SPATIAL LOADING BASED ON CHANNEL COVARIANCE FEEDBACK AND CHANNEL ESTIMATES

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ABSTRACT

Transmission schemes for flat multi-input, multi-output (MIMO) channels are well established for the cases where perfect channel state information or no channel state information is available at the transmitter. However, communication over channels where the transmitter has access to partial or imperfect information has received less attention. If exploited, such information has the potential of improving system performance and reducing the bandwidth requirements of feedback links or the required quality of channel estimates. Herein, a simple design scheme is introduced, that approximately maximizes the data rates of MIMO communication systems where the transmitter has access to partial channel state information in the form of covariance feedback or erroneous channel estimates. An algorithm is presented which is computationally attractive and performance gains are shown when compared to systems not using this information.

1. INTRODUCTION

By employing multiple transmit and receive antennas in a communication system, dramatic increases in data rates can be achieved as compared to single antenna alternatives [1, 2]. Several problems still remain when designing a well optimized MIMO system in practice. For example, well established techniques exist for cases where either perfect channel information or no channel information is available at the transmitter, see e.g. [2, 3]. However, the case when partial or imperfect channel estimates are available at the transmitter are not as well understood.

Recently, some schemes have been developed that take advantage of partial channel information at the transmitter, see e.g. [4]. In these schemes, the transmitted data is optimized in order to minimize the error rate at the receiver given a certain bit rate. While this is desirable in some situations, in others it might be more attractive to, given a certain design bit error rate (BER), maximize the data rate of the system. When the channel is perfectly known, a practical solution to this optimization problem is spatial loading [2, 5]. Here, parallel, non-interfering spatial channels are first created using a linear transformation and then bit constellations and power are allocated for the different "spatial carriers" in order to maximize the data rate given some quality constraint on the received data, much in analogy with adaptive loading techniques commonly used in discrete multi-tone (DMT) systems [6]. In [7] we extended the concept of spatial loading to the case where imperfect channel state information is available at the transmitter. In contrast to the case where the channel is perfectly known and the case of DMT with imperfect channel estimates [8], when the MIMO channel estimates at the transmitter are erroneous it is not possible to create non-interfering parallel channels. This complicates the system design and increases the complexity of the receiver.

Herein our earlier work [7] is extended to also include the case where channel statistics, but no estimates of the individual channel realizations, are available at the transmitter. A simple and computationally efficient approximative method for maximizing the data rate given second order channel statistics and a design error rate is presented and numerical examples illustrate the capability to exploit some of the potential gain in the available channel information.

2. SYSTEM MODEL

We consider a MIMO communication system consisting of n_t transmitters communicating with a terminal with n_r receivers over a flat fading channel. Transmission over the channel is modeled through a channel matrix, $\mathbf{H} \in \mathbb{C}^{(n_\mathrm{t} \times n_\mathrm{r})}$, the elements of which model the attenuations and phase differences between the various transmitter/receiver pairs. The output, $\mathbf{x} \in \mathbb{C}^{n_\mathrm{r}}$, resulting from a single usage of the channel to transmit the data $\mathbf{s} \in \mathbb{C}^{n_\mathrm{t}}$, is then found as,

$$\mathbf{x} = \mathbf{H}\mathbf{s} + \mathbf{n}, \tag{1}$$

where $\mathbf{n} \in \mathbb{C}^{n_\mathrm{r}}$ is additive white complex Gaussian noise. In order to make the required output power of the different transmission schemes presented in the paper comparable, the signal to noise ratio (SNR) is defined as the quotient between the power of the received data signal, $\mathrm{E}\,|\mathbf{H}\mathbf{s}|^2$, and the received noise power, $\mathrm{E}\,|\mathbf{n}|^2$, when equally powered uncorrelated data is transmitted, i.e when $\mathrm{E}\{\mathbf{s}\mathbf{s}^*\}$ is a scaled identity matrix. Without loss of generality, the received noise is normalized so that $\mathbf{n} \in \mathscr{CN}(0, \mathbf{I})$ and the channel matrix is normalized so that $\mathrm{E}\,\|\mathbf{H}\|_\mathrm{F}^2 = n_\mathrm{t} n_\mathrm{r}$. Applying the definition and normalizations above then gives the SNR as $\mathrm{E}\,|\mathbf{s}|^2 = P$.

