HOW ACCURATE CHANNEL PREDICTION NEEDS TO BE FOR ADAPTIVE MODULATION IN RAYLEIGH MIMO CHANNELS ?

Shengli Zhou and *Georgios B. Giannakis*

Dept. of ECE, Univ. of Minnesota, 200 Union Str. SE, Minneapolis, MN 55455, USA

ABSTRACT

Adaptive modulation improves the system throughput considerably by matching transmitter parameters to time-varying wireless fading channels. Crucial to adaptive modulation is the quality of channel state information (CSI) at the transmitter. In this paper, we consider a channel predictor based on pilot symbol assisted modulation (PSAM) for multi-input multi-output (MIMO) Rayleigh fading channels. We analyze the impact of the channel prediction error on the bit error rate (BER) performance of an adaptive system assuming perfect CSI. Our numerical results reveal the critical value of the normalized prediction error, below which the predicted channels can be treated as perfect by the adaptive modulator; otherwise, explicit consideration of the channel imperfection must be accounted for at the transmitter.

1. INTRODUCTION

By matching transmitter parameters to time-varying channel conditions, adaptive modulation increases the system throughput considerably, which justifies its popularity in future high-rate wireless applications; see [1, 4, 5] and references therein. Critical to adaptive modulation is the quality of channel state information (CSI) at the transmitter, that is obtained through feedback. Due to the transmission delay and the processing delay both at the transmitter and at the receiver, the delayed CSI feedback at the transmitter becomes outdated, unless the channel variations are sufficiently slow. Taking into account the feedback delay, an effective approach in adaptive systems is to predict the channel values at future times when they will be used, and feed those predicted channels back to the transmitter [3].

Adaptive designs assuming perfect CSI perform well only when CSI imperfections induced by channel estimation errors and/or feedback delays are limited [1]. For general Nakagami fading channels, the BER performance was analyzed in [1] for single antenna systems with delayed but noiseless channel estimates. For Rayleigh fading channels, BER performance analysis was carried out in [6] for systems equipped with single transmit- and multiple-receive antennas, based on noisy predicted channels.

In this paper, we investigate an adaptive system with multiple transmit and multiple receive antennas, where each information symbol is transmitted across multiple transmit-antennas using beamforming. Based on the minimum-mean-square-error (MMSE) channel predictor in [9], we analyze the impact of channel prediction error on the BER performance of adaptive MIMO systems. With an arbitrary number of transmit- and receive- antennas, we obtain a closed-form BER expression that requires multi-level integration. We also derive simple closed-form expressions, when the minimum number of transmit- and/or receive- antennas is less than or equal to two.

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Notation: Bold upper (lower) letters denote matrices (column vectors); $(\cdot)^*$, $(\cdot)^T$ and $(\cdot)^{\mathcal{H}}$ denote conjugate, transpose, and Hermitian transpose, respectively; $\mathrm{E}\{\cdot\}$ stands for expectation, and $\delta(\cdot)$ for Kronecker's delta; $\mathbf{I}_K$ denotes the identity matrix of size K; $\mathbf{0}_{K\times P}$ denotes an all-zero matrix of size $K \times P$; The special notation $\mathbf{h} \sim \mathcal{CN}(\bar{\mathbf{h}}, \mathbf{\Sigma}_h)$ indicates that $\mathbf{h}$ is complex Gaussian distributed with mean $\bar{\mathbf{h}}$, and covariance matrix $\mathbf{\Sigma}_h$.

2. SYSTEM MODELING AND CHANNEL PREDICTION

We consider an adaptive system equipped with multiple transmit- and receive- antennas, as depicted in Fig. 1. Based on CSI obtained from the feedback channel, the transmitter optimally varies its modulation parameters, as will be detailed in Section 3. To assist the receiver in performing channel estimation and symbol detection, known pilot symbols are periodically inserted at the transmitter — a technique that is known as pilot symbol assisted modulation (PSAM) [2]. At the receiver, the samples corresponding to the known pilots are extracted, based on which CSI is interpolated using optimal Wiener filtering [2]. Coherent detection is then performed for symbol demodulation. To enable adaptive modulation, the receiver also predicts the channels at a future time, and feeds the predicted channels back to the transmitter [3, 6].

