatorname{tr}(\mathbf{F}_{i,i}\mathbf{Q}_i) \geq \delta_i\left[M + \sum_{j=1\, j\neq i,l(i)}^{N} \operatorname{tr}\left(\mathbf{F}_{i,j}\mathbf{Q}_j\right)\right]. \tag{16}$$

Then, the problem (14) can be written as

$$\begin{aligned} &\text{minimize} \quad \sum_{i=1}^{N} \operatorname{tr}(\mathbf{Q}_i) \\ &\text{subject to} \quad \sum_{j=1}^{N} \operatorname{tr}\left(\mathbf{F}'_{i,j}\mathbf{Q}_j\right) \geq \delta_i M \quad i = 1\cdots N \end{aligned} \tag{17}$$

where $\mathbf{F}'_{i,i} = \mathbf{F}_{i,i}$, $\mathbf{F}'_{i,l(i)} = 0$ and $\mathbf{F}'_{i,j\neq i,l(i)} = -\delta_i\mathbf{F}_{i,j}$.

By concatenating the matrices $\mathbf{F}'_{i,j}$ and $\mathbf{Q}_i$ in diagonal matrices problem (17) can be written as:

$$\begin{aligned} &\text{minimize} \quad \operatorname{tr}(\mathbf{Q}) \\ &\text{subject to} \quad \operatorname{tr}(\mathbf{Z}_i\mathbf{Q}) \geq \delta_i M \quad i = 1\cdots N. \\ &\qquad \mathbf{Q} \succeq 0, \end{aligned} \tag{18}$$

where $\mathbf{Z}_i = \operatorname{diag}(\mathbf{F}'_{i,1}\cdots\mathbf{F}'_{i,N})$ and $\mathbf{Q} = \operatorname{diag}(\mathbf{Q}_1\cdots\mathbf{Q}_N)$. The operator $\mathbf{X} = \operatorname{diag}(\mathbf{Y}_1\cdots\mathbf{Y}_N)$ returns a square matrix $\mathbf{X}$ where the matrices $\mathbf{Y}_i$ represent its diagonal elements.

From [14] we know that the transmit signaling matrices $\mathbf{Q}_i$ are positive semidefinite. It follows that all eigenvalues of these matrices are nonnegative. On the other hand, we can show easily that the characteristic polynomial of the matrix $\mathbf{Q}$ is the multiplication of the characteristic polynomial of all its components $\mathbf{Q}_i$. Therefore, the positive semidefiniteness constraint is conserved. In fact, in problem (18) we show explicitly the positive semedefitness constraint of the matrix $\mathbf{Q}$, in order to be coherent with the general SDP form. The former of (18) is now convex due to the SDP formulation. The object function is linear, and the constraints are linear matrix inequalities. Thus, they are convex. The convexity

Centralized optimization
Build : $\mathbf{F}_{i,j}$ & $\mathbf{Z}_i$; $\forall i, j \in [1 \cdots N]$
$\mathbf{Z}_i = \mathbf{Z}_i/(M\delta_i)$; $\forall i \in [1 \cdots N]$
$\mathbf{V} = [\cdots \text{vec}(\mathbf{Z}_i), \text{vec}(\mathbf{Z}_{i+1}) \cdots]$;
$\mathbf{A} = [-\mathbf{I}_N, \mathbf{V}^T]$;
$\mathbf{b} = \text{ones}(N, 1)$;
$\mathbf{c} = [\text{zeros}(N, 1); \text{vec}(\mathbf{I}_{NM})]$;
$\text{K}.l = N$;
$\text{K}.s = NM$;
$\mathbf{x} = \text{sedumi}(\mathbf{A}, \mathbf{b}, \mathbf{c}, \text{K}, \text{pars})$;
$\mathbf{Q} = \text{mat}(\mathbf{x}(N + 1 : \text{end}))$;
extract $\mathbf{Q}_i$; $\forall i \in [1 \cdots N]$
$\mathbf{G}_i = \text{Cholesky}(\mathbf{Q}_i)$; $\forall i \in [1 \cdots N]$

Algorithm 3: SDP solver.