3. PARTIAL CHANNEL STATE INFORMATION

In what follows, the receiver is assumed to have perfect knowledge of $\mathbf{H}$ when it tries to detect the transmitted symbols. However, the channel knowledge at the transmitter is not necessarily perfect or complete. There are several possibilities for the transmitter channel estimate to be in error. For example, the channel may have changed between the estimation and the usage of the estimates due to delay or the channel estimate may have been obtained via a low rate feedback channel not able to provide accurate estimates due to heavy quantization. In scenarios where the channel changes too fast to keep the transmitter estimates updated it may be more attractive to estimate the channel second order statistics which change at a slower pace. This will reduce the bandwidth requirements on the feedback channel.

In order to exploit the partial channel knowledge at the transmitter $\mathbf{H}$ is modeled stochastically. The model for $\mathbf{H}$ depends on the type of information available. Here it is assumed that $\mathbf{H}$, given the available channel knowledge, is complex Gaussian,

$$\begin{aligned} \operatorname{vec}\mathbf{H} &\in \mathscr{CN}(\operatorname{vec}\hat{\mathbf{H}}, \mathbf{R}_\mathbf{H}), \\ \mathbf{R}_\mathbf{H} &= E\{\operatorname{vec}\mathbf{H}\operatorname{vec}\mathbf{H}^*\}, \end{aligned} \tag{2}$$

where the channel state information consists of $\hat{\mathbf{H}}$ and $\mathbf{R}_\mathbf{H}$.

In this work two special cases of the model above are considered, mean and covariance feedback, see [9].

3.1 Mean Feedback

The channel state information consists of the channel mean $\hat{\mathbf{H}}$ and the covariance matrix $\mathbf{R}_\mathbf{H} = \sigma_\mathbf{H}^2\mathbf{I}$. Note that $\hat{\mathbf{H}}$ can be seen as an

*The support of LIASIT (www.liasit.lu) and SES GLOBAL S.A., Luxembourg to this work is gratefully acknowledged. The author can be contacted at cristoff@s3.kth.se.

estimate of $\mathbf{H}$ and $\sigma^2_{\mathbf{H}}$ as a measure of the uncertainty in this estimate. The normalizations in the previous section imply that $\sigma^2_{\mathbf{H}} = 1$ results in $\hat{\mathbf{H}} = 0$ or no channel knowledge while $\sigma^2_{\mathbf{H}} = 0$ results in $\hat{\mathbf{H}} = \mathbf{H}$ or perfect channel knowledge. In [7] a simple method for optimizing the transmitted data given partial channel knowledge as above is developed.

For details regarding this method as well as numerical results, the reader is referred to [7].

3.2 Covariance Feedback

Consider the "Kronecker channel model" [10] which is realistic for indoor non-line of sight conditions and limited array apertures [11]. Here the channel mean, $\hat{\mathbf{H}}$ is zero and the covariance matrix $\mathbf{R}_{\mathbf{H}}$ is structured as $\mathbf{R}_{\mathbf{H}} = \mathbf{R}_{\mathrm{t}}^{\mathrm{T}} \otimes \mathbf{R}_{\mathrm{r}}$ (where $\otimes$ is the Kronecker product), i.e. $\mathbf{H}$ may be generated as

$$\mathbf{H} = \mathbf{R}_{\mathrm{r}}^{1/2} \mathbf{G} \mathbf{R}_{\mathrm{t}}^{1/2} \tag{3}$$

where $\mathbf{G}$ is an n_{r} by n_{t} zero mean complex Gaussian matrix with IID elements distributed as $\mathscr{CN}(0,1)$. The non-negative definite matrices $\mathbf{R}_{\mathrm{t}}$ and $\mathbf{R}_{\mathrm{r}}$ can be interpreted as the covariance between the transmitters, the rows of $\mathbf{H}$, and the receivers, the columns of $\mathbf{H}$, respectively. The normalization imposed in Section 2 implies that $\mathbf{R}_{\mathrm{r}}$ and $\mathbf{R}_{\mathrm{t}}$ should be chosen so that $\mathrm{Tr}\,\mathbf{R}_{\mathrm{t}} = n_{\mathrm{t}}$ and $\mathrm{Tr}\,\mathbf{R}_{\mathrm{r}} = n_{\mathrm{r}}$.