Let N_t denote the number of transmit antennas, N_r the number of receive antennas, and $h_{\mu\nu}(n)$ the frequency-flat channel between the μth transmit- and the νth receive-antennae, at time index n. We collect channel coefficients into the $N_t \times N_r$ channel matrix $\mathbf{H}(n)$ having (μ,ν)th entry $h_{\mu\nu}(n)$. Let $x_\mu(n)$ denote the transmitted symbol from the μth antenna at time n. The received signal at the νth receive antenna can then be expressed as:

$$y_\nu(n) = \sum_{\mu=1}^{N_t} h_{\mu\nu}(n)x_\mu(n) + w_\nu(n), \quad \nu \in [1, N_r], \tag{1}$$

where $w_\nu(n)$ denotes zero-mean additive Gaussian noise.

We adopt the following assumptions throughout the paper:

AS0): the channels $\{h_{\mu\nu}(n)\}_{\mu=1,\nu=1}^{N_t,N_r}$ *are independent and identically distributed (i.i.d.) with Gaussian distribution* $\mathcal{CN}(0,1)$*; hence,* $\mathbf{H}(n) \sim \mathcal{CN}\big(\mathbf{0}_{N_t\times N_r}, N_r\mathbf{I}_{N_t}\big)$.

AS1): the channels $\{h_{\mu\nu}(n)\}_{\mu=1,\nu=1}^{N_t,N_r}$ *are slowly time-varying according to Jakes' model with Doppler spread* f_d*; thus, we have* $\mathrm{E}\{h_{\mu\nu}^*(n)h_{\mu\nu}(n')\} = J_0(2\pi f_d|n-n'|T_s)$, $\forall \mu,\nu$*, where* T_s *is the symbol period.*

AS2): the additive Gaussian noise is white both in space and time; i.e., $\mathrm{E}\{w_\nu^*(n)w_{\nu'}(n')\} = N_0\delta(\nu-\nu')\delta(n-n')$.

Based on AS0)-AS2), an MMSE predictor for the MIMO channel has been developed in [9] based on PSAM. Specifically, the data stream is parsed into blocks of length L_{b}, and N_t known symbol is inserted per block [9]. Based on the extracted pilot signals up to block i, the receiver predicts the MIMO channel values

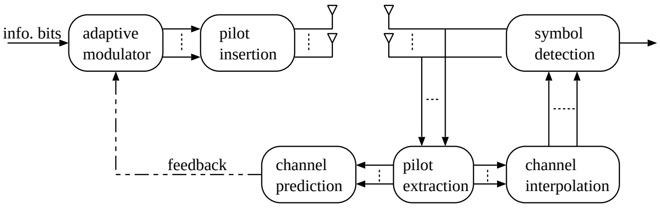

Fig. 1. The transceiver diagram

Q blocks ahead, where we assume that the feedback delay is a multiple of the block duration $L_{\rm b}T_s$ [9]. Let $\hat{\mathbf{H}}((i+Q)L_{\rm b})$ denote the predicted channels, and define the corresponding prediction error matrix $\boldsymbol{\Xi}((i+Q)L_{\rm b})$ so that:

$$\mathbf{H}((i+Q)L_{\rm b}) = \hat{\mathbf{H}}((i+Q)L_{\rm b}) + \boldsymbol{\Xi}((i+Q)L_{\rm b}). \quad (2)$$

The normalized channel prediction MSE is defined as:

$$\mathrm{NMSE} = \frac{\mathrm{E}\{\|\mathbf{H}((i+Q)L_{\rm b}) - \hat{\mathbf{H}}((i+Q)L_{\rm b})\|_{\rm F}^2\}}{\mathrm{E}\{\|\mathbf{H}((\mathrm{i}+\mathrm{Q})\mathrm{L_b})\|_{\rm F}^2\}}, \quad (3)$$

where $\|\cdot\|_{\rm F}$ stands for the Frobenius norm. With MMSE predictor, we show in [9] that $\hat{\mathbf{H}}((i+Q)L_{\rm b})$ and $\boldsymbol{\Xi}((i+Q)L_{\rm b})$ are uncorrelated thanks to the orthogonality principle. Furthermore, we establish that $\hat{\mathbf{H}}((i+Q)L_{\rm b}) \sim \mathcal{CN}(\mathbf{0}_{N_t\times N_r}, N_r\rho^2\mathbf{I}_{N_t})$, and $\boldsymbol{\Xi}((i+Q)L_{\rm b}) \sim \mathcal{CN}(\mathbf{0}_{N_t\times N_r}, N_r\sigma_\epsilon^2\mathbf{I}_{N_t})$, where

