Zero Forcing Precoding and Generalized Inverses

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***Abstract*— We consider the problem of linear zero forcing precoding design, and discuss its relation to the theory of generalized inverses in linear algebra. Special attention is given to a specific generalized inverse known as the pseudo-inverse. We begin with the standard design under the assumption of a total power constraint and prove that precoders based on the pseudo-inverse are optimal in this setting. Then, we proceed to examine individual per-antenna power constraints. In this case, the pseudo-inverse is not necessarily the optimal generalized inverse. In fact, finding the optimal inverse is non-trivial and depends on the specific performance measure. We address two common criteria, fairness and throughput, and show that the optimal matrices may be found using standard convex optimization methods. We demonstrate the improved performance offered by our approach using computer simulations.**

***Index Terms*— Zero forcing precoding, Beamforming, Generalized inverses, Semidefinite relaxation, per-antenna constraints.**

I. Introduction

Transmitter design for the multiple input single output (MISO) multiuser broadcast channel is an important problem in modern wireless communication systems. The main difficulty in this channel is that coordinated receive processing is not possible and that all the signal processing must be employed at the transmitter side. From an information theory perspective, the capacity region of this channel was only recently characterized [1]. From a signal processing point of view there are still many open questions and there is ongoing search aimed at finding efficient yet simple transmitter design algorithms. In particular, linear precoding schemes which seem to provide a promising tradeoff between performance and complexity received considerable attention [2]–[4].

The most common linear precoding scheme is zero forcing (ZF) beamforming. This simple method decouples the multiuser channel into multiple independent sub-channels, and reduces the design into a power allocation problem. It performs very well in the high signal-to-noise-ratio (SNR) regime or when the number of users is sufficiently large, and is known to provide full degrees of freedom [1]. Moreover, it is easy to generalize this method to incorporate non-linear dirty paper coding (DPC) mechanisms [1]. There are dozens of papers on ZF precoding focusing on different design criteria [4]–[10]. Among these, two common criteria are maximal fairness and maximum throughput. Due to its simplicity, ZF precoding is also an appealing transmission method in multiple input multiple output (MIMO) broadcast channels [11]–[15].

This work was supported by the EU 6th framework programme, via the NEWCOM network of excellence, by the Israel Science Foundation, and by the Glasberg-Klein Research Fund. A. Wiesel, Y. C. Eldar and S. Shamai (Shitz) are with the Technion, Israel Institute of Technology. Emails: amiw@tx.technion.ac.il, yonina@ee.technion.ac.il, and sshlomo@ee.technion.ac.il.

Traditionally, the transmitter is designed under the assumption of a total power constraint [1]–[10]. In practice, there is increasing interest in addressing more complicated scenarios, such as individual per-antenna power constraints. These are more realistic since each transmit antenna has its own power amplifier. Moreover, state-of-the-art communication systems will utilize multiple transmitters, which are geographically separated, but cooperatively send data to the receiving units. In such systems, it is clear that each transmitter has its own power restrictions. Recently, our work on linear precoding [2] was generalized to incorporate per-antenna power constraints in [16]. The problem with these methods is their prohibitive computational complexity. Therefore, ZF precoding methods were also generalized to address per-antenna power constraints [17]–[19].

Interestingly, ZF precoding design is highly related to the concept of generalized inverses in linear algebra [20]. This is easy to understand as the ZF precoder basically inverts the multiuser channel. Previous works using total power constraints [4]–[10] as well as individual per-antenna power constraints [17]–[19] began with the assumption that the precoder has the form of a specific generalized inverse known as the pseudo-inverse. We prove that the pseudo-inverse based precoder is optimal for maximizing any performance measure under a total power constraint. However, when per-antenna power constraints are involved, it is no longer optimal and other generalized inverses may outperform it. Finding the optimal inverse is non-trivial and depends on the specific performance criterion. We consider the two classical criteria, fairness and throughput, and transform the design problems into convex optimization programs which can be solved efficiently using off-the-shelves numerical packages.

The ZF precoding design for maximizing throughput turns out to be a non-convex optimization problem. One of the methods for handling such problems is to lift it into a higher dimension and then relax the non-convex constraints. Consequently, there is an increasing interest in analyzing the tightness of such relaxations [21], [22]. We apply this method and use Lagrange duality to prove that the relaxation is always tight in our setting.

The paper is organized as follows. In Section II we introduce the ZF precoding design problem. A brief review on generalized inverses is provided in Section III. Next, precoding under total power constraint is addressed in Section IV, whereas precoding under individual per-antenna power constraints is considered in Section V. A few numerical results are demonstrated in Section VI.

The following notation is used. Boldface upper case letters denote matrices, boldface lower case letters denote column vectors, and standard lower case letters denote scalars. The superscripts $(\cdot)^T$, $(\cdot)^{-1}$, $(\cdot)^{-}$ and $(\cdot)^{\dagger}$ denote the transpose, matrix inverse, generalized inverse and pseudo-inverse, respectively. The operators $\mathrm{Tr}\{\cdot\}$, $\|\cdot\|$ and $\|\cdot\|_F$ denote the trace, the Euclidean norm and the Frobenius norm, respectively. The operators $\mathrm{diag}\{\mathbf{d}\}$ and $\mathrm{diag}\{d_k\}$ denote a diagonal matrix with the elements $\mathbf{d}$ and d_k, respectively. The matrix $\mathbf{I}$ denotes the identity matrix, $\mathbf{1}$ is the vector of ones, and $\mathbf{e}_k$ is a zeros vector with a one in the k'th element. Finally, $\mathbf{X} \succeq \mathbf{0}$ means that $\mathbf{X}$ is positive semidefinite.

II. Problem formulation

We consider the standard MISO multiuser broadcast channel

$$y_k = \mathbf{h}_k^T \mathbf{x} + w_k, \quad k = 1, \cdots, K, \tag{1}$$

where y_k is the received sample of the k'th user, $\mathbf{h}_k$ is the length N channel to this user, $\mathbf{x}$ is the length N transmitted vector and w_k are zero mean and unit variance Gaussian noise samples. For simplicity, we use the following matrix notation

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{w}, \tag{2}$$

where $\mathbf{y} = [y_1, \cdots, y_K]^T$, $\mathbf{H} = [\mathbf{h}_1, \cdots, \mathbf{h}_K]^T$ and $\mathbf{w} = [w_1, \cdots, w_K]^T$. Throughout the paper we will assume that $K \leq N$ and $\mathbf{H}$ is full row-rank.