Below, a simple and computationally efficient method is proposed that approximately maximizes the data rate of a spatially multiplexed MIMO system. It is applicable when covariance feedback is available according to the model above.

4. SPATIAL MULTIPLEXING AND LOADING

The basic idea behind bit and power loading algorithms is to optimize the transmitted vector data so that the available transmit power is used most efficiently. For the system (1) the optimal transmit data design when the channel is known at the transmitter is, from a capacity [1] viewpoint, to diagonalize $\mathbf{H}$, creating parallel spatial channels. This is achieved by using a singular value decomposition and to transmit Gaussian distributed data symbols with power allocated using the well known water-filling solution. This way, transmit power is allocated to the directions where it is put to best use, i.e. in directions with little attenuation, more power is allocated and higher data rates can be supported.

For practical systems, using Gaussian distributed symbols is not an option. Instead the transmitted data symbols belong to some finite alphabet, resulting in an optimization problem where different constellation sizes and transmit powers are allocated to different directions in order to satisfy some constraint on the quality of the received data and to maximize data rates. Here, we term this type of technique spatial loading and in the subsections below such schemes are discussed and presented for different scenarios. In all cases we attempt to optimize the transmit data rate, given some design uncoded BER and transmit power constraint.

In the design of a general spatial loading system it is natural to introduce some structure in order to characterize the spatial properties of the channel and to simplify the following adaptive loading. To that end, let $\mathbf{s} = \mathbf{V}_{\mathrm{Tx}} \mathbf{P}^{1/2} \mathbf{d}$ and $\mathbf{y} = \mathbf{U}_{\mathrm{Rx}} \mathbf{x}$, where $\mathbf{V}_{\mathrm{Tx}}$ and $\mathbf{U}_{\mathrm{Rx}}$ are unitary matrices characterizing the directivity of the spatial loading system, $\mathbf{P}$ is a diagonal matrix defining the power loading in the different "directions", $\mathbf{y}$ is the received data to be considered by the detector and $\mathbf{d}$ are the transmitted symbols. Based on these definitions, the effective system between transmitter and receiver can be modeled as,

$$\mathbf{y} = \mathbf{U}_{\mathrm{Rx}}(\mathbf{H}\mathbf{V}_{\mathrm{Tx}}\mathbf{P}^{1/2}\mathbf{d} + \mathbf{n}) = \mathbf{H}'\mathbf{P}^{1/2}\mathbf{d} + \mathbf{n}', \tag{4}$$

where $\mathbf{H}'$ is the effective channel matrix and $\mathbf{n}'$ is the effective noise of the MIMO channel between $\mathbf{d}$ and $\mathbf{y}$. Note that since $\mathbf{U}_{\mathrm{Rx}}$ is unitary the effective noise is still white complex Gaussian, each element of variance one. Also, since $\mathbf{U}_{\mathrm{Rx}}$ and $\mathbf{V}_{\mathrm{Tx}}$ are invertible and the distributions of $\mathbf{n}$ and $\mathbf{n}'$ are identical the system (4) is equivalent to (1). The transmitted symbols are considered uncorrelated, with zero mean and normalized to variance one. The normalizations from Section 2 imply that $\mathbf{P}$ should be chosen such that $\mathrm{Tr}\,\mathbf{P} = P$.