$$\rho = \sqrt{1-\mathrm{NMSE}}, \quad \sigma_\epsilon^2 = 1-\rho^2. \quad (4)$$

3. ADAPTIVE MODULATION WITH PERFECT CSI

Although the predicted channels $\hat{\mathbf{H}}((i+Q)L_{\rm b})$ differ from the true channels $\mathbf{H}((i+Q)L_{\rm b})$ as shown in (2), most existing adaptive transmitters assume the former to be perfect. For notational brevity, we will drop the time index, and denote e.g., $\hat{\mathbf{H}}((i+Q)L_{\rm b})$ by $\hat{\mathbf{H}}$.

We focus on a multi-antenna transmitter with beamforming, which is optimal in terms of maximizing the SNR at the receiver, assuming perfect CSI with $\hat{\mathbf{H}} = \mathbf{H}$ [8]. Specifically, the adaptive transmit-beamformer first draws an information symbol $s(n)$ from a suitable constellation with energy E_s, and then transmits the vector $\mathbf{u}^*s(n)$ across N_t antennas, using the optimal beam-steering vector $\mathbf{u} := [u_1,\ldots,u_{N_t}]^T$ that we will specify soon.

We assume that the channel estimates are error-free at the receiver, as in [1, 6, 9]. With maximum ratio combining (MRC) across the N_r receive antennas, the overall SNR is $\gamma = \mathbf{u}^{\mathcal{H}}\mathbf{H}\mathbf{H}^{\mathcal{H}}\mathbf{u}E_s/N_0$. Hence, each beamformed information symbol with MRC at the receiver adheres to an equivalent scalar input-output relationship:

$$y(n) = h_{\rm eqv}s(n) + w(n), \qquad h_{\rm eqv} := \sqrt{\mathbf{u}^{\mathcal{H}}\mathbf{H}\mathbf{H}^{\mathcal{H}}\mathbf{u}}. \quad (5)$$

Let the eigen decomposition of $\hat{\mathbf{H}}\hat{\mathbf{H}}^{\mathcal{H}}$ be:

$$\hat{\mathbf{H}}\,\hat{\mathbf{H}}^{\mathcal{H}} = \mathbf{U}_{\rm H}\mathbf{D}_{\rm H}\mathbf{U}_{\rm H}^{\mathcal{H}}, \qquad \mathbf{D}_{\rm H} := \mathrm{diag}(\lambda_1,\lambda_2,\ldots,\lambda_{N_t}), \quad (6)$$

where $\mathbf{U}_{\rm H} := [\mathbf{u}_{\rm H,1},\ldots,\mathbf{u}_{\rm H,N_t}]$ contains N_t eigenvectors, and $\mathbf{D}_{\rm H}$ has the corresponding N_t eigenvalues on its diagonal in a non-increasing order. With perfect CSI $\mathbf{H} = \hat{\mathbf{H}}$, the optimal beam-steering vector $\mathbf{u}$, that maximizes the received SNR, is [9]:

$$\mathbf{u} = \mathbf{u}_{\rm H,1}. \quad (7)$$

Having specified the optimal beam direction, we consider next the constellation switching module of our adaptive transmitter. We will adopt N rectangular (and square) quadrature-amplitude-modulation (QAM) constellations with size $M_i = 2^i, i = 1,\ldots,N$ [8]. When the channels experience deep fades, we will allow our adaptive design to suspend data transmission (this will correspond to setting $M_0 = 0$). Since the adaptive transmitter sees an equivalent channel in (5) with $h_{\rm eqv}^2 = \lambda_1$ when $\mathbf{H} = \hat{\mathbf{H}}$, it partitions the interval $[0,\infty)$ into $N+1$ disjoint but consecutive regions, with the boundary points denoted as $\{\alpha_i\}_{i=0}^{N+1}$, where $\alpha_0 = 0$ and $\alpha_{N+1} = \infty$. The constellation is then chosen according to:

$$M = M_i, \quad \text{when } \lambda_1 \in [\alpha_i, \alpha_{i+1}). \quad (8)$$