In linear precoding methods, the transmitted vector is a linear transformation of the information symbols (see Fig. 1)

$$\mathbf{x} = \mathbf{T}\mathbf{s}, \tag{3}$$

where the length K information vector $\mathbf{s}$ satisfies $E\{\mathbf{s}\mathbf{s}^T\} = \mathbf{I}$. The precoding matrix $\mathbf{T}$ is then designed to maximize some performance measure. Typical metrics involve functions of the received signal-to-interference-plus-noise ratios (SINRs):

$$q_k = \frac{[\mathbf{HT}]_{k,k}^2}{\sum_{j \neq k} [\mathbf{HT}]_{k,j}^2 + 1}, \quad k = 1, \cdots, K. \tag{4}$$

Such measures usually lead to untractable optimization problems. ZF precoding is a standard approach for addressing such problems which is known to provide a promising tradeoff between complexity and performance. Here, $\mathbf{T}$ is designed to achieve zero interference between the users, i.e., $[\mathbf{HT}]_{k,j} = 0$ if $k \neq j$. Moreover, without loss of generality, we assume that $[\mathbf{HT}]_{k,k} \geq 0$ for $k = 1, \cdots, K$. Using matrix notation, the ZF condition is equivalent to

$$\mathbf{HT} = \mathrm{diag}\{\sqrt{\mathbf{q}}\}, \tag{5}$$

where $\sqrt{\mathbf{q}} = \left[\sqrt{q_1}, \cdots, \sqrt{q_K}\right]^T$ is a vector with non-negative elements. These restrictions simplify the design and decouple the broadcast channel into K independent scalar sub-channels

$$y_k = \sqrt{q_k} s_k + w_k, \quad k = 1, \cdots, K. \tag{6}$$

Traditionally, precoders are designed subject to a total power constraint of the form

$$E\{\|\mathbf{x}\|^2\} = \mathrm{Tr}\left\{\mathbf{T}\mathbf{T}^T\right\} = \|\mathbf{T}\|_F^2 \leq P, \tag{7}$$

where $P > 0$. As we will show in the next sections, the total power constraint simplifies the design problem and leads to simple and efficient precoders. Nonetheless, in practice, many systems are subject to individual per antenna power constraints as illustrated in Fig. 1,

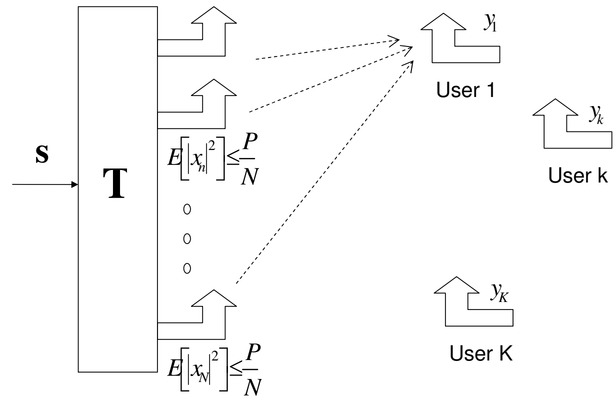

Fig. 1. ZF precoding with per-antenna power constraints.

$$E\{|x_n|^2\} = \left[\mathbf{T}\mathbf{T}^T\right]_{n,n} \leq \frac{P}{N}, \qquad n = 1, \cdots, N. \tag{8}$$

In order to properly formulate the design problem we need to define its objective. Depending on the application, different criteria may be considered. Two typical performance measures are:

- Fairness: $f(\mathbf{q}) = \min_k q_k$
- Throughput: $f(\mathbf{q}) = \sum_k \log(1 + q_k)$

Therefore, we treat two fundamental design problems. In section IV, we consider the optimal $\mathbf{T}$ for maximizing $f(\mathbf{q})$ subject to the zero forcing constraint and a total power constraint. In Section V we generalize the setting to individual per-antenna power constraints. Both fairness and throughput are addressed in the two problems.

III. Generalized inverses

The ZF precoding design problem is highly related to the concept of generalized inverses in linear algebra [20], [23]. Therefore, we now briefly review this topic.

Formally, the generalized inverse of a size $K \times N$ matrix $\mathbf{H}$ is any matrix $\mathbf{H}^-$ of size $N \times K$ such that $\mathbf{H}\mathbf{H}^-\mathbf{H} = \mathbf{H}$. If $\mathbf{H}$ is square and invertible, then $\mathbf{H}^- = \mathbf{H}^{-1}$. Otherwise, the generalized inverse is not unique. The pseudo-inverse $\mathbf{H}^\dagger$ is a specific generalized inverse that satisfies $\mathbf{H}\mathbf{H}^\dagger\mathbf{H} = \mathbf{H}$, $\mathbf{H}^\dagger\mathbf{H}\mathbf{H}^\dagger = \mathbf{H}^\dagger$, $\left(\mathbf{H}^\dagger\mathbf{H}\right)^T = \mathbf{H}^\dagger\mathbf{H}$ and $\left(\mathbf{H}\mathbf{H}^\dagger\right)^T = \mathbf{H}\mathbf{H}^\dagger$. It is unique and is known to have minimal Frobenius norm among all the generalized inverses.

In this paper, we assume that $\mathbf{H}$ is a full row-rank matrix. Under this assumption, the generalized inverse is any matrix $\mathbf{H}^-$ such that $\mathbf{H}\mathbf{H}^- = \mathbf{I}$. The pseudo-inverse is given by $\mathbf{H}^\dagger = \mathbf{H}^T\left(\mathbf{H}^T\mathbf{H}\right)^{-1}$ and any generalized inverse may be expressed as

$$\mathbf{H}^- = \mathbf{H}^\dagger + \mathbf{P}_\perp \mathbf{U}, \tag{9}$$

where $\mathbf{P}_\perp = \mathbf{I} - \mathbf{H}^\dagger\mathbf{H}$ is the orthogonal projection onto the null space of $\mathbf{H}$ and $\mathbf{U}$ is an arbitrary matrix.

Using the above definitions and properties, it is easy to see the relation between ZF precoding and generalized inverses.

