Link Performance Estimation Techniques for MIMO-OFDM Systems with Maximum Likelihood Receiver

Sung-Hyun Moon, *Member, IEEE*, Kyoung-Jae Lee, *Member, IEEE*, Jihoon Kim, and Inkyu Lee, *Senior Member, IEEE*

***Abstract*—Link adaptation allows a communication system to adapt its transmission modes according to channel conditions. Although a maximum likelihood (ML) receiver for multiple-input multiple-output (MIMO) systems provides optimal performance, estimating its link performance has been a difficult problem. In this paper, we propose a new link performance abstraction technique for MIMO orthogonal frequency-division multiplexing systems with the ML receiver. The performance of ML detection (MLD) is estimated by employing capacity bounds of two simple linear receivers. Then, we give a simple parametrization to compute the desired per-stream signal-to-noise ratio (SNR) values, which can be applied for both vertically and horizontally coded MIMO systems. Based on the derived per-stream SNR estimates, the block error rate is obtained using the received-bit information rate metrics. We also examine the effect of imperfect channel estimation as well as spatial correlations among antennas. Finally, extensive simulation results show that the proposed method provides superior estimation accuracy in the MIMO-MLD link evaluation with very low computational complexity.**

***Index Terms*—Link adaptation, PHY abstraction, MIMO-OFDM, maximum-likelihood receiver.**

I. Introduction

NEXT generation wireless cellular systems are expected to support high-speed packet data services, providing users with rapid access to high quality multimedia applications. To satisfy this growing demand, multiple-input multiple-output (MIMO) technologies have been extensively studied to improve spectral efficiency, which provides a linear growth of capacity with the number of antennas without increasing bandwidth or transmit powers [1][2]. Besides, reliable wideband transmission becomes feasible over frequency selective fading channels by adopting orthogonal frequency-division multiplexing (OFDM) modulation techniques which do not require complicated equalizers [3]. Combined with bit-interleaved coded modulation (BICM) [4], the MIMO-OFDM system promises extremely high spectral efficiency as well as good diversity gains for high-speed broadband applications [5]–[7], and thus has been adopted in emerging fourth generation (4G) cellular standards such as 3GPP long term evolution (LTE)-advanced [8] and IEEE 802.16m WiMAX [9].

In order to approach the theoretical capacity limit of MIMO-OFDM systems, the use of link adaptation techniques [10]–[13] is indispensable. Among various link adaptation strategies, adaptive modulation and coding (AMC) is a physical layer (PHY) technique for coded OFDM transmission, which decides adequate modulation levels and/or channel code rates according to the current channel state [14]. To choose proper modulation and coding sets (MCSs), it is necessary to estimate the link performance of each packet transmission accurately. To this end, theoretical studies on the analysis of the error performance have been carried out for a variety of MIMO systems including diversity techniques [15]–[17] and space-time codes [18][19], and also for bit-interleaved coded OFDM systems [14][20].

On the other hand, estimating the link performance plays also an important role as an interface between link level and system level simulations in ensuring simple and accurate performance evaluation of wireless communication systems. This link-to-system interface is often referred to as a PHY abstraction model and is based on an effective signal-to-noise ratio (SNR) mapping (ESM) concept, which is a compression of many measured SNR values to a single effective one [21]. A number of ESM methods have been introduced in order to provide a more effective way of predicting the link quality of coded OFDM systems in single-input single-output (SISO) cases [21]–[23].

Since maximum likelihood detection (MLD) provides the optimum MIMO detection performance, the MLD or near-ML detectors have widely been considered to be adopted as a powerful receiver algorithm. However, it is well recognized that accurate link estimation becomes challenging for MIMO systems when an ML detector is applied. Although a couple of extensions of existing ESM methods to the MIMO-MLD have been introduced [24][25], they require high computational

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S.-H. Moon was with the School of Electrical Eng., Korea University, Seoul, Korea. He is now with the Electronics and Telecommunications Research Institute (ETRI), Daejeon, Korea (e-mail: sh.moon@etri.re.kr).

K.-J. Lee is with the Department of Electrical and Computer Eng., the University of Texas at Austin, Austin, TX, USA (e-mail: kj@austin.utexas.edu).

J. Kim is with Samsung Electronics, Suwon, Korea (e-mail: jihoon27.kim@samsung.com).

I. Lee is with the School of Electrical Eng., Korea University, Seoul, Korea (e-mail: inkyu@korea.ac.kr).

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complexity or do not provide reasonable estimation accuracy. In [26], a new approach of the PHY abstraction for the MIMO-MLD was proposed for *horizontal encoding* structures, where each transmit antenna is connected to separate channel encoders. The same idea was applied to the *vertical encoding* case [27], where all data streams are simultaneously encoded by a single channel encoder.