The focus of this preliminary study is on the uncertainty aspect of the channel, not on the receiver algorithm or bit loading scheme being used. In order to simplify the interpretation of the results and the discussion below, a maximum likelihood (ML) detector is employed in all cases and the well known greedy Hughes-Hartogs algorithm [12, 6] has been selected for the spatial bit and power loading. While these choices may be too computationally demanding for practical implementations, they simplify the derivation and presentation. For reference, the Hughes-Hartogs adaptive loading algorithm for parallel channels consists in principle of the following steps,

1. Try to increase the constellation size by one for all the symbols of $\mathbf{d}$, one at the time. Add enough power so that the bit error constraint is not violated.
2. Increase the constellation size and allocate power to the symbol requiring the least additional power in the previous step.
3. Repeat until the available power is insufficient to add more bits given the error constraint. If desirable, any remaining power can be spread over the bits to improve the error rate performance of the wireless link.

4.1 Perfect Channel Knowledge

When the transmitter has perfect channel knowledge, a well known spatial loading scheme based on a singular value decomposition of the channel matrix can be applied [2, 5]. By choosing $\mathbf{U}_{\mathrm{Rx}}$ and $\mathbf{V}_{\mathrm{Tx}}$ as the transposed conjugate of the matrix containing the left singular vectors and the matrix containing right singular vectors respectively, the channel between $\mathbf{d}$ and $\mathbf{y}$ is diagonalized and $\min(n_{\mathrm{r}}, n_{\mathrm{t}})$ non-interfering scalar channels between the transmitted and the received data are formed. Since each of these parallel channels are characterized by an SNR given by the singular values of $\mathbf{H}$, bit and power loading using the algorithm above is straightforward.

4.2 No Channel Knowledge

For the case when the transmitter has no knowledge of the channel it is not possible to optimize the directivity of the transmitting array. Here, we assume that a non-line of sight system is considered where the antenna elements are sufficiently separated so that the elements of $\mathbf{H}$ can be considered independent Rayleigh fading.

For this type of system several techniques such as BLAST [13] or more sophisticated space-time coding schemes [3] have been designed. While elaborate techniques are required for efficient detection of the transmitted symbols and coding is required for optimal performance we here only consider a system where the transmitter transmits uncoded symbols, $\mathbf{y}$, with equally distributed power, $\mathbf{P} = P/n_{\mathrm{t}}\mathbf{I}$, and the receiver uses an ML-detector to estimate the transmitted symbols.

Note that these type of systems can be expected to perform well as long as the channel elements are independent. However, if the elements of $\mathbf{H}$ are correlated some directions in space will suffer a higher attenuation than others and this scheme will waste transmit power in those directions.

4.3 Beamforming

With access to channel statistics at the transmitter, beamforming schemes can be designed by choosing the transmitted data vectors so that the average received signal power is maximized. For example, in the case of covariance feedback according to the model in Section 3.2, this would mean allocating all data and power to the direction corresponding to the maximum eigenvalue of $\mathbf{R}_{\mathrm{t}}$, i.e. all data is transmitted over a single spatial channel. Note that this solution is optimal if the elements of $\mathbf{H}$ are perfectly correlated and only one spatial channel can be supported. In other cases, where $\mathbf{H}$ has a rank higher than one, the technique may be wasteful since available spatial dimensions are not being used.

4.4 Covariance Feedback

If covariance feedback is available, one method of optimizing the system could be to, depending on the amount of correlation, chose one of the two methods above. Such a solution however, is not very elegant and suffers from suboptimal performance except in the extreme cases of perfectly correlated or uncorrelated channels. Below we instead propose to use a spatial loading scheme to optimize the transmitted data and adapt it to the available channel information to provide a smooth transition between the cases above. When perfect channel knowledge is not available at the transmitter, optimizing the transmitted data becomes more complicated. For example, it is no longer possible to completely diagonalize the channel and the parallel data streams will interfere at the receiver. Instead we take an approximate, sub-optimal approach that results in a simple and efficient design algorithm and illustrate its performance with numerical examples.