Due to (5), the general structure of any ZF precoder is

$$\begin{aligned}\mathbf{T} &= \mathbf{H}^{-}\mathrm{diag}\left\{\sqrt{\mathbf{q}}\right\} \\ &= \left[\mathbf{H}^{\dagger}+\mathbf{P}_{\perp}\mathbf{U}\right]\mathrm{diag}\left\{\sqrt{\mathbf{q}}\right\}. \end{aligned} \tag{10}$$

This reduces the precoder design problem to an optimization with respect to the elements of $\mathbf{q}$ and the specific choice of generalized inverse via $\mathbf{U}$. Roughly speaking, we will show that the optimization of $\mathbf{q}$ depends on the design criteria (fairness vs. throughput), whereas the optimization of $\mathbf{U}$ is associated with the power constraints (total vs. per-antenna). In fact, the discussion above suggests that the pseudo-inverse ($\mathbf{U}=\mathbf{0}$) is optimal with respect to the total power constraint which is associated with the Frobenius norm. We will show that when more complicated constraints are involved the optimal $\mathbf{U}$ is not necessarily zero.

IV. Total power constraint

The problem of ZF precoding design under a total power constraint has already received considerable attention [4]–[9]. To our knowledge, in all of the previous works it was taken for granted that the precoder $\mathbf{T}$ must be based on the pseudo-inverse rather than any other generalized inverse. This simplified the design and reduced it to a power allocation problem. The next theorem proves that the pseudo-inverse is indeed optimal under a total power constraint:

Theorem 1: Let $f(\cdot)$ be an arbitrary function of $\mathbf{q}$. The optimal solution to

$$\begin{array}{ll}\max_{\mathbf{T},\mathbf{q}} & f(\mathbf{q}) \\ \mathrm{s.t.} & \mathbf{HT}=\mathrm{diag}\left\{\sqrt{\mathbf{q}}\right\}; \\ & \mathrm{Tr}\left\{\mathbf{TT}^{T}\right\}\le P,\end{array} \tag{11}$$

is $\mathbf{T}^{\mathrm{opt}}=\mathbf{H}^{\dagger}\mathrm{diag}\left\{\sqrt{\mathbf{q}^{\mathrm{opt}}}\right\}$ where $\mathbf{q}^{\mathrm{opt}}$ is the solution to

$$\begin{array}{ll}\max_{\mathbf{q}\ge\mathbf{0}} & f(\mathbf{q}) \\ \mathrm{s.t.} & \sum_k q_k\left[\left(\mathbf{H}^{\dagger}\right)^{T}\mathbf{H}^{\dagger}\right]_{k,k}\le P.\end{array} \tag{12}$$

Proof: Due to (10), we can rewrite (11) as

$$\begin{array}{ll}\max_{\mathbf{T},\mathbf{q}} & f(\mathbf{q}) \\ \mathrm{s.t.} & \mathrm{Tr}\left\{\left[\mathbf{H}^{\dagger}+\mathbf{P}_{\perp}\mathbf{U}\right]\mathrm{diag}\left\{\mathbf{q}\right\}\left[\mathbf{H}^{\dagger}+\mathbf{P}_{\perp}\mathbf{U}\right]^{T}\right\}\le P.\end{array} \tag{13}$$

Now,

$$\begin{aligned}&\mathrm{Tr}\left\{\left[\mathbf{H}^{\dagger}+\mathbf{P}_{\perp}\mathbf{U}\right]\mathrm{diag}\left\{\mathbf{q}\right\}\left[\mathbf{H}^{\dagger}+\mathbf{P}_{\perp}\mathbf{U}\right]^{T}\right\} \\ &\qquad\ge \mathrm{Tr}\left\{\mathbf{H}^{\dagger}\mathrm{diag}\left\{\mathbf{q}\right\}\left[\mathbf{H}^{\dagger}\right]^{T}\right\},\end{aligned} \tag{14}$$

since $\mathbf{P}_{\perp}\mathbf{H}^{\dagger}=\mathbf{0}$ and $\mathbf{P}_{\perp}\mathbf{U}\mathrm{diag}\left\{\mathbf{q}\right\}\mathbf{U}^{T}\mathbf{P}_{\perp}\succeq\mathbf{0}$. Therefore, the following problem

$$\begin{array}{ll}\max_{\mathbf{T},\mathbf{q}} & f(\mathbf{q}) \\ \mathrm{s.t.} & \mathrm{Tr}\left\{\mathbf{H}^{\dagger}\mathrm{diag}\left\{\mathbf{q}\right\}\left[\mathbf{H}^{\dagger}\right]^{T}\right\}\le P,\end{array} \tag{15}$$

is a relaxation of (13) and an upper bound on its optimal value. However, this bound can be achieved by choosing $\mathbf{U}=0$ and is therefore tight. Finally, choosing $\mathbf{U}=\mathbf{0}$ is equivalent to $\mathbf{T}=\mathbf{H}^{\dagger}\mathrm{diag}\left\{\sqrt{\mathbf{q}}\right\}$ and results in (12). ■

The importance of this result stems from the fact that (12) is a simple power allocation problem. In particular, assuming that $f(\mathbf{q})$ is concave in $\mathbf{q}\ge\mathbf{0}$, the problem is a concave maximization with one linear constraint. For example, in the throughput problem the problem boils down to [5], [7]

$$\begin{array}{ll}\max_{\mathbf{q}\ge 0} & \sum_k \log\left(1+q_k\right) \\ \mathrm{s.t.} & \sum_k q_k\left[\left(\mathbf{HH}^{T}\right)^{-1}\right]_{k,k}\le P,\end{array} \tag{16}$$

which can be solved using the well known water filling solution.

V. Per-antenna power constraints

We now treat the more difficult case of ZF precoding design under individual per-antenna power constraints. Here, the pseudo-inverse is not necessarily the optimal generalized inverse. In fact, finding the optimal inverse is a non-trivial optimization problem which depends on the specific performance measure. Therefore, we begin by presenting general performance bounds and then address the two standard metrics, fairness and throughput, separately.