In this paper, by extending the general SISO ESM approach, we propose an improved link error prediction technique for MIMO-OFDM systems with ML receiver. First, utilizing capacity upper and lower bounds, we develop a simple yet accurate streamwise SNR representation process for both vertical and horizontal encoding MIMO-MLD systems. After obtaining the SNR estimates per each stream, the corresponding block error rate (BLER) performance is found for each encoding block through the SISO ESM using the received-bit information rate (RBIR) metrics [23]. From a practical viewpoint, we also examine the system with imperfect channel estimation as well as spatial correlations among transmit and receive antennas, and study their effects on the accuracy of our PHY abstraction. From simulation results, we confirm that the proposed method is quite accurate in the MIMO-MLD link performance evaluation while preserving very low computational complexity. Moreover, we also show that by applying the AMC based on the proposed link estimation method, we can achieve high throughput performance which is very close to the optimum in the MIMO-MLD systems.

The remainder of this paper is organized as follows: In Section II, we describe the system model for MIMO-OFDM with AMC. Section III reviews the ESM link abstraction models and in Section IV, we explain the proposed link error prediction technique for the MIMO-MLD. Section V addresses the impact of the imperfect channel estimation and the spatial correlation. Section VI verifies the accuracy of the proposed method from extensive simulation results, and we finish the paper with conclusions in Section VII.

Throughout this paper, we use the following notations. Boldface upper-case letters and boldface lower-case letters indicate matrices and column vectors, respectively. Also, $(\cdot)^T$, $(\cdot)^H$, $\otimes$ and $\mathrm{Tr}(\cdot)$ are denoted as transpose, Hermitian transpose, Kronecker product and trace, respectively. The notation $[\mathbf{A}]_{kk}$ represents the k-th diagonal entry of a matrix $\mathbf{A}$, and $\mathrm{vec}(\mathbf{A})$ stacks the columns of $\mathbf{A}$ into a column vector. An $N \times N$ identity matrix is defined by $\mathbf{I}_N$ and the expectation operation is given as $\mathbb{E}[\cdot]$.

II. System Model

We consider MIMO-OFDM systems with AMC which employs N_c subcarriers and N_t transmit and N_r receive antennas. In each time slot, a receiver chooses a proper MCS for each encoding block according to the current channel condition and feeds back the indices to the AMC controller at the transmitter. The MCS level determines the quadrature amplitude modulation (QAM) size and the channel code rate. At the transmitter, based on the BICM structure, the information bits are encoded either vertically or horizontally, bit-wise interleaved and mapped to symbol constellations after the serial-to-parallel conversion. Following the bits-to-symbol mapping, data symbols are modulated by the N_c-size inverse fast Fourier transform (FFT).

Assuming proper cyclic prefix (CP), the N_r-dimensional complex baseband received signal vector at the k-th subcarrier after the FFT demodulation is given by

$$\mathbf{y}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{n}_k \quad \text{for} \quad k = 1, \cdots, N_c \tag{1}$$

where $\mathbf{x}_k = [x_{k,1} \cdots x_{k,N_t}] \in \mathbb{C}^{N_t \times 1}$ is the transmitted symbol vector, $\mathbf{n}_k \in \mathbb{C}^{N_r \times 1}$ denotes the additive white Gaussian noise (AWGN) vector with zero mean and covariance matrix $\sigma_n^2 \mathbf{I}_{N_r}$, and $\mathbf{H}_k = [\mathbf{h}_1 \cdots \mathbf{h}_{N_t}] \in \mathbb{C}^{N_r \times N_t}$ equals the Rayleigh fading MIMO channel matrix whose entries have an independent and identically distributed (i.i.d.) complex Gaussian distribution with $\mathcal{CN}(0, 1)$. In the absence of the channel state information (CSI) at the transmitter, the symbol vector $\mathbf{x}_k$ satisfies $\mathbb{E}[\mathbf{x}_k \mathbf{x}_k^H] = \frac{P}{N_t} \mathbf{I}_{N_t}$ with uniform power allocation across the transmit antennas, where P is the total transmit power. For simplicity, we assume an ideal channel estimator such that all subchannel matrices $\mathbf{H}_1, \cdots, \mathbf{H}_{N_c}$ are perfectly known at the receiver. Later in Section V, a practical system model which includes imperfect channel estimation and spatial correlation will be considered.

III. Review of Effective SNR Mapping Models

In this section, we review the principle of the physical layer link performance abstraction by focusing on existing ESM methods. First, we start with the single antenna case and then explain the MIMO case with MLD, which is the main scope of this work.

A. Single-input single-output case

For SISO OFDM systems, most ESM methods calculate the effective SNR, denoted by $\hat{\gamma}$, in the frequency domain according to a mapping function $\mathcal{F}$ as

$$\hat{\gamma} = \mathcal{F}^{-1} \left(\frac{1}{N_c} \sum_{k=1}^{N_c} \mathcal{F}(\gamma_k) \right) \tag{2}$$

where γ_k is the received SNR of the k-th subcarrier determined as $\gamma_k = \frac{P|h_k|^2}{\sigma_n^2}$. Here, h_k represents the SISO channel gain of the k-th subcarrier. Once $\hat{\gamma}$ is computed from (2), the BLER of the link is mapped from $\hat{\gamma}$ by looking up the AWGN reference curves which is generated in advance and stored as a table for each MCS. Simply, by setting $\mathcal{F}(x) = x$, we may choose $\hat{\gamma}$ as the sample mean $\hat{\gamma} = \frac{1}{N_c} \sum_{k=1}^{N_c} \gamma_k$. However, this linear estimation cannot explain the effect of forward error correction (FEC) codes, and it cannot capture different diversity gains coming from deviations of multipath channel delay profiles, which results in poor accuracy.