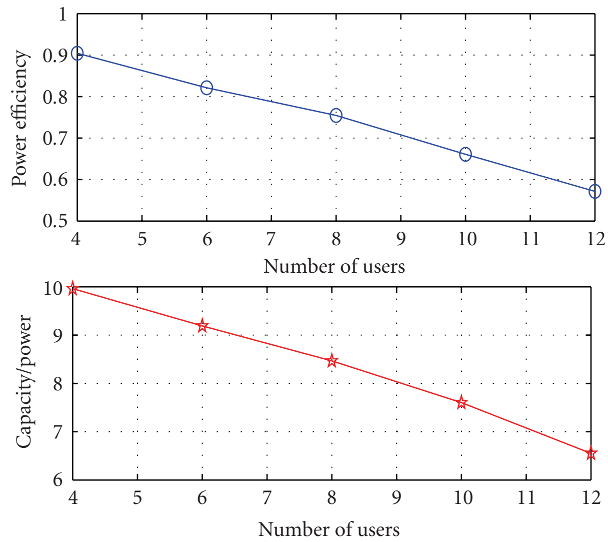

Figure 3: Power efficiency versus number of users for $M = 4$, $\delta = 0.1$.

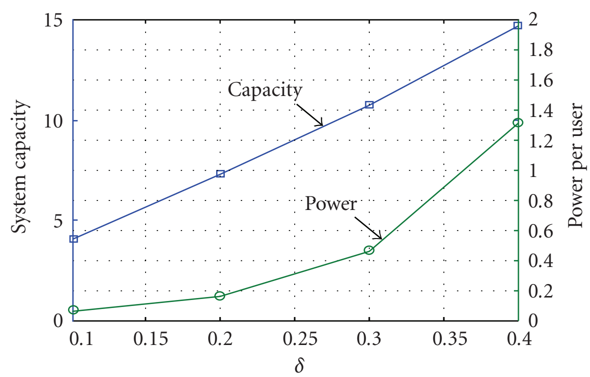

Figure 4: System capacity and total power versus different QoS threshold for $M = 4$, $N = 10$.

ensures that the global optimum exists, and it can be found in polynomial time. Once the matrix $\mathbf{Q}$ is obtained, $\mathbf{Q}_i$ can be extracted and factorized using Cholesky factorization to obtain the transmit gain matrices $\mathbf{G}_i$.

At the global optimum the constraints are active, that is, the inequality becomes equality. Thus, problem (18) is a straightforward form of (15). This can be proved by contradiction. Assume that the global optimum is reached and the constraints are still inactive. Therefore, by minimizing the total power (cost function) we can decrease the QS for all users until all the constraints become active, and this fact contradicts with the optimality of our solution.

A general approach to solve for problem (18) using SeDuMi [25] tool is proposed in Algorithm 3.

According to our proposition, a centralized optimization algorithm is performed. More precisely, the global CSI (for all user) must be available at a central processing unit which can calculate and feedback the transmit covariance matrices for each user. Although the centralization is not allowed in ad hoc networks, our global algorithm can be considered as a benchmark for other propositions in this field of research.

4.5. Numerical Results. In this section, we conduct an extensive set of simulations to access the performance of our proposed algorithm. These simulations were carried out using SeDuMi Matlab-based toolbox as shown in Algorithm 3. Basically, the metric used is the power efficiency [12]. This metric consists of the ratio between two power entities. The first one is the total power used to maintain the requested QS set, in the case without interferences. The second stands for the total power provided by our solver when interferences are taken into account. In fact, the latter power value stands for the optimum solution in our problem. As it can be perceived, the power efficiency metric will be always less than one. A closed to one power efficiency is obtained when powerful signaling schemes are used. We simulate different random networks with different number of nodes. Moreover, in each simulated network, the results are averaged on sufficiently high number of channel realizations. We adopt fixed antenna array size ($M = 4$) and QS thresholds ($\delta_i = 0.1$, for all i) in our simulations, unless stated otherwise.

Noting that since our problem design is not addressed before in MIMO ad hoc networks, we do not compare our results to other results in literature. More explicitly, we cannot compare a power-minimizing problem under capacity constraints with another power-minimizing problem under QS constraints. As stated before, our algorithm stands as a benchmark for other proposition in the same context.