The overall probability that the constellation M_i is chosen is:

$$\Pr(M_i) = \Pr\big(\lambda_1 \in [\alpha_i,\alpha_{i+1})\big) = \int_{\alpha_i}^{\alpha_{i+1}} p_{\lambda_1}(\lambda_1)d\lambda_1, \quad (9)$$

where $p_{\lambda_1}(\lambda_1)$ is the probability density function (p.d.f.) of λ_1. The average transmission rate of this adaptive MIMO system is:

$$R = \frac{L_{\rm b}-N_t}{L_{\rm b}}\sum_{i=1}^{N}\log_2(M_i)\Pr(M_i), \quad (10)$$

where the spectral efficiency loss incurred by the pilots has been considered in the numerator.

To specify these boundary points with perfect CSI, we rely on the approximate BER performance [5, 8]:

$$\mathrm{BER}(M_i,\lambda_1) \approx 0.2\exp(-\lambda_1 g_i E_s/N_0), \quad (11)$$

where the constellation specific constant g_i is chosen as: $g_i = 3/[2(M_i-1)]$ for square QAM, and $g_i = 6/(5M_i-4)$ for rectangular QAM [8]. To maintain a target BER denoted as $\mathrm{BER_{target}}$, the transmitter determines the boundary points as [c.f. (8),(11)]:

$$\alpha_i = \frac{-\ln(5\,\mathrm{BER_{target}})}{g_iE_s/N_0}, \quad i = 1,\ldots,N. \quad (12)$$

Based on (8) and (11), the average BER for constellation M_i is:

$$\overline{\mathrm{BER}}(M_i) = \int_{\alpha_i}^{\alpha_{i+1}} \mathrm{BER}(M_i,\lambda_1)p(\lambda_1)d\lambda_1. \quad (13)$$

The overall system BER is the ratio of the number of bits in error over the total number of transmitted bits, expressed as [1]:

$$\overline{\mathrm{BER}} = \frac{\sum_{i=1}^{N}\log_2(M_i)\overline{\mathrm{BER}}(M_i)}{\sum_{i=1}^{N}\log_2(M_i)\Pr(M_i)}. \quad (14)$$

Since inside each interval $[\alpha_i,\alpha_{i+1})$, we have $\mathrm{BER}(M_i,\lambda_1) \le \mathrm{BER_{target}}$, we infer that the average BER is guaranteed to be below the target, if indeed the channel prediction is perfect. However, the actual BER may increase due to the imperfect channel prediction. We next throughly investigate how the BER performance is affected by the channel prediction errors.

4. BER PERFORMANCE WITH IMPERFECT CSI

For a given realization of $\hat{\mathbf{H}}$, the true channel $\mathbf{H}$ can be viewed as a Gaussian random matrix with non-zero mean and white covariance [c.f. (2)]. Define $\tilde{\mathbf{h}} := \mathbf{H}^{\mathcal{H}}\mathbf{u} = (\hat{\mathbf{H}}+\boldsymbol{\Xi})^{\mathcal{H}}\mathbf{u}$. Conditioned on $\hat{\mathbf{H}}$, we have $\tilde{\mathbf{h}} \sim \mathcal{CN}(\hat{\mathbf{H}}^{\mathcal{H}}\mathbf{u}, \sigma_\epsilon^2 \mathbf{I}_{N_r})$. Furthermore, with $\mathbf{u} = \mathbf{u}_{\mathrm{H},1}$, we have $\|\hat{\mathbf{H}}^{\mathcal{H}}\mathbf{u}\|^2 = \lambda_1$. For each feedback $\hat{\mathbf{H}}$, the average BER, averaged over all possible $\mathbf{H}$, can be expressed as [9]:

$$\overline{\mathrm{BER}}(M_i, \hat{\mathbf{H}}) = 0.2\,\mathrm{E}_{\tilde{\mathbf{h}}}\{\exp(-\tilde{\mathbf{h}}^{\mathcal{H}}\tilde{\mathbf{h}} g_i E_s/N_0)\}. \quad (15)$$