In order to accurately model the link performance, exponential ESM (EESM) has been proposed using the Chernoff bound of the coded symbol error rate performance [21], which computes $\hat{\gamma}$ in (2) with the exponential function $\mathcal{F}(x) = \exp(-\frac{x}{\beta})$, where β is a predetermined system parameter. Another approach for the ESM is to define the mapping $\mathcal{F}$ based on the mutual information function such as the RBIR [23] and the mean mutual information per bit (MMIB) [22][24]. For SISO systems, these mutual information based

ESM methods are shown to have pretty good accuracy because the optimization of system parameters is not required. Also they are suitable for hybrid automatic repeat request (ARQ) schemes [23]. Recently, in order to simplify the mapping procedure further, a generalized-type ESM method based on a notion of bit-wise SNR has also been proposed [28].

B. MIMO case with ML receiver

For MIMO spatial multiplexing systems which adopt a linear receiver or a successive interference cancellation (SIC) type receiver, the post-processing SNR of each of N_t multiplexed streams can be easily obtained [29]. Thus, the link adaptation in this case is simply N_t repetitions of the SISO ESM of (2), and any well-designed SISO strategy mentioned in the previous subsection can be directly applied.

In contrast, it becomes challenging with MIMO-MLD because the link quality of each individual data stream is difficult to estimate due to non-linear joint detection process. Although the MMIB method was applied for the MIMO-MLD, quite complicated operations are required for optimizing its system parameters [24] and it does not work well with horizontal encoding. Moreover, the RBIR procedure suggested in [25] is found to be invalid for the MIMO-MLD even for the simplest case of $N_t = N_r = 2$ [30]. Therefore, there is a need for an improved PHY abstraction model which accurately estimates the MLD link performance for both vertical and horizontal encoding structures.

IV. Proposed PHY Abstraction Model for MIMO-MLD

In this section, motivated by previous discussions, we propose a new PHY abstraction technique which provides accurate link level performance of the MIMO ML receiver. Moreover, we investigate a unified approach which can be applied for both vertical and horizontal encoding systems with an arbitrary number of antennas.

Our ultimate goal is to obtain a single or multiple estimates on the link level performance, i.e., the effective SNR and the corresponding BLER, depending on the employed channel code. To achieve this goal, the proposed scheme carries out the following three steps.

1) Per-stream SNR representation (PSSR): At each subcarrier, per-stream SNR values of the MLD are estimated based on the ratio of upper and lower bounds of the MLD capacity.
2) Effective SNR mapping based on RBIR: From the estimated N_tN_c SNR values in step 1), a single or N_t effective SNRs are obtained using the RBIR mapping model for vertical or horizontal encoding, respectively.
3) BLER mapping: Finally, the BLER estimate for each encoding block is one-to-one mapped from the effective SNR by the look-up table of AWGN reference curves.

The key building block of the proposed scheme is the first step, i.e., the PSSR process. For this step, we propose a simple and effective parametrization which offers both low computational complexity and easy off-line search process. We start with defining the two bounds of the MIMO-MLD capacity. For now, we drop the subcarrier index k for notational simplicity.

A. Proposed PSSR techniques

The purpose of the PSSR method is to estimate the post-detection SNR values of the MLD, denoted by $\gamma_1^{\text{ML}}, \cdots, \gamma_{N_t}^{\text{ML}}$, for a given channel matrix $\mathbf{H}$. First, we define the information rate of the n-th data stream from the SNRs as $C_n^{\text{ML}} \triangleq \log_2(1+\gamma_n^{\text{ML}})$. Then, the *artificial* capacity of the MIMO-MLD can be written as

$$C_{\text{ML}} = \sum_{n=1}^{N_t} C_n^{\text{ML}} = \sum_{n=1}^{N_t} \log_2(1+\gamma_n^{\text{ML}}). \tag{3}$$

Here, C_{ML} means the maximum achievable rate when the MLD is employed at the receiver, which must be distinguished from the MIMO open-loop capacity $C_{\text{open}} = \log_2 \det\left(\mathbf{I}_{N_r} + \rho\mathbf{H}\mathbf{H}^H\right)$ where $\rho = \frac{P}{N_t\sigma_n^2}$ [1]. We simply conjecture that $C_{\text{ML}} \le C_{\text{open}}$.

Because the true values of $\{\gamma_n^{\text{ML}}\}_{n=1}^{N_t}$ are unknown, we adopt two simple bounds for (3) to estimate $\{\gamma_n^{\text{ML}}\}_{n=1}^{N_t}$. First, an upper bound of C_{ML} is derived by assuming that interference among data symbols is perfectly removed at the receiver, which is called as perfect interference cancellation (PIC). Also, as a lower bound, the linear minimum mean-square error (MMSE) receiver $\mathbf{G}_{\text{MMSE}} = (\mathbf{H}^H\mathbf{H} + \rho^{-1}\mathbf{I}_{N_t})^{-1}\mathbf{H}^H$ is considered. The received SNR of the PIC and the signal-to-interference-plus-noise ratio (SINR) of the MMSE receiver for the n-th stream are given, respectively, as

$$\gamma_n^{\text{PIC}} = \rho\|\mathbf{h}_n\|^2 \tag{4}$$

$$\gamma_n^{\text{MMSE}} = \frac{1}{\left[\left(\mathbf{I}_{N_t} + \rho\mathbf{H}^H\mathbf{H}\right)^{-1}\right]_{nn}} - 1. \tag{5}$$