Figure 3 shows the power efficiency performance with respect to the number of nodes. As it can be seen, the performance of the proposed algorithm depends tightly on the number of transmitters in the network. If the number of users is limited, the interuser interference level is limited, and the power efficiency is near to one. When the number of users increases, the interferences inundate the network, and the power efficiency will be reduced.

From capacity point of view, we depict in the same figure the ratio of the system capacity on the total transmit power.

Herein, the capacity is expressed by bit/s/Hz and the power is normalized with respect to the variance of the noise.

Recall that in our problem modeling we are not interested to maximize the total capacity by itself, directly. Nevertheless, by enforcing a certain set of QS thresholds we can fulfil some capacity requirements. In Figure 4, we depict the system capacity with respect to the QS threshold (δ). As it can be noticed, a higher capacity can be obtained when a higher threshold is imposed. However, imposing a high QS threshold will increase the total transmit power.

5. Conclusion

In this work, the optimum transmission strategies in MIMO ad hoc network are considered. We first deal with the capacity optimization problem. In this context, a fast, cooperative, and distributed algorithm is proposed in order to give an optimum solution without inundating the system by the feedback information. Our proposition is based on the quasi-Newton methods for solving nonlinear optimization problems. Compared to other algorithms in this context, our algorithm presents the better convergence rate and enjoys a provable and satisfactory convergence quality.

Then, we devise a novel problem formulation based on the received signal quality constraints rather than capacity constraints. This novel formulation is more beneficial for WLAN networks. To solve our problem, we converted it into SDP formulation, and we proposed a centralized algorithm to calculate the precoders using Sedumi toolbox. Finally, we evaluate our proposition through an extensive set of simulation. In the future we aim to develop a distributed version of the latter algorithm.

Appendix

The relation between the QS (quality of the received signal across the received antenna array) and the SINR (of each stream) is derived in this section. Assume that the power of the received signal is composed by two entities: the power of the desired signal (denoted by d), the power of the total interuser interference plus noise (denoted by n). Let d_i be the power of the stream i and d_{-i} the power of all the streams except the stream i. Obviously, $d = d_i + d_{-i}$. Now we can derive the relationship between the QS (denoted by c hereafter) and the SINR for the stream i:

$$\begin{aligned} \mathrm{SINR}_i &= \frac{d_i}{(d_{-i}+n)}, \\ c &= \frac{d}{n}. \end{aligned} \tag{A.1}$$

Then,

$$\mathrm{SINR}_i = \frac{1}{(d/d_i)(1-1/c)-1}. \tag{A.2}$$

It follows that the SINR is an increasing function of $c.c$ represents the QS reached by optimizing the precoder. If we set a bigger QS threshold, then we obtain a better SINR values. However we cannot control the SINR repartition between the streams (this is represented by the ratio d/d_i).

References

[1] I. E. Telatar, "Capacity of multi-antenna Gaussian channels," *European Transactions on Telecommunications*, vol. 10, no. 6, pp. 589–595, 1999.

[2] A. J. Paulraj, D. A. Gore, R. U. Nabar, and H. Bölcskei, "An overview of MIMO communications—a key to gigabit wireless," *Proceedings of the IEEE*, vol. 92, no. 2, pp. 198–218, 2004.

[3] M. Zorzi, J. Zeidler, A. Anderson, et al., "Cross-layer issues in MAC protocol design for MIMO ad hoc networks," *IEEE Wireless Communications*, vol. 13, no. 4, pp. 62–76, 2006.

[4] D. P. Palomar, J. M. Cioffi, and M. A. Lagunas, "Joint Tx-Rx beamforming design for multicarrier MIMO channels: a unified framework for convex optimization," *IEEE Transactions on Signal Processing*, vol. 51, no. 9, pp. 2381–2401, 2003.

[5] H. Sampath, P. Stoica, and A. Paulraj, "Generalized linear precoder and decoder design for MIMO channels using the weighted MMSE criterion," *IEEE Transactions on Communications*, vol. 49, no. 12, pp. 2198–2206, 2001.