As we detail in [9], we can simplify (15) to:

$$\overline{\mathrm{BER}}(M_i, \hat{\mathbf{H}}) = \frac{0.2}{(1+\sigma_\epsilon^2\phi_i)^{N_r}} \exp\Big(-\frac{\lambda_1\phi_i}{1+\sigma_\epsilon^2\phi_i}\Big), \quad (16)$$

where for brevity, we define

$$\phi_i = g_i E_s/N_0. \quad (17)$$

As in (13), the average BER for each constellation is:

$$\overline{\mathrm{BER}}(M_i) = \int_{\alpha_i}^{\alpha_{i+1}} \overline{\mathrm{BER}}(M_i, \hat{\mathbf{H}}) p(\lambda_1) d\lambda_1. \quad (18)$$

Plugging (18) into (14), the overall system BER can then be found in the presence of prediction errors. To calculate the overall BER, we need to find $\Pr(M_i)$ and $\overline{\mathrm{BER}}(M_i)$.

4.1. General Result for MIMO

For ease of notation, we define two constants:

$$k := \min(N_t, N_r), \qquad d := |N_t - N_r|. \quad (19)$$

For systems with N_t transmit- and N_r receive- antennas, there are at most k non-zero eigenvalues for $\hat{\mathbf{H}}\hat{\mathbf{H}}^{\mathcal{H}}$ [c.f. (6)]. Let $\{\xi_i\}_{i=1}^k$ denote the ordered eigenvalues of the matrix $(1/\rho^2)\hat{\mathbf{H}}\hat{\mathbf{H}}^{\mathcal{H}}$, for which we have $\lambda_i = \rho^2\xi_i, \forall i \in [1, k]$. Since each entry of $(1/\rho)\hat{\mathbf{H}}$ is Gaussian with distribution $\mathcal{CN}(0, 1)$, the joint distribution of the ordered eigenvalues $\{\xi_i\}_{i=1}^k$ is [7]:

$$p(\xi_1, \ldots, \xi_k) = C_{k,d} \exp\Big(-\sum_i \xi_i\Big) \prod_i \xi_i^d \prod_{i<j} (\xi_i - \xi_j)^2, \quad (20)$$

where $C_{k,d}$ is a normalizing constant.

From (20), we want to find the marginal p.d.f. of ξ_1:

$$p_{\xi_1}^{(k)}(\xi_1) = \int_0^{\xi_1} d\xi_2 \cdots \int_0^{\xi_{k-1}} d\xi_k \; p(\xi_1, \ldots, \xi_k). \quad (21)$$

Based on $p_{\xi_1}^{(k)}(\xi_1)$, let us define the integral:

$$\Psi_{\xi_1}^{(k)}(a, x) = \int_0^x e^{-(a-1)\xi_1} p_{\xi_1}^{(k)}(\xi_1) d\xi_1. \quad (22)$$

Since $\lambda_1 = \rho^2\xi_1$, we obtain from (9) and (22):

$$\Pr(M_i) = \Psi_{\xi_1}^{(k)}\Big(1, \frac{\alpha_{i+1}}{\rho^2}\Big) - \Psi_{\xi_1}^{(k)}\Big(1, \frac{\alpha_i}{\rho^2}\Big). \quad (23)$$

Plugging (16) into (18), we obtain:

$$\overline{\mathrm{BER}}(M_i) = \frac{0.2\left[\Psi_{\xi_1}^{(k)}\Big(b_i, \frac{\alpha_{i+1}}{\rho^2}\Big) - \Psi_{\xi_1}^{(k)}\Big(b_i, \frac{\alpha_i}{\rho^2}\Big)\right]}{[1 + (1-\rho^2)\phi_i]^{N_r}}, \quad (24)$$

where the constant b_i is defined as

$$b_i = 1 + \frac{|\rho|^2\phi_i}{1+\sigma_\epsilon^2\phi_i} = \frac{1+\phi_i}{1+(1-\rho^2)\phi_i}. \quad (25)$$

Plugging (23) and (24) into (10) and (14), we obtain the average transmission rate, and the average BER. Notice that the evaluation in (23) and (24) involves k-fold integration, which is numerically plausible but involved.