Then, the corresponding instantaneous capacities C_{PIC} and C_{MMSE} are expressed by

$$\begin{aligned} C_{\text{PIC}} &= \sum_{n=1}^{N_t} C_n^{\text{PIC}} = \sum_{n=1}^{N_t} \log_2(1+\gamma_n^{\text{PIC}}) \\ C_{\text{MMSE}} &= \sum_{n=1}^{N_t} C_n^{\text{MMSE}} = \sum_{n=1}^{N_t} \log_2(1+\gamma_n^{\text{MMSE}}). \end{aligned}$$

From these bounds, it follows that γ_n^{ML} is bounded as $\gamma_n^{\text{MMSE}} \le \gamma_n^{\text{ML}} \le \gamma_n^{\text{PIC}}$, which leads to the same relationship among the capacities as $C_{\text{MMSE}} \le C_{\text{ML}} \le C_{\text{PIC}}$. On the other hand, we can easily prove that $C_{\text{MMSE}} \le C_{\text{open}} \le C_{\text{PIC}}$, which is shown in Appendix A. As a consequence, we have

$$C_{\text{MMSE}} \le C_{\text{ML}} \le C_{\text{open}} \le C_{\text{PIC}} \tag{6}$$

where the equalities hold if all columns of $\mathbf{H}$ are orthogonal. Note that for a given channel $\mathbf{H}$, $C_{\text{MMSE}}, C_{\text{open}}$ and C_{PIC} are known values, while C_{ML} is unknown. From now on, we will explain how to determine the SNR values for MLD $\gamma_1^{\text{ML}}, \cdots, \gamma_{N_t}^{\text{ML}}$ by utilizing the relation (6) for both vertical and horizontal encoding systems.

B. Vertical encoding case

First, we introduce two parameters α and β to denote the ratios of the capacity gaps from (6), respectively, as

$$\alpha = \frac{C_{\text{open}} - C_{\text{MMSE}}}{C_{\text{PIC}} - C_{\text{MMSE}}}, \quad 0 \le \alpha \le 1 \tag{7}$$

$$\beta = \frac{C_{\text{ML}} - C_{\text{MMSE}}}{C_{\text{open}} - C_{\text{MMSE}}}, \quad 0 \le \beta \le 1 \tag{8}$$

TABLE I
THE OPTIMAL VALUES OF β FOR DIFFERENT MCS LEVELS

Modulation level \ Code rate	1/2	2/3	3/4	5/6	7/8
4-QAM	0.6	0.8	0.9	1.0	1.0
16-QAM	0.4	0.6	0.7	0.8	0.8
64-QAM	0.2	0.4	0.5	0.6	0.6

where the ranges of α and β are obtained from $C_{\text{open}} \leq C_{\text{PIC}}$ and $C_{\text{ML}} \leq C_{\text{open}}$. In order to formulate an expression of γ_n^{ML}, we also define ω_n as the ratio of the capacity gaps for the n-th data stream as

$$\omega_n = \frac{C_n^{\text{ML}} - C_n^{\text{MMSE}}}{C_n^{\text{PIC}} - C_n^{\text{MMSE}}}, \qquad \text{for } n = 1, \cdots, N_t. \tag{9}$$

Naturally, ω_n may be different for all N_t individual streams. However, these different values of $\omega_1, \cdots, \omega_{N_t}$ cannot be quantitatively evaluated since C_n^{ML} is unknown.

Accordingly, to simplify the derivation, we assume that all substreams have the same ratio of (9) for any $\mathbf{H}$ as

$$\omega_n = \frac{C_{\text{ML}} - C_{\text{MMSE}}}{C_{\text{PIC}} - C_{\text{MMSE}}} = \alpha \cdot \beta, \qquad \text{for } n = 1, \cdots, N_t. \tag{10}$$

For vertical encoding systems where a single MCS is employed across streams, this approximation is true in an average sense over all channel realizations[1]. Moreover, simulations show that $\omega_1, \cdots, \omega_{N_t}$ are not very distinct, even if $\mathbf{H}$ is ill-conditioned.

Now, by rearranging (9) and (10), we have $C_n^{\text{ML}} = \alpha\beta\, C_n^{\text{PIC}} + (1 - \alpha\beta) C_n^{\text{MMSE}}$. Consequently, the SNR of the n-th substream for the MIMO-MLD is finally represented as

$$\gamma_n^{\text{ML}} = \left(1 + \gamma_n^{\text{PIC}}\right)^{\alpha\beta} \left(1 + \gamma_n^{\text{MMSE}}\right)^{1-\alpha\beta} - 1. \tag{11}$$

Note that in (11), γ_n^{PIC}, γ_n^{MMSE} and α are directly obtained from (4), (5) and (7) as a function of $\mathbf{H}$, respectively. Then, only β needs to be optimized in advance via an off-line process. The procedure of finding β is described in Appendix B.