The optimal ZF precoder with per-antenna power constraints for maximizing an arbitrary objective function $f(\mathbf{q})$ is the solution to

$$f(\mathbf{q}^{\mathrm{opt}})=\left\{\begin{array}{ll}\max_{\mathbf{T},\mathbf{q}\ge\mathbf{0}} & f(\mathbf{q}) \\ \mathrm{s.t.} & \mathbf{HT}=\mathrm{diag}\left\{\sqrt{\mathbf{q}}\right\}; \\ & \left[\mathbf{TT}^{T}\right]_{n,n}\le\frac{P}{N},\quad\forall\, n.\end{array}\right. \tag{17}$$

In general, (17) is a difficult non-convex optimization problem. However, we can easily bound its optimal value:

$$L\le f(\mathbf{q}^{\mathrm{opt}})\le U \tag{18}$$

where

$$L=\left\{\begin{array}{ll}\max_{\mathbf{q}\ge\mathbf{0}} & f(\mathbf{q}) \\ \mathrm{s.t.} & \sum_k q_k\left[\mathbf{H}^{\dagger}\right]_{n,k}^{2}\le\frac{P}{N},\quad\forall\, n,\end{array}\right. \tag{19}$$

$$U=\left\{\begin{array}{ll}\max_{\mathbf{q}\ge\mathbf{0}} & f(\mathbf{q}) \\ \mathrm{s.t.} & \sum_k q_k\left[\left(\mathbf{H}^{\dagger}\right)^{T}\mathbf{H}^{\dagger}\right]_{k,k}\le P.\end{array}\right. \tag{20}$$

As proof, just note that the lower bound in (19) can be achieved by using the pseudo-inverse $\mathbf{T}=\mathbf{H}^{\dagger}\mathrm{diag}\left\{\sqrt{\mathbf{q}}\right\}$. Indeed, this $\mathbf{T}$ yields $\left[\mathbf{TT}^{T}\right]_{n,n}=\sum_k q_k\left[\mathbf{H}^{\dagger}\right]_{n,k}^{2}$ as expressed in the constraints of (19). The upper bound is equal to the optimal value of (11) or (12). Clearly, if $\mathbf{T}$ is feasible for (17) then it will also be feasible for (11). Therefore, (11) is a relaxation of (17) and results in an upper bound.

Although simple, these bounds provide some insight on the problem without the need for solving (17) explicitly. Indeed, a sufficient condition for the optimality of the pseudo-inverse is $U=L$. Moreover, when the condition does not hold, we can bound the performance loss due to using the pseudo-inverse by examining the value of $U-L$. Depending on the application, if this difference is sufficiently small, then there is no need to solve (17). Otherwise, there may be an advantage in finding the optimal generalized inverse. This optimization is usually more complicated and depends on the specific performance measure. In the following sections, we treat two standard objectives: fairness and throughput.

A. Fairness

We begin with the fairness criterion which yields the following optimization problem:

$$\begin{array}{ll} \max_{\mathbf{T},\mathbf{q}\geq \mathbf{0}} & \min_k q_k \\ \text{s.t.} & \mathbf{HT} = \text{diag}\left\{\sqrt{\mathbf{q}}\right\}; \\ & \left[\mathbf{TT}^T\right]_{n,n} \leq \frac{P}{N}, \quad \forall\, n. \end{array} \tag{21}$$

As can be expected, the fairness criterion implies that

$$\mathbf{q} = q\mathbf{1}, \tag{22}$$

for some $q \geq 0$ is optimal. As proof, assume that the optimal solution is $\overline{\mathbf{T}}$ and $\overline{\mathbf{q}} \geq \mathbf{0}$. If $\overline{q}_k = 0$ for some k then $\mathbf{T} = \mathbf{0}$ and $\mathbf{q} = \mathbf{0}$ are also optimal. Otherwise, define $q = \min_k \overline{q}_k$, $\mathbf{T} = \sqrt{q}\overline{\mathbf{T}}\left[\text{diag}\left\{\sqrt{\overline{\mathbf{q}}}\right\}\right]^{-1}$ and $\mathbf{q} = q\mathbf{1}$. Then, $\mathbf{T}$ and $\mathbf{q}$ are also feasible (since $q/\overline{q}_k \leq 1$ for all k) and provide the same objective value as $\overline{\mathbf{T}}$.

Interestingly, the observation that (22) is optimal in the fairness case, provides a simple sufficient condition for the optimality of the pseudo-inverse:

Proposition 1: Let

$$a_n = \left[\mathbf{H}^\dagger\left(\mathbf{H}^\dagger\right)^T\right]_{n,n}, \quad n = 1, \cdots, N. \tag{23}$$

If $a_n = a$ for all n are equal, then the optimal solution to (28) is $\mathbf{T} = \sqrt{q}\mathbf{H}^\dagger$ where $q = P/(Na)$.

Proof: Due to (22), the constraints of (19) are simply $qa_n \leq P/N$. If $a_n = a$ then the feasible set is $q \leq P/(Na)$. Similarly, the feasible set of (20) can be simplified to

$$q\text{Tr}\left\{\left(\mathbf{H}^\dagger\right)^T\mathbf{H}^\dagger\right\} = q\text{Tr}\left\{\mathbf{H}^\dagger\left(\mathbf{H}^\dagger\right)^T\right\} = qNa \leq P. \tag{24}$$

Consequently, the sets are identical and $L = U$. ∎

Proposition 1 holds in many practical deterministic channels. For example, it applies whenever the right singular vectors of $\mathbf{H}$ are the Fourier vectors. More details on such matrices and geometrically uniform frames can be found in [24]. Moreover, the condition holds asymptotically in the number of users under different random $\mathbf{H}$ models. Two typical examples that arise in wireless communication systems are when the elements of $\mathbf{H}$ are zero mean, equal variance and independent Gaussian random variables [25], and when $\mathbf{H}$ is modeled using the circular Wyner model [18], [19].

We now continue with the general solution to (21). Due to (10) and (22) we obtain

$$\mathbf{T} = \sqrt{q}\left[\mathbf{H}^\dagger + \mathbf{P}_\perp\mathbf{U}\right], \tag{25}$$

for some $\mathbf{U}$. This reduces the problem to

$$\begin{array}{ll} \max_{\mathbf{U},q\geq 0} & q \\ \text{s.t.} & q\|\left[\mathbf{H}^\dagger + \mathbf{P}_\perp\mathbf{U}\right]^T\mathbf{e}_n\|^2 \leq \frac{P}{N}, \quad \forall\, n. \end{array} \tag{26}$$

Now, it is clear that

$$q = \frac{P}{N\max_n \|\left[\mathbf{H}^\dagger + \mathbf{P}_\perp\mathbf{U}\right]^T\mathbf{e}_n\|^2}, \tag{27}$$

where $\mathbf{U}$ is the solution to

$$\begin{array}{ll} \min_{\mathbf{U},t} & t \\ \text{s.t.} & \left\|\left(\mathbf{H}^\dagger + \mathbf{P}_\perp\mathbf{U}\right)^T\mathbf{e}_n\right\| \leq t \quad \forall\, n. \end{array} \tag{28}$$

Problem (28) is a convex second order cone program (SOCP). It can be solved efficiently using standard optimization packages [26], [27].