We next pursue simple solutions for special cases with $k = 1$ and $k = 2$. Let $\Gamma(m) := \int_0^\infty t^{m-1}e^{-t}dt$ denote the Gamma function with parameter m. With a positive integer m, the *normalized* incomplete Gamma function is obtained as:

$$\overline{\Gamma}(m, x) := \frac{1}{\Gamma(m)} \int_0^x t^{m-1}e^{-t}dt = 1 - e^{-x}\sum_{j=0}^{m-1}\frac{x^j}{j!}. \quad (26)$$

4.2. Multi-Input Single-Output or Single-Input Multi-Output

We first look at the simple case with $k = \min(N_t, N_r) = 1$, and $d = \max(N_t, N_r) - 1$. The p.d.f. of ξ_1 is deduced from (20) as:

$$p_{\xi_1}^{(1)}(\xi_1) = \frac{\xi_1^d}{\Gamma(d+1)} \exp(-\xi_1). \quad (27)$$

Plugging (27) into (22), we obtain:

$$\Psi_{\xi_1}^{(1)}(a, x) = a^{-(d+1)}\overline{\Gamma}(d+1, ax). \quad (28)$$

Setting $k = 1$ in (23) and (24), we end up with simple closed-forms for $\Pr(M_i)$ and $\overline{\mathrm{BER}}(M_i)$.

4.3. Multi-Input Two-Output or Two-Input Multi-Output

Here we consider the case with $k = 2$, and $d = \max(N_t, N_r) - 2$. From (20), we have the bi-variate p.d.f.

$$p(\xi_1, \xi_2) = C_{2,d} e^{-\xi_1-\xi_2}\xi_1^d\xi_2^d(\xi_1 - \xi_2)^2, \quad (29)$$

where the normalizing constant is $C_{2,d} = [\Gamma(d+2)\Gamma(d+1)]^{-1}$. Plugging (29) into (21) and (22), we obtain [9]:

$$\begin{aligned}\Psi_{\xi_1}^{(2)}(a, x) = {} & \frac{(d+2)}{a^{d+3}}\,\overline{\Gamma}(d+3, ax) - \frac{2(d+1)}{a^{d+2}}\,\overline{\Gamma}(d+2, ax) \\ & + \frac{(d+2)}{a^{d+1}}\,\overline{\Gamma}(d+1, ax) - \frac{d(d+1)}{(1+a)^{d+2}}\,\overline{\Gamma}\big(d+2, (1+a)x\big) \\ & - \frac{d+2}{(1+a)^{d+1}}\,\overline{\Gamma}\big(d+1, (1+a)x\big) \qquad (30) \\ & - \sum_{j=0}^{d}\frac{(d-j)(d-j-1)(d+j+2)!}{(j+2)!(1+a)^{d+j+3}(d+1)!}\overline{\Gamma}\big(d+j+3, (1+a)x\big).\end{aligned}$$

Setting $k = 2$ in (23) and (24), we again arrive at closed-forms for $\Pr(M_i)$ and $\overline{\mathrm{BER}}(M_i)$.

5. NUMERICAL RESULTS

We choose QAM constellations with sizes $\{M_i = 2^i\}_{i=1}^8$. We set $\mathrm{BER}_{\mathrm{target}} = 10^{-3}$, and fix $L_{\mathrm{b}} = 15$ when computing the transmission rate using (10). With $E_s/N_0 = 10$dB, we plot in Figs. 2 and 3 the dependence on the prediction NMSE of the system BER, and the transmission rate, respectively. From Fig. 2, we observe that the BERs remain almost constant when $\mathrm{NMSE} < 10^{-2}$, but deteriorate quickly when $\mathrm{NMSE} > 10^{-2}$. On the other hand, the transmission rates remain nearly constant when $\mathrm{NMSE} < 10^{-1}$, and decrease quickly when $\mathrm{NMSE} > 10^{-1}$, as shown in Fig. 3.