In Table I, the optimal values of β over 15 different MCS levels are listed. The link level simulation environments for Table I are illustrated in Section VI. Here, we emphasize advantages of our parametrization using a single system parameter β. First, it turns out that β is independent of N_t and N_r. That is, Table I is valid for any MIMO antenna configurations. Second, we find that β is insensitive to the channel power delay profile and depends on the employed channel code. This is a very desirable feature for a good PHY abstraction method as mentioned in Section III-A. These will be verified from simulation results later. Furthermore, one can notice from Table I that β monotonically increases with the code rate and decreases with the modulation level. This property ensures that by applying simple linear interpolation, β for any other new MCS level can be readily found without additional simulation efforts.

[1]This is because all columns of $\mathbf{H}$ are statistically equivalent (i.i.d. random vectors). However, this assumption may be broken if the modulation level in each stream are not identical, which can occur in horizontal encoding systems. The description for the horizontal encoding is provided in the next subsection.

C. Horizontal encoding case

For horizontally coded MIMO systems, different modulation levels can be allocated to each data stream unlike the vertical encoding case. If different modulation levels are applied in other substreams, the assumption $\omega_1 = \cdots = \omega_{N_t}$ of (10) is no longer valid, because the MLD performance of each layer, represented by C_n^{ML} in (9), is influenced by different minimum Euclidean distances of the joint symbol constellation. In this case, the accuracy in our predictions $\gamma_1^{\text{ML}}, \cdots, \gamma_{N_t}^{\text{ML}}$ made in (11) may become reduced.

For example, let us consider the $N_t = 2$ case where 4-QAM and 16-QAM are adopted for the first symbol x_1 and the second symbol x_2, respectively, with equal power $\mathbb{E}[|x_1|^2] = \mathbb{E}[|x_2|^2] = \rho\sigma_n^2$. Then, compared to the case where 4-QAM is employed for both symbols, the detection accuracy for x_1 becomes less reliable, because the minimum Euclidean distance of the joint constellation is decreased due to 16-QAM constellation in the second stream. On the contrary, compared to the case of 16-QAM signaling for both streams, x_2 experiences higher detection accuracy since 4-QAM signal x_1 improves the overall minimum distance.

In order to reflect these changes due to non-identical modulation levels, proper compensation should be made to each of $\omega_1, \cdots, \omega_{N_t}$. For this purpose, we adopt a tuning parameter $\Delta\beta_n$ per each stream to properly adjust the value of β in (10). By definition, α is not related to the MLD performance. By replacing β with $\beta + \Delta\beta_n$, we rewrite (10) as

$$\omega_n = \frac{C_n^{\text{ML}} - C_n^{\text{MMSE}}}{C_n^{\text{PIC}} - C_n^{\text{MMSE}}} = \alpha\left(\beta + \Delta\beta_n\right).$$

Then, similar to the vertical encoding case in (11), we can estimate the per-stream SNR of the MIMO-MLD γ_n^{ML} with different modulation levels as

$$\gamma_n^{\text{ML}} = \left(1 + \gamma_n^{\text{PIC}}\right)^{\alpha(\beta+\Delta\beta_n)} \left(1 + \gamma_n^{\text{MMSE}}\right)^{1-\alpha(\beta+\Delta\beta_n)} - 1. \tag{12}$$

If all modulation levels are identical, we have $\Delta\beta_1 = \cdots = \Delta\beta_{N_t} = 0$ and (12) reduces to (11). Also, it is found that the values of $\Delta\beta_n$ are independent of the code rate since the detection performance is not affected by channel coding, which was confirmed by simulations. As a result, the total number of combinations for different modulation levels are only $3, 7$ and 12 for $N_t = 2, 3$ and 4, respectively, assuming 4, 16 and 64-QAM.

Table II lists the optimal values of $\Delta\beta_n$ found by simulations for $N_t = 2$ and 3. Note that $\Delta\beta_n$ is also easily obtained off-line in the same way as β. Therefore, for both the vertical and the horizontal encoding, the proposed PSSR technique avoids prohibitive off-line search process such as in the conventional ESM methods [24] and [25], where one should search the optimal parameters for a variety of different SNRs and channel condition numbers.

D. Effective SNR and BLER mapping based on RBIR

So far, we have investigated how to estimate the post-processing SNR values $\{\gamma_n^{\text{ML}}\}_{n=1}^{N_t}$ of MIMO-MLD for each subcarrier from the proposed PSSR techniques. The next step is to map those SNR estimates to the effective SNRs and BLERs, as many as the number of FEC encoding blocks.

TABLE II
TUNING PARAMETERS $\Delta\beta_n$ FOR NON-IDENTICAL MODULATION LEVELS WITH $N_t = 2$ AND 3

	Modulation levels	$\{\Delta\beta_n\}_{n=1}^{N_t}$
$N_t = 2$	$(4,16), (4,64), (16,64)$	$(-0.3, 0.7), (-0.4, 1.2), (-0.2, 0.6)$
$N_t = 3$	$(4,4,16), (4,4,64), (4,16,16), (4,16,64),$ $(4,64,64), (16,16,64), (16,64,64)$	$(-0.3,-0.3,0.6), (-0.3,-0.3,1.5), (-0.6,0.3,0.3), (-0.8,0.3,1.2),$ $(-0.4,0.8,0.8), (-0.2,-0.2,0.6), (-0.2,0.4,0.4)$

Among existing ESM models, we adopt the RBIR approach [23] since it is simple and has a couple of advantages as stated in Section III-A[2].