B. Throughput

Next, we consider the throughput objective function:

$$\begin{array}{ll} \max_{\mathbf{T},\mathbf{q}} & \sum_k \log\left(1+q_k\right) \\ \text{s.t.} & \mathbf{HT} = \text{diag}\left\{\sqrt{\mathbf{q}}\right\}; \\ & \left[\mathbf{TT}^T\right]_{n,n} \leq \frac{P}{N}, \quad \forall\, n. \end{array} \tag{29}$$

This is a difficult non-concave maximization problem due to the squared roots of $\mathbf{q}$. In the sequel, we will show how it can be solved using modern convex optimization tools. But before that, we examine the optimality of the pseudo-inverse using our general bounds and obtain the following proposition:

Proposition 2: Let a_n be defined as in (23). If $a_n = a$ for all n are equal and the power P is sufficiently large, then the optimal solution to (28) is $\mathbf{T} = \sqrt{q}\mathbf{H}^\dagger$ where $q = P/(Na)$.

Proof: The solution is feasible for (29) and provides an optimal value of $K\log(1+q)$ where $q = P/(Na)$. It remains to show that this value is equal to the upper bound in (20). But this is simple since uniform power allocation is the optimal solution to (20) with $f(\mathbf{q}) = \sum_k \log\left(1+q_k\right)$ when the power P is sufficiently large [28]. Thus, $\mathbf{q} = q\mathbf{1}$ for some $q \geq 0$, and $a_n = a$ for all n implies that $U = K\log(1+q)$. ∎

In the remainder of this section, we provide an exact solution to (29) which finds the optimal generalized inverse. For this purpose, it is convenient to rewrite the problem using the notation in (1), i.e., $\mathbf{h}_k = \mathbf{H}^T\mathbf{e}_k$ and $\mathbf{t}_k = \mathbf{T}\mathbf{e}_k$ for $k = 1, \cdots, K$. Thus, $q_k = \left(\mathbf{h}_k^T\mathbf{t}_k\right)^2$ and (29) is equivalent to

$$\begin{array}{ll} \max_{\mathbf{t}_k} & \log\left|\mathbf{I} + \text{diag}\left\{\left(\mathbf{h}_k^T\mathbf{t}_k\right)^2\right\}\right| \\ \text{s.t.} & \left(\mathbf{h}_j^T\mathbf{t}_k\right)^2 = 0, \quad \forall\, k \neq j; \\ & \sum_k \left[\mathbf{t}_k\mathbf{t}_k^T\right]_{n,n} \leq \frac{P}{N}, \quad \forall\, n. \end{array} \tag{30}$$

Next, we linearize the quadratic terms by defining $\mathbf{T}_k = \mathbf{t}_k\mathbf{t}_k^T \succeq \mathbf{0}$ for $k = 1, \cdots, K$, which results in

$$\begin{array}{ll} \max_{\mathbf{T}_k} & \log\left|\mathbf{I} + \text{diag}\left\{\mathbf{h}_k^T\mathbf{T}_k\mathbf{h}_k\right\}\right| \\ \text{s.t.} & \mathbf{h}_j^T\mathbf{T}_k\mathbf{h}_j = 0, \quad \forall\, k \neq j; \\ & \sum_k \left[\mathbf{T}_k\right]_{n,n} \leq \frac{P}{N}, \quad \forall\, n; \\ & \mathbf{T}_k \succeq \mathbf{0}, \quad \forall\, k; \\ & \text{rank}\left(\mathbf{T}_k\right) = 1, \quad \forall\, k. \end{array} \tag{31}$$

The only non-convex constraints in (31) are the rank-one restrictions. Therefore, we now relax the problem and omit these problematic constraints to obtain

$$\begin{array}{ll} \max_{\mathbf{T}_k} & \log\left|\mathbf{I} + \text{diag}\left\{\mathbf{h}_k^T\mathbf{T}_k\mathbf{h}_k\right\}\right| \\ \text{s.t.} & \mathbf{h}_j^T\mathbf{T}_k\mathbf{h}_j = 0, \quad \forall\, k \neq j; \\ & \sum_k \left[\mathbf{T}_k\right]_{n,n} \leq \frac{P}{N}, \quad \forall\, n; \\ & \mathbf{T}_k \succeq \mathbf{0}, \quad \forall\, k. \end{array} \tag{32}$$

Problem (32) is a standard determinant maximization (MAXDET) program subject to linear matrix inequalities [29]. It is a convex optimization problem and there are off-the-shelf numerical optimization packages which can solve it efficiently [27]. If the optimal $\mathbf{T}_k$ are all of rank-one, then we can recover $\mathbf{t}_k$ from them and find the optimal solution to (29). Fortunately, the following theorem proves that the relaxation is always tight:

Theorem 2: Problem (32) always has a solution with rank-one matrices. This solution can be found as follows: Let $\mathbf{T}_k^{\text{opt}}$

for $k = 1, \cdots, K$ be a (possibly high rank) optimal solution to (32). For each k define $\mathbf{t}_k$ as the optimal solution to

$$\begin{array}{ll} \max_{\mathbf{t}} & \mathbf{h}_k^T \mathbf{t} \\ \text{s.t.} & \mathbf{h}_j^T \mathbf{t} = 0, \quad \forall\, k \neq j; \\ & -\beta_{k,n} \leq [\mathbf{t}]_n \leq \beta_{k,n} \quad \forall\, n, \end{array} \tag{33}$$

where $\beta_{k,n} = \sqrt{\left[\mathbf{T}_k^{\mathrm{opt}}\right]_{n,n}}$. Then, $\overline{\mathbf{T}}_k^{\mathrm{opt}} = \mathbf{t}_k \mathbf{t}_k^T$ for $k = 1, \cdots, K$ is a rank-one solution to (32).

Proof: See Appendix I. ■

In practice, our experience shows that the MAXDET software [27] usually provides a rank-one solution automatically. If it does not, then the theorem provides a constructive method for finding a rank-one solution by solving K simple linear programs of the form (33).