[6] E. A. Jorswieck and H. Boche, "Transmission strategies for the MIMO MAC with MMSE receiver: average MSE optimization and achievable individual MSE region," *IEEE Transactions on Signal Processing*, vol. 51, no. 11, pp. 2872–2881, 2003.

[7] M. Bengtsson and B. Ottersten, "Optimal and suboptimal transmit beamforming," in *Handbook of Antennas in Wireless Communications*, CRC Press, 2000.

[8] E. Visotsky and U. Madhow, "Optimum beamforming using transmit antenna arrays," in *Proceedings of the 49th IEEE Vehicular Technology Conference*, pp. 851–856, 1999.

[9] S. Ye and R. S. Blum, "Optimized signaling for MIMO interference systems with feedback," *IEEE Transactions on Signal Processing*, vol. 51, no. 11, pp. 2839–2848, 2003.

[10] J. H. Winters, "Smart antenna techniques and their application to wireless ad hoc networks," *IEEE Wireless Communications*, vol. 13, no. 4, pp. 77–83, 2006.

[11] R. A. Iltis, S.-J. Kim, and D. A. Hoang, "Noncooperative iterative MMSE beamforming algorithms for ad hoc networks," *IEEE Transactions on Communications*, vol. 54, no. 4, pp. 748–759, 2006.

[12] D. Hoang and R. A. Iltis, "Noncooperative eigencoding for MIMO ad hoc networks," *IEEE Transactions on Signal Processing*, vol. 56, no. 2, pp. 865–869, 2008.

[13] R. S. Blum, "MIMO capacity with interference," *IEEE Journal on Selected Areas in Communications*, vol. 21, no. 5, pp. 793–801, 2003.

[14] Z. Motamedi and M. R. Soleymani, "On the optimality of beamforming in MIMO fading ad-hoc networks," in *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM '06)*, pp. 1–5, 2006.

[15] Z.-Q. Luo and J.-S. Pang, "Analysis of iterative water-filling algorithm for multiuser power control in digital subscriber lines," *EURASIP Journal on Applied Signal Processing*, 2006.

[16] K. W. Shum, K.-K. Leung, and C. W. Sung, "Convergence of iterative waterfilling algorithm for Gaussian interference channels," *IEEE Journal on Selected Areas in Communications*, vol. 25, no. 6, pp. 1091–1100, 2007.

[17] G. Arslan, M. F. Demirkol, and Y. Song, "Equilibrium efficiency improvement in MIMO interference systems: a

decentralized stream control approach," *IEEE Transactions on Wireless Communications*, vol. 6, no. 8, pp. 2984–2993, 2007.

[18] G. Scutari, D. P. Palomar, and S. Barbarossa, "Competitive design of multiuser MIMO systems based on game theory: a unified view," *IEEE Journal on Selected Areas in Communications*, vol. 26, no. 7, pp. 1089–1103, 2008.

[19] G. Scutari, D. P. Palomar, and S. Barbarossa, "The MIMO iterative waterfilling algorithm," *IEEE Transactions on Signal Processing*, vol. 57, no. 5, pp. 1917–1935, 2009.

[20] K. Fakih, J. F. Diouris, and G. Andrieux, "BMAC: beamformed MAC protocol with channel tracker in MANET using smart antennas," in *Proceedings of the 9th European Conference on Wireless Technology*, pp. 185–188, Manchester, UK, September 2006.

[21] D. G. Luenberger, *Linear and Nonlinear Programming*, Addison-Wesley, Reading, Mass, USA, 1984.

[22] J. Liu, Y. T. Hou, and H. D. Sherali, "Conjugate gradient projection approach for multi-antenna Gaussian broadcast channels," Tech. Rep., The Bradley Department of ECE, Virginia Tech, November 2006.

[23] S. Boyd and L. Vandenberghe, *Convex Optimization*, Stanford University.

[24] J. R. Magnus and H. Neudecker, *Matrix Differential Calculus with Applications in Statistics and Economics*, John Wiley & Sons, New York, NY, USA, 1989.

[25] J. F. Sturm, "Using SeDuMi 1.02, a MATLAB toolbox for optimization over symmetric cones," *Optimization Methods and Software*, vol. 11-12, no. 1, pp. 625–653, 1999.