For the horizontal encoding, the RBIR of each substream can be represented by

$$\text{RBIR}_n = \sum_{k=1}^{N_c} \frac{\text{SI}\left(\gamma_{k,n}^{\text{ML}}, m_{k,n}\right)}{\log_2\left(m_{k,n}\right)}, \quad \text{for} \quad n = 1, \cdots, N_t, \quad (13)$$

where $\log_2\left(m_{k,n}\right)$ denotes the number of bits allocated to the k-th subcarrier at the n-th stream and $\text{SI}(\gamma, m)$ is the symbol mutual information (SI) with the modulation level m derived as [23]

$$\text{SI}(\gamma, m) = \frac{1}{m}\sum_{j=1}^{m}\int_l f_{LLR_j(\gamma)}(l)\log_2\frac{m}{1+e^{-l}}dl. \quad (14)$$

Here, $f_{LLR_j(\gamma)}$ represents the probability density function of the symbol level log-likelihood ratio (LLR) of the j-th constellation point with SNR equal to γ [23]. To avoid repeated complex calculations, (14) is computed once for a wide range of SNRs and saved in a lookup table after scaling to $[0,1]$ [25, Table 25]. According to (13) and the SNR-to-SI mapping table, RBIR_n for each stream is obtained based on $\{\gamma_{k,n}^{\text{ML}}\}_{k=1}^{N_c}$. Then, RBIR_n is inversely mapped after normalization by $\frac{1}{N_c}$ to get the effective SNR $\hat{\gamma}_n$.

In the vertical encoding case, we only need a single effective SNR estimate $\hat{\gamma}$. This can be simply resolved by averaging N_t RBIR values obtained from (13) over the spatial domain as

$$\overline{\text{RBIR}} = \frac{1}{N_t}\sum_{n=1}^{N_t}\text{RBIR}_n. \quad (15)$$

Then, in the same way, $\overline{\text{RBIR}}$ is inversely mapped to the effective SNR $\hat{\gamma}$.

Finally, as the last step, the BLER of each encoding block can be directly mapped from $\{\hat{\gamma}_n\}_{n=1}^{N_t}$ for the horizontal encoding and from $\hat{\gamma}$ for the vertical encoding by looking up the AWGN reference curves, i.e., the AWGN look-up table.

V. EFFECT OF CHANNEL MISMATCH AND SPATIAL CORRELATION

In the previous sections, we have described a link error prediction technique under the i.i.d. channel matrix $\mathbf{H}_k$ according to the model in Section II. However, it is important to examine the behavior of our scheme in more realistic channel models which include spatially correlated links and the channel estimation error at the receiver. In this section, we model these non-ideal channel conditions and discuss their impact on the estimation accuracy of the proposed method. Again we omit the subcarrier index k.

A general form of the spatial correlation for $\mathbf{H}$ is expressed by the covariance matrix $\mathbf{R} = \mathbb{E}[\overline{\mathbf{h}}\,\overline{\mathbf{h}}^H]$ where $\overline{\mathbf{h}} = \text{vec}(\mathbf{H}) \in \mathbb{C}^{N_t N_r \times 1}$. However, due to its complicated nature, other simple structured representations for $\mathbf{R}$ have been proposed as an alternative. One widely adopted model is the Kronecker model, which assumes the separability in correlation induced by the transmit and the receive antennas [31][32]. By employing this model, $\mathbf{R}$ is structured by $\mathbf{R} = \mathbf{R}_t \otimes \mathbf{R}_r$ where $\mathbf{R}_t = \mathbb{E}[\mathbf{H}^H\mathbf{H}] \in \mathbb{C}^{N_t \times N_t}$ and $\mathbf{R}_r = \mathbb{E}[\mathbf{H}\mathbf{H}^H] \in \mathbb{C}^{N_r \times N_r}$ refer to the covariance matrices among the transmit and receive antennas. Then, the channel matrix $\mathbf{H}$ can be decomposed as

$$\mathbf{H} = \mathbf{R}_r^{\frac{1}{2}}\mathbf{H}_w\mathbf{R}_t^{\frac{1}{2}} \quad (16)$$

where $\mathbf{H}_w \in \mathbb{C}^{N_r \times N_t}$ consists of i.i.d. entries with $\mathcal{CN}(0,1)$.