VI. Numerical results

We now demonstrate our results using two numerical examples. In the first example, we consider the fairness ZF precoding design under individual per-antenna power constraints. We simulate a system with $K = 3$ users and $P = 1$ (In the fairness case, the value of P is not important as it just scales the resulting power). The elements of the matrix $\mathbf{H}$ are randomly generated as independent, zero mean and unit variance Gaussian random variables. We estimate the average received power q in (25). For comparison, we also estimate this mean power when we assume $\mathbf{U} = \mathbf{0}$, i.e., restrict the precoder to be a standard pseudo-inverse, and when we replace the per-antenna power constraints with a total power constraint. The results are presented in Fig. 2 as a function of the number of transmit antennas N. As expected, the stricter per-antenna constraints result in a lower received power. However, the graph shows that part of this loss can be recovered by optimizing $\mathbf{U}$ and finding the appropriate generalized inverse.

In the second example, we consider the maximization of the throughput under the same setting as before except that now $N = 4$ and we simulate different Ps. The estimated sum-rates are provided in Fig. 3. Again, it is easy to see the degradation in performance due to the individual per-antenna power constraints, as well as the advantage of optimizing the generalized inverse.

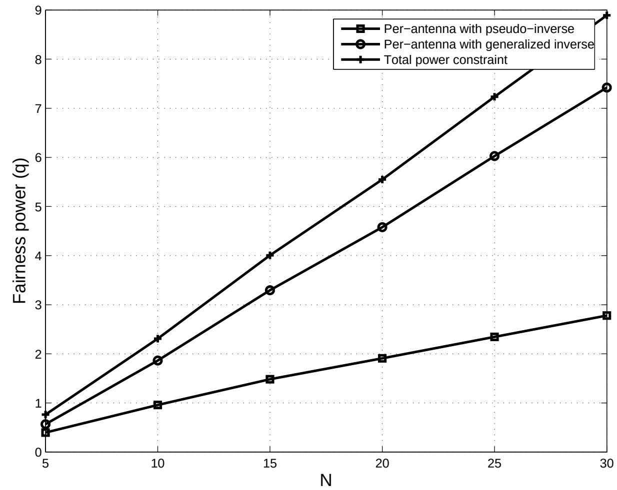

Fig. 2. Maximal fairness ZF precoding for different N.

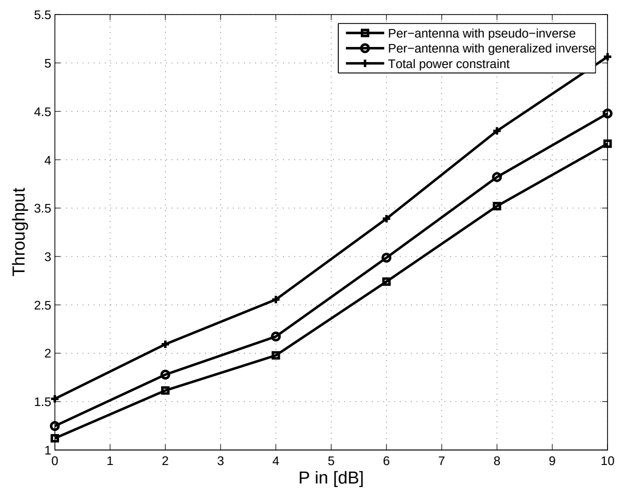

Fig. 3. Maximal throughput ZF precoding for different P.

VII. Conclusion

In this paper we consider ZF precoding design in MISO broadcast channels. We discussed the intimate relation between ZF precoding and the theory of generalized inverses. Our results show that designing the precoders based on the standard pseudo-inverse is optimal under the assumption of a total power constraint. However, when more complex power constraints are involved, e.g., individual total per-antenna power constraints, the pseudo-inverse is no longer sufficient and other generalized inverses may provide better performance. In general, finding the optimal inverse is a difficult optimization problem which is highly dependent on the specific design criterion. We consider two classical criteria, fairness and throughput and demonstrate how to transform these problems into standard convex optimization programs.

Using the methods that we developed it is straightforward to generalize the setting to a variety of applications. More practical criteria may be addressed using the semidefinite relaxation approach as long as these are concave in the received powers, e.g., weighted sum-rate. In addition, other power constraints may be implemented, e.g., the expected value of the squared norm of sub-blocks of $\mathbf{x}$. Such constraints may be important in modern systems where multiple base stations, each with multiple antennas, cooperatively transmit data to the same users.

Precoding with generalized power constraints is an important problem in modern communication systems and there are still many open questions. More advanced linear precoding schemes should be addressed. For example, it is well known that in low SNR conditions, and under channel uncertainty, regularizing the pseudo-inverse can considerably improve the performance. It is interesting to examine this property in the context of generalized inverses. Future work should also address the implications of our results on non-linear schemes such as ZF DPC precoding.

Another extension of our work is to consider the well known duality between receive and transmit processing. It has already been shown in [16] that precoding with per-antenna power constraints is the dual of decoding under noise uncertainty conditions. ZF decoding using the pseudo-inverse (the decorrelator) is probably the most common decoding algorithm. Our results suggest that other generalized inverses may outperform it under uncertainty conditions.

Appendix I
Proof of Theorem 2

First, we rewrite (32) using additional slack variables:

$$\begin{array}{ll} \max_{\mathbf{p}_k \geq \mathbf{0}} & \sum_k \log\left(1+\gamma_k\left(\mathbf{p}_k\right)\right) \\ \text{s.t.} & \sum_k \left[\mathbf{p}_k\right]_n \leq \frac{P}{N}, \quad \forall\, n, \end{array} \tag{34}$$

where

$$\gamma_k\left(\mathbf{p}_k\right) = \left\{ \begin{array}{ll} \max_{\mathbf{T}_k \succeq \mathbf{0}} & \mathbf{h}_k^T \mathbf{T}_k \mathbf{h}_k \\ \text{s.t.} & \mathbf{h}_j^T \mathbf{T}_k \mathbf{h}_j = 0, \quad \forall\, k \neq j; \\ & \left[\mathbf{T}_k\right]_{n,n} \leq \left[\mathbf{p}_k\right]_n, \quad \forall\, n. \end{array} \right. \tag{35}$$

Using this new formulation, all we need to show is that (35) always has an optimal solution of rank-one. In fact we will prove a more general result:

Lemma 1: Consider the following optimization problem

$$\mathcal{S} = \left\{ \begin{array}{ll} \max_{\mathbf{Q} \succeq \mathbf{0}} & \mathbf{c}^T \mathbf{Q} \mathbf{c} \\ \text{s.t.} & \operatorname{Tr}\left\{\mathbf{Q}\mathbf{A}_i\right\} \leq b_i, \quad i = 1, \cdots, I, \end{array} \right. \tag{36}$$

where $b_i \geq 0$ and $\mathbf{A}_i \succeq \mathbf{0}$. If $\mathcal{S}$ is bounded, then there is always a rank-one solution to (36).