Let $\mathbf{R}_\mathrm{t} = \mathbf{V}_\mathrm{t}\mathbf{\Lambda}_\mathrm{t}\mathbf{V}_\mathrm{t}^*$ and $\mathbf{R}_\mathrm{r} = \mathbf{V}_\mathrm{r}\mathbf{\Lambda}_\mathrm{r}\mathbf{V}_\mathrm{r}^*$ be the eigenvalue decompositions of the transmit and receive covariance matrices. The transmitter and receiver directive matrices, $\mathbf{V}_\mathrm{Tx}$ and $\mathbf{U}_\mathrm{Rx}$ are selected as $\mathbf{V}_\mathrm{Tx} = \mathbf{V}_\mathrm{t}$ and $\mathbf{U}_\mathrm{Rx} = \mathbf{V}_\mathrm{r}^*$ resulting in an efficient system,

$$\mathbf{y} = \mathbf{\Lambda}_\mathrm{r}^{1/2}\mathbf{G}'\mathbf{\Lambda}_\mathrm{t}^{1/2}\mathbf{P}^{1/2}\mathbf{d} + \mathbf{n}', \tag{5}$$

where $\mathbf{G}' = \mathbf{V}_\mathrm{r}^*\mathbf{G}\mathbf{V}_\mathrm{t}$ has the same distribution as $\mathbf{G}$ since $\mathbf{V}_\mathrm{r}$ and $\mathbf{V}_\mathrm{t}$ are unitary. While we do not claim that this choice of $\mathbf{V}_\mathrm{Tx}$ and $\mathbf{U}_\mathrm{Rx}$ is optimal it can be motivated in a number of ways. Firstly, given the channel knowledge at the transmitter, the received signal power for the first symbol in $\mathbf{d}$, $\mathrm{E}|\mathbf{U}_\mathrm{Rx}\mathbf{H}\mathbf{V}_\mathrm{Tx}\mathbf{P}^{1/2}\mathbf{d}_1|^2$ is maximized. Here, $\mathbf{d}_k$ is a vector where all entries are zero except for the kth entry which is identical to kth element of $\mathbf{d}$. Similarly the second element is transmitted in the orthogonal direction, in $\mathbb{C}^{n_\mathrm{t}}$, to the first, that maximizes the received signal power and so on. Hence given this choice of directive matrices it is possible to ensure that data is transmitted in the directions where the receive conditions are likely to be the most favorable. Secondly, this choice can be motivated by capacity arguments, see e.g. [14, 9]. Lastly, this choice of $\mathbf{U}_\mathrm{Rx}$ ensures that the elements of $\mathbf{H}'$ are uncorrelated significantly simplifying the BER computations in the following loading step of the proposed design process. Note that since $\mathbf{U}_\mathrm{Rx}$ is unitary and an ML-detector is used the choice of $\mathbf{U}_\mathrm{Rx}$ in the receiver does not affect the resulting error probability for the designed system.

In order to provide a practical spatial bit and power loading scheme it is necessary to be able compute the resulting BER for various constellation sizes and output powers efficiently. Since the communication channels are interfering this is complicated and for a computationally attractive scheme some approximations are necessary. Firstly, we assume that the design BER is chosen so low that more than one symbol error per received vector $\mathbf{y}$ is rare. Thus, when computing the error rates of the ML-detector for each of the transmitted symbols in $\mathbf{d}$ it is assumed that the other symbols have been correctly detected and subtracted from the received data, i.e error propagation is ignored. Note that this approximation can be expected to work better when there are more receive antennas than spatial channels, and in practice it is good to limit the number of channels to $\min(n_\mathrm{r}, n_\mathrm{t})$ or less. Furthermore, we assume that the transmitted symbols have been Gray-encoded so that, given the low design BER, the number of bit errors can be approximated by the number of symbol errors. These approximations, result in a simplified model where it suffices to compute the error probabilities of scalar symbols, transmitted over non-interfering vector channels consisting of independent Rayleigh fading elements. For these channels, efficient techniques for computing the error probability for many types of constellations exist [15]. Note that since the variances of the vector channel elements are determined by $\mathbf{R}_\mathrm{t}$ and $\mathbf{R}_\mathrm{r}$, see (5), the bit and power loading in the different directions are adapted to the uncertainty of the channel.