Next, we model the effect of imperfect channel estimation. We assume that the receiver performs the MMSE estimation for $\mathbf{H}_w$ in the presence of antenna correlations in (16) with the perfect knowledge of $\mathbf{R}_t$ and $\mathbf{R}_r$. Denoting the estimated channel as $\tilde{\mathbf{H}}_w$, $\mathbf{H}_w$ can be represented by

$$\mathbf{H}_w = \tilde{\mathbf{H}}_w + \mathbf{E}_w \quad (17)$$

where $\mathbf{E}_w \triangleq \mathbf{H}_w - \tilde{\mathbf{H}}_w$ denotes the estimation error matrix. From well known properties of the MMSE estimator, entries of $\mathbf{E}_w$ are i.i.d. zero mean complex Gaussian and uncorrelated with $\tilde{\mathbf{H}}_w$. We define the variance of the entries of $\mathbf{E}_w$ as σ_e^2. Then, the variance of the entries of $\tilde{\mathbf{H}}_w$ is given by $1 - \sigma_e^2$ from the orthogonality principle. By inserting (17) into (16), the actual channel in the presence of channel mismatch and spatial correlation becomes

$$\mathbf{H} = \mathbf{R}_r^{\frac{1}{2}}\big(\tilde{\mathbf{H}}_w + \mathbf{E}_w\big)\mathbf{R}_t^{\frac{1}{2}} \triangleq \tilde{\mathbf{H}} + \mathbf{E} \quad (18)$$

where $\tilde{\mathbf{H}}$ and $\mathbf{E}$ indicate the total estimated channel $\tilde{\mathbf{H}} = [\tilde{\mathbf{h}}_1 \cdots \tilde{\mathbf{h}}_{N_t}] = \mathbf{R}_r^{\frac{1}{2}}\tilde{\mathbf{H}}_w\mathbf{R}_t^{\frac{1}{2}}$ and the total estimation error $\mathbf{E} = \mathbf{R}_r^{\frac{1}{2}}\mathbf{E}_w\mathbf{R}_t^{\frac{1}{2}}$, respectively.

By substituting (18), the system model in (1) is written as

$$\mathbf{y} = \big(\tilde{\mathbf{H}} + \mathbf{E}\big)\mathbf{x} + \mathbf{n} = \tilde{\mathbf{H}}\mathbf{x} + \mathbf{w} \quad (19)$$

where $\mathbf{w} \triangleq \mathbf{E}\mathbf{x} + \mathbf{n}$ is the effective noise vector which is also zero mean Gaussian due to linearity. While the covariance matrix of $\mathbf{w}$, defined as $\mathbf{Q_w} = \mathbb{E}[\mathbf{w}\mathbf{w}^H]$, is calculated as

$$\begin{aligned}\mathbf{Q_w} &= \mathbf{R}_r^{\frac{1}{2}}\,\mathbb{E}_{\mathbf{E}_w,\mathbf{x}}\left[\mathbf{E}_w\mathbf{R}_t^{\frac{1}{2}}\mathbf{x}\mathbf{x}^H\mathbf{R}_t^{\frac{1}{2}}\mathbf{E}_w^H\right]\mathbf{R}_r^{\frac{1}{2}} + \mathbb{E}_\mathbf{n}[\mathbf{n}\mathbf{n}^H] \\ &= \sigma_e^2\mathbf{R}_r^{\frac{1}{2}}\ \text{Tr}\left(\mathbf{R}_t\mathbb{E}_\mathbf{x}[\mathbf{x}\mathbf{x}^H]\mathbf{I}_{N_r}\right)\mathbf{R}_r^{\frac{1}{2}} + \sigma_n^2\mathbf{I}_{N_r} \quad (20) \\ &= P\sigma_e^2\mathbf{R}_r + \sigma_n^2\mathbf{I}_{N_r} \quad (21)\end{aligned}$$

where (20) comes from the fact that $\mathbb{E}_{\mathbf{E}_w}[\mathbf{E}_w\mathbf{A}\mathbf{E}_w^H] = \sigma_e^2\text{Tr}(\mathbf{A})\mathbf{I}_{N_r}$ for any deterministic $\mathbf{A}$. As a result, our new

[2]Note that other SISO ESM methods such as the EESM and the MMIB can also be applied at this step in a similar way.

model (19) includes a doubly correlated MIMO channel $\tilde{\mathbf{H}}$ as well as the colored Gaussian noise $\mathbf{w}$. Thus, the optimal MLD for (19) after noise whitening becomes equivalent to finding $\tilde{\mathbf{x}}$ which minimizes $(\mathbf{y} - \tilde{\mathbf{H}}\tilde{\mathbf{x}})^H \mathbf{Q}_{\mathbf{w}}^{-1}(\mathbf{y} - \tilde{\mathbf{H}}\tilde{\mathbf{x}})$.

In order for the proposed PSSR technique to be applied in this model, the changes in $\tilde{\mathbf{H}}$ and $\mathbf{w}$ should be taken into account in the computation of (4), (5) and (7). Based on the MMSE criterion, the post-detection SNR or the SINR in (4) and (5) can be evaluated as

$$\tilde{\gamma}_n^{\text{PIC}} = \rho\sigma_n^2 \|\mathbf{Q}_{\mathbf{w}}^{-\frac{1}{2}}\tilde{\mathbf{h}}_n\|^2 \quad (22)$$

$$\tilde{\gamma}_n^{\text{MMSE}} = \frac{1}{\left[\left(\mathbf{I}_{N_t} + \rho\sigma_n^2 \tilde{\mathbf{H}}^H \mathbf{Q}_{\mathbf{w}}^{-1}\tilde{\mathbf{H}}\right)^{-1}\right]_{nn}} - 1. \quad (23)$$