Proof: See Appendix II. ■

Problem (35) is a special case of Lemma 1. Due to $\mathbf{T}_k \succeq \mathbf{0}$ and $\left[\mathbf{T}_k\right]_{n,n} \leq \left[\mathbf{p}_k\right]_n$ its optimal value is bounded, and it must have an optimal solution of rank-one. The fact that (35) has an optimal rank-one solution also provides a simple way of finding it. Let $\mathbf{T}_k^{\mathrm{opt}}$ be the optimal solution of (35) for some k. Then,

$$\gamma_k\left(\mathbf{p}_k\right) = \left\{ \begin{array}{ll} \max_{\mathbf{T}_k \succeq \mathbf{0}} & \mathbf{h}_k^T \mathbf{T}_k \mathbf{h}_k \\ \text{s.t.} & \mathbf{h}_j^T \mathbf{T}_k \mathbf{h}_j = 0, \quad \forall\, k \neq j; \\ & \left[\mathbf{T}_k\right]_{n,n} \leq \left[\mathbf{T}_k^{\mathrm{opt}}\right]_{n,n}, \quad \forall\, n. \end{array} \right. \tag{37}$$

Due to Lemma 1, we can restrict the attention to rank-one matrices $\mathbf{T}_k = \mathbf{t}_k \mathbf{t}_k^T$ and solve

$$\gamma_k\left(\mathbf{p}_k\right) = \left\{ \begin{array}{ll} \max_{\mathbf{t}_k} & \left(\mathbf{t}_k^T \mathbf{h}_k\right)^2 \\ \text{s.t.} & \mathbf{t}_k^T \mathbf{h}_j = 0, \quad \forall\, k \neq j; \\ & \left(\mathbf{t}_k^T \mathbf{e}_n\right)^2 \leq \left[\mathbf{T}_k^{\mathrm{opt}}\right]_{n,n}, \quad \forall\, n. \end{array} \right. \tag{38}$$

Now, if $\mathbf{t}_k$ is optimal for (38) then $-\mathbf{t}_k$ is also optimal (it is feasible and provides the same objective value). Therefore, without loss of generality we can assume that $\mathbf{t}_k^T \mathbf{h}_k \geq 0$ and use the monotonicity of x^2 in $x \geq 0$ to obtain

$$\sqrt{\gamma_k\left(\mathbf{p}_k\right)} = \left\{ \begin{array}{ll} \max_{\mathbf{t}_k} & \mathbf{t}_k^T \mathbf{h}_k \\ \text{s.t.} & \mathbf{t}_k^T \mathbf{h}_j = 0, \quad \forall\, k \neq j; \\ & \left(\mathbf{t}_k^T \mathbf{e}_n\right)^2 \leq \left[\mathbf{T}_k^{\mathrm{opt}}\right]_{n,n}, \quad \forall\, n, \end{array} \right. \tag{39}$$

which can also be expressed as the linear programs in (33).

Appendix II
Proof of Lemma 1

We begin by eliminating all the constraints for which $b_i = 0$. Assume that $b_j = 0$ for all j in $J = \{j_1, \cdots, j_J\}$, and positive for all other indices. Define $\overline{\mathbf{A}} = [\mathbf{A}_{j_1}, \cdots, \mathbf{A}_{j_J}]$, and let $\mathbf{P} = \mathbf{I} - \overline{\mathbf{A}}\overline{\mathbf{A}}^\dagger$ be the orthogonal projection onto the null space of $\overline{\mathbf{A}}$. Now, $\operatorname{Tr}\{\mathbf{Q}\mathbf{A}_j\} = 0$ for all $j \in J$ if and only if $\mathbf{Q} = \mathbf{P}\mathbf{Q}\mathbf{P}$. Thus, $\mathcal{S}$ in (36) is equivalent to

$$\begin{array}{ll} \max_{\mathbf{Q} \succeq \mathbf{0}} & \mathbf{c}^T \mathbf{P}\mathbf{Q}\mathbf{P}\mathbf{c} \\ \text{s.t.} & \operatorname{Tr}\left\{\mathbf{P}\mathbf{Q}\mathbf{P}\mathbf{A}_i\right\} \leq b_i, \quad i \notin J, \\ & \mathbf{Q} = \mathbf{P}\mathbf{Q}\mathbf{P}. \end{array} \tag{40}$$

Next, we omit the $\mathbf{Q} = \mathbf{P}\mathbf{Q}\mathbf{P}$ constraint and obtain:

$$\begin{array}{ll} \max_{\mathbf{Q} \succeq \mathbf{0}} & \overline{\mathbf{c}}^T \mathbf{Q} \overline{\mathbf{c}} \\ \text{s.t.} & \operatorname{Tr}\left\{\mathbf{Q}\overline{\mathbf{A}_i}\right\} \leq b_i, \quad i \notin J, \end{array} \tag{41}$$

where $\overline{\mathbf{c}} = \mathbf{P}\mathbf{c}$, $\overline{\mathbf{A}_i} = \mathbf{P}\mathbf{A}_i\mathbf{P}$ and $b_i > 0$ for $i \not\in J$ are all strictly positive. If $\mathbf{Q}^{\mathrm{opt}}$ is a rank-one optimal solution to (41) then $\mathbf{P}\mathbf{Q}^{\mathrm{opt}}\mathbf{P}$ is a rank-one optimal solution to (40). Therefore, we can prove the lemma for (41) instead of (36). For simplicity, we continue with the notation in (36) but assume that $b_i > 0$ for all i.