Using the selected $\mathbf{V}_\mathrm{Tx}$ and $\mathbf{U}_\mathrm{Rx}$ and the approximations above, the spatial loading can be performed in a simple and computationally efficient manner following the method of Section 3. While the resulting design is clearly suboptimal, note that for completely uncorrelated channel elements, i.e. when $\mathbf{R}_\mathrm{t} = \mathbf{I}$ and $\mathbf{R}_\mathrm{r} = \mathbf{I}$, our solution converges to the well know solution of Section 4.2. Also, when the channel elements are perfectly correlated, our algorithm produces a beamforming solution, concentrating all transmit power on the single available spatial channel.

5. NUMERICAL RESULTS AND ANALYSIS

Since an analytical analysis on the performance of the method proposed in the previous section would be difficult, a numerical analysis is performed. The simulations performed in this study were simplified by limiting the bit-loading algorithm to square M-QAM constellations, where $M = 2^{2b}$ and is b integer valued. Note that results such as those in [15] allow a larger selection of constellations which may be desirable.

To make the simulations efficient, the ML-detector at the receiver was implemented in the form of a sphere decoder [16]. For reasonably sized arrays the sphere decoding algorithm is on average very efficient, significantly shortening the time required to find the ML-solution compared with a full search. In the case of spatial loading, the sphere decoding algorithm needs to consider the different constellations transmitted in the different elements of $\mathbf{d}$.

While the algorithm presented herein is applicable to general $\mathbf{R}_\mathrm{r}$ and $\mathbf{R}_\mathrm{t}$, to keep things simple, in all examples below, the transmitter correlation matrix, $\mathbf{R}_\mathrm{t}$, is selected as

$$\mathbf{R}_\mathrm{t} = \begin{bmatrix} 1 & \rho_\mathrm{t}^* & \rho_\mathrm{t}^{2*} & \cdots & \rho_\mathrm{t}^{n_\mathrm{t}-1*} \\ \rho_\mathrm{t} & 1 & \rho_\mathrm{t}^* & & \rho_\mathrm{t}^{n_\mathrm{t}-2*} \\ \vdots & & & \ddots & \\ \rho_\mathrm{t}^{n_\mathrm{t}-1} & \rho_\mathrm{t}^{n_\mathrm{t}-2} & & \cdots & 1 \end{bmatrix}. \tag{6}$$

A similar model is used for $\mathbf{R}_\mathrm{r}$, but with ρ_r instead of ρ_t, $|\rho_\mathrm{r}| < 1$, $|\rho_\mathrm{t}| < 1$, and in the examples below $\rho_\mathrm{r} = \rho_\mathrm{t}$.

5.1 Example: Data Rate Performance

Fig. 1 illustrates how the proposed method can exploit some of the available information in order to increase the data rate of the system. The data rate performance of the algorithm is compared with the two simpler schemes of Sections 4.2 and 4.3. In this downlink scenario an $n_\mathrm{t} = 6$, $n_\mathrm{r} = 3$ antenna system with $\rho_\mathrm{r} = \rho_\mathrm{t} = 0.8$ is considered operating at SNRs of 15 and 25 dB. During the loading procedure described in Section 4.4, the number of spatial channels were limited to three and to make the comparison fair in terms of transmit power, any residual power left after the loading procedure has been added evenly over those channels.

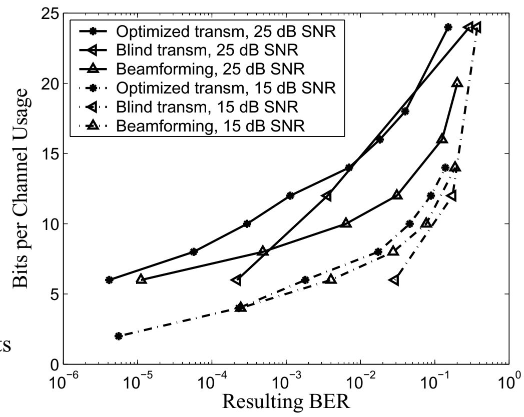

Figure 1: Data rate performance, $\rho_\mathrm{r} = \rho_\mathrm{t} = 0.8$, $n_\mathrm{t} = 6$, $n_\mathrm{r} = 3$.