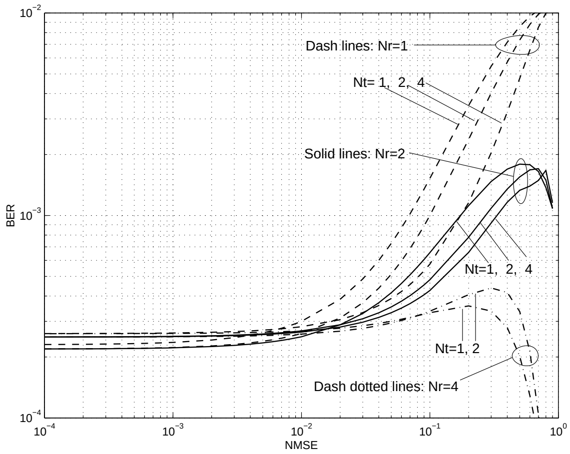

Fig. 2. BER performance at E_s/N_0 =10dB

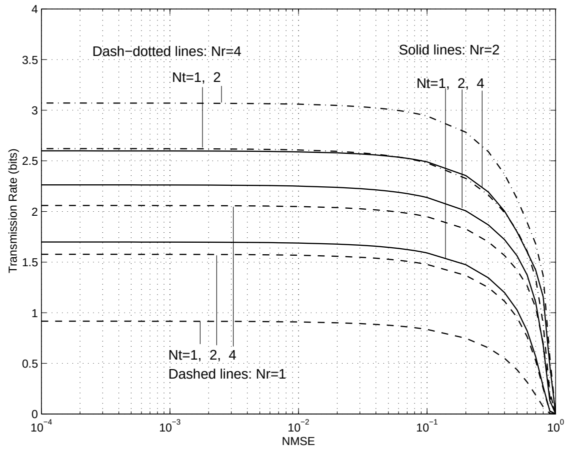

Fig. 3. Transmission rate at E_s/N_0 =10dB

We can now formally answer the question: *how accurate channel prediction needs to be*, so that the predicted channels can be used as if they were perfect. For each E_s/N_0 and NMSE, we calculate two BERs: one is $\mathrm{BER}_{\mathrm{ideal}}$, which is obtained by assuming that the true channels coincide with predicted channels, and the other is $\mathrm{BER}_{\mathrm{actual}}$, namely the actual BER in the presence of prediction error. For each E_s/N_0, we gradually increase NMSE from 10^{-6}, and locate the first NMSE value for which:

$$\mathrm{BER}_{\mathrm{actual}} = 1.1\ \mathrm{BER}_{\mathrm{ideal}}. \qquad (31)$$

Those NMSE values are collected in Fig. 4. Hence, for each antenna configuration, when the actual NMSE is below the corresponding curve in Fig. 4, the transmitter is assured that the actual BER is off from the $\mathrm{BER}_{\mathrm{ideal}}$ by less than 10%.

In a nutshell, our analytical and numerical results suggest the following design guidelines for practical adaptive MIMO systems:

G1: For each antenna configuration (N_t, N_r) and operating SNR (E_s/N_0), determine from Fig. 4 the critical NMSE value.

G2: Determine the actual NMSE based on various system parameters, as detailed in [9].

G3: If the actual NMSE is below the critical value, the adaptive transmitter can treat the predicted channels as being perfect. Otherwise, the transmitter needs to figure out the actual BER and transmission rate, as done in Figs. 2 and 3. Depending on the designer's judgment on whether these actual BER and rates are acceptable or not, transmitter designs without, or, with explicit CSI imperfection considered [4, 8], will be decided for deployment.

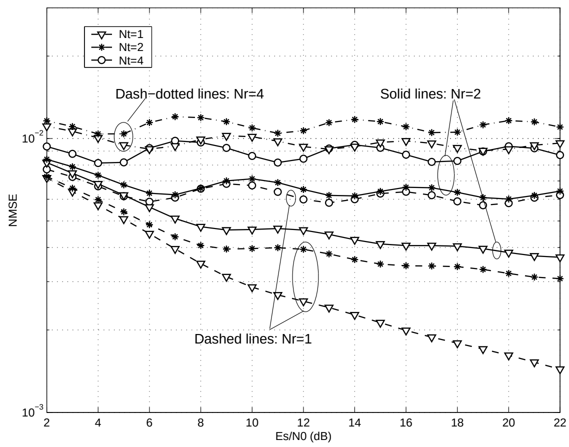

Fig. 4. The critical NMSE with $\mathrm{BER}_{\mathrm{actual}} \leq 1.1\,\mathrm{BER}_{\mathrm{ideal}}$

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