Consider the following problem

$$\mathcal{Q} = \left\{ \begin{array}{ll} \max_{\mathbf{q}} & \left(\mathbf{q}^T \mathbf{c}\right)^2 \\ \text{s.t.} & \mathbf{q}^T \mathbf{A}_i \mathbf{q} \leq b_i. \end{array} \right. \tag{42}$$

Program $\mathcal{S}$ is the SDP relaxation of $\mathcal{Q}$. That is $\operatorname{val}(\mathcal{S}) \geq \operatorname{val}(\mathcal{Q})$, and if $\mathbf{q}$ is optimal for $\mathcal{Q}$ then $\mathbf{Q} = \mathbf{q}\mathbf{q}^T$ is feasible for $\mathcal{S}$. Thus, all we need to prove is that $\operatorname{val}(\mathcal{S}) \leq \operatorname{val}(\mathcal{Q})$. We will do this by considering their corresponding dual programs.

We begin with $\mathcal{S}$ which is a convex optimization problem. Its Lagrange dual is

$$d\mathcal{S} = \left\{ \begin{array}{l} \min_{\lambda \succeq \mathbf{0}} \sum_i \lambda_i b_i \\ \text{s.t.} \sum_i \lambda_i \mathbf{A}_i - \mathbf{c}\mathbf{c}^T \succeq \mathbf{0}. \end{array} \right. \tag{43}$$

The problem is strictly feasible since b_i are all positive. Therefore, Slater's condition for strong duality holds and $\operatorname{val}(\mathcal{S}) = \operatorname{val}(d\mathcal{S})$.

We now move on to $\mathcal{Q}$. Unfortunately, this is a nonconvex problem due to quadratic objective. However, if $\mathbf{q}$ is optimal then so is $-\mathbf{q}$. Therefore, we can assume that $\mathbf{q}^T\mathbf{a} \geq 0$ and use the monotonicity of x^2 in $x \geq 0$. This yields

$$\mathcal{L} = \left\{ \begin{array}{ll} \max_{\mathbf{q} \succeq \mathbf{0}} & \mathbf{q}^T \mathbf{c} \\ \text{s.t.} & \mathbf{q}^T \mathbf{A}_i \mathbf{q} \leq b_i, \end{array} \right. \tag{44}$$

which is guaranteed to satisfy $\left(\operatorname{val}(\mathcal{L})\right)^2 = \operatorname{val}(\mathcal{Q})$. The main advantage of this linearization is that $\mathcal{L}$ is a convex optimization problem which can be solved using its Lagrange dual program

$$d\mathcal{L} = \min_{\lambda \geq 0} \max_{\mathbf{q}} -\mathbf{q}^T\mathbf{c} - \sum_i \lambda_i \mathbf{q}^T \mathbf{A}_i \mathbf{q} + \sum \lambda_i b_i. \tag{45}$$

Adding an auxiliary variable $t \geq 0$ yields

$$d\mathcal{L} = \left\{ \begin{array}{ll} \min_{\lambda, t \geq 0} & t + \sum \lambda_i b_i \\ \text{s.t.} & \sum_i \lambda_i \mathbf{q}^T \mathbf{A}_i \mathbf{q} + \mathbf{q}^T \mathbf{c} + t \geq 0, \ \forall\, \mathbf{q}. \end{array} \right. \tag{46}$$

If $t = 0$ then $\mathbf{c} = \mathbf{0}$ and the proof is completed since $\operatorname{val}(\mathcal{S}) = \operatorname{val}(\mathcal{Q}) = 0$. Otherwise, $t > 0$ and we can use

Lemma 2: [30, p. 112,135] Let $\mathbf{A}$ be a symmetric matrix and $s > 0$. The condition $\mathbf{x}^T\mathbf{S}\mathbf{x} + 2\mathbf{s}^T\mathbf{x} + s \geq 0$ holds for all $\mathbf{x}$ if and only if $\mathbf{S} - \frac{1}{s}\mathbf{s}\mathbf{s}^T \succeq \mathbf{0}$.
Using the Lemma, we transform $d\mathcal{L}$ into an SDP

$$d\mathcal{L} = \begin{cases} \min_{\lambda \geq 0, t>0} \sum_i \lambda_i b_i + t \\ \text{s.t.} \sum_i \lambda_i \mathbf{A}_i - \frac{1}{4t}\mathbf{c}\mathbf{c}^T \succeq \mathbf{0}. \end{cases} \tag{47}$$

As before, Slater's condition holds due to the strict feasibility. Thus, strong duality assures that $\text{val}\,(\mathcal{L}) = \text{val}\,(d\mathcal{L})$ and if we square the objective again and use the monotonicity of x^2 in $x \geq 0$, we obtain the following dual of $\mathcal{Q}$ (this is not the Lagrange dual but just the squared value of $d\mathcal{L}$)

$$d\mathcal{Q} = (d\mathcal{L})^2 = \begin{cases} \min_{\lambda \geq 0, t>0} \left(\sum_i \lambda_i b_i + t\right)^2 \\ \text{s.t.} \sum_i \lambda_i \mathbf{A}_i - \frac{1}{4t}\mathbf{c}\mathbf{c}^T \succeq \mathbf{0} \end{cases} \tag{48}$$

which satisfies $\text{val}\,(\mathcal{Q}) = \text{val}\,(d\mathcal{Q})$. Next, we exchange variables and optimize over $\overline{\lambda}_i = 4t\lambda_i \geq 0$ instead of λ_i

$$d\mathcal{Q} = \begin{cases} \min_{\overline{\lambda} \geq 0, t>0} \left(\frac{\sum_i \overline{\lambda}_i b_i}{4t} + t\right)^2 \\ \text{s.t.} \sum_i \overline{\lambda}_i \mathbf{A}_i - \mathbf{c}\mathbf{c}^T \succeq \mathbf{0}. \end{cases} \tag{49}$$

Now examining (43) and (49) we see that their feasible set is identical, and in order to prove that $\text{val}\,(d\mathcal{Q}) \geq \text{val}\,(d\mathcal{S})$ all we need to show is that

$$\frac{\mu}{4t} + t \geq \sqrt{\mu} \qquad \text{for all} \qquad t > 0 \tag{50}$$

where $\mu = \sum_i \lambda_i b_i \geq 0$. But this is easily proved by noting that the left hand side of (50) is convex in $t > 0$ and attains its minimum when

$$\frac{\partial}{\partial t}\left[\frac{\mu}{4t} + t\right] = -\frac{\mu}{4t^2} + 1 = 0 \tag{51}$$

and

$$t_{\min} = \frac{1}{2}\sqrt{\mu} \tag{52}$$

which yields

$$\frac{\mu}{4t_{\min}} + t_{\min} = \sqrt{\mu} \tag{53}$$

as required.

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