From the figure, notice how the algorithm presented herein is capable of outperforming the two simpler methods. This illustrates that this method, while simple, has the capability to exploit some of the information in the available channel statistics in order to increase the data rates of the system.

5.2 Example: Bit Loading Strategy

To further illustrate the behavior of the proposed algorithm, Table 1 shows how the transmitted bits are allocated as a function of $\rho_r = \rho_t$ for this $n_r = n_t = 4$ scenario. While the design BER in the example is 0.003 for the entire Table, as the resulting error rates vary between the different channels, this Table is not intended to indicate the resulting bit rates of a practical system but to show how the bits are distributed over the different spatial channels. Note that when $\rho_r = \rho_t \to 0$ signal power and transmitted data are transmitted as evenly as possible in space given the restriction in constellation sizes. On the other hand, when $\rho_r = \rho_t \to 1$ power and loaded bits are concentrated in the direction with the lowest attenuation. This intuitive result illustrates how the proposed method is capable of adapting the transmitted data to the available channel knowledge and providing a transition between the extreme cases of an uncorrelated channel and a perfectly correlated channel.

$\rho_r = \rho_t$	0.0	...	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Chan. 1:	6	...	6	6	8	8	8	8	6	8
Chan. 2:	6	...	6	6	6	6	6	4	4	0
Chan. 3:	6	...	6	6	4	4	4	2	2	0
Chan. 4:	6	...	6	4	4	4	2	2	0	0

Table 1: Bit allocation, design SNR 25 dB, BER 0.003, $n_t = n_r = 4$.

5.3 Example: Performance of the Approximation

Finally, the performance of the approximations leading up to the bit loading algorithm is evaluated. Fig. 2 shows the resulting BER as a function of the design BER for an $n_t = 6$, $n_r = 3$ system operating at an SNR of 20 dB. Like in Section 5.1 the number of spatial channels were limited to three but in order to be able to evaluate the performance of the approximations, remaining power after the bit allocation is not allocated to any spatial channel. As the approximations used in deriving the proposed method are underestimating the probability of error, the design BER is lower than the resulting BER. While this means that the design BER must be chosen lower than that required by the system, the design achieves balancing in the loading between the different spatial channels. Furthermore, notice that as $\rho_r = \rho_t$ approaches one, the approximations improve. This is expected as large $\rho_r = \rho_t$ means that almost all power and bits are allocated to a single channel and thus there is less interference and error propagation between the spatial channels and the approximation ignoring these effects improves.

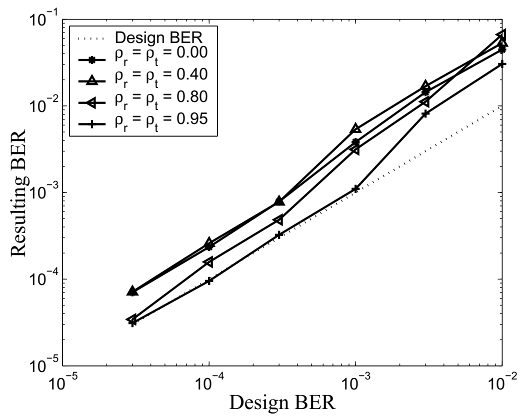

Figure 2: Approximation performance, $n_t = 6$, $n_r = 3$, 20 dB SNR.

6. CONCLUSIONS

Herein, a computationally efficient method for data rate optimization of a spatially multiplexed MIMO communication systems with covariance feedback is proposed and evaluated. Results from simulations indicate that the algorithm provides gains compared to pure diversity techniques and methods that simply maximize received SNR. Also, for cases where the elements of the channel matrix are perfectly correlated or uncorrelated, the scheme converges to well known solutions, providing a seamless transition between beamforming techniques and transmission schemes used over unknown independent Rayleigh fading channels.

ACKNOWLEDGMENTS

We would like to thank our colleague Joakim Jaldén for providing us with the sphere decoder used in our experiments.

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