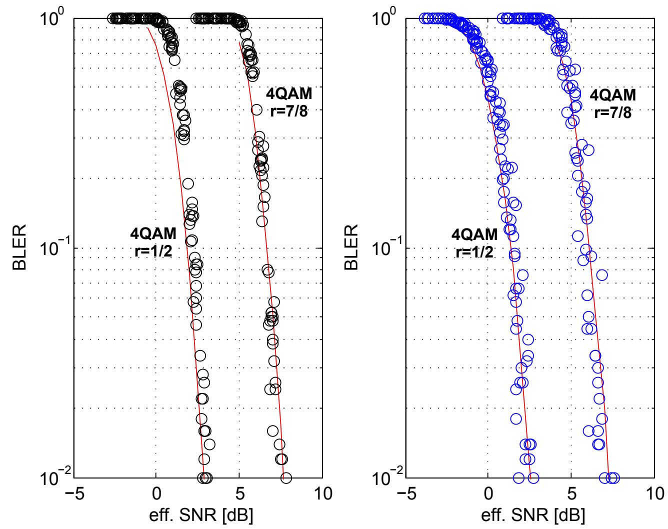
Similarly, the MIMO open-loop capacity for (19) is computed by $\tilde{C}_{\text{open}} = \log_2 \det\left(\mathbf{I}_{N_r} + \rho\sigma_n^2 \tilde{\mathbf{H}}\mathbf{Q}_{\mathbf{w}}^{-1}\tilde{\mathbf{H}}^H\right)$. Then, we can obtain the SNR estimates of the MIMO-MLD in the same manner from (11) or (12). We will show in the simulation section that the proposed scheme provides acceptable accuracy even in the presence of the spatial correlation and channel estimation errors.

As a special case, if the channel is uncorrelated ($\mathbf{H} = \mathbf{H}_w$), the covariance matrix (21) reduces to $\mathbf{Q}_{\mathbf{w}} = (P\sigma_e^2 + \sigma_n^2)\mathbf{I}_{N_r}$, which suggests that $\mathbf{w}$ is preserved to be white with the scaled variance. Consequently, under a Gaussian approximation of $\mathbf{w}$, (19) becomes equivalent to the ideal model of (1) with the scaled SNR $\tilde{\rho} = \frac{(1-\sigma_e^2)\sigma_n^2}{P\sigma_e^2+\sigma_n^2}\rho$. This fact indicates that with no spatial correlation, the channel estimation error does not influence the estimation accuracy of the proposed PHY abstraction method[3]. This feature will also be confirmed in the next section.

VI. Simulation Results

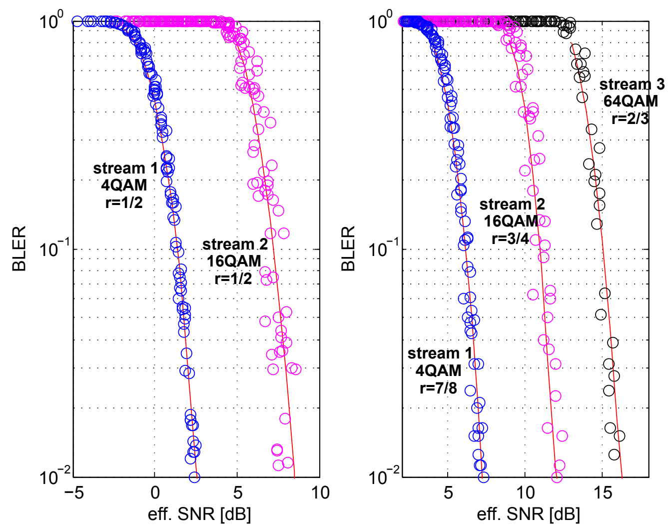
In this section, we provide the link level simulation results to demonstrate the BLER estimation accuracy of the proposed link error prediction technique for the MIMO-MLD. We consider an OFDM system with $N_c = 64$ and the CP length of 16 samples. Also, an encoding block is set to one OFDM symbol, and thus the block length becomes N_c for horizontal encoding and $N_t N_c$ for vertical encoding. We assume block Rayleigh fading channels with a 5-tap exponentially decaying delay profile, if not specified otherwise. For the channel code, the rate-compatible punctured convolutional (RCPC) code with polynomials $(133, 171)$ in octal is employed [33].

In Figures 1 and 2, we compare the BLER estimates from the proposed scheme (circle) with the AWGN reference curves (solid line) for both vertical and horizontal encoding systems with the identical MCS across the streams. For each MCS, 20 independent spatially uncorrelated channel realizations are simulated assuming ideal channel estimation and each channel is averaged over $3,000$ noise samples. Also, we utilize Table I for the optimal values of the parameter b. Figure 1 shows the fitting results for 4×4 MIMO systems over 4-QAM modulation with the code rate $r = 1/2$ and $7/8$. We emphasize that for both the vertical and the horizontal encoding, almost all the estimated $\hat{\gamma}$ in the graphs are very close to the reference curves.



(a) vertical encoding (b) horizontal encoding

Fig. 1. Link prediction accuracy for 4×4 vertical and horizontal encoding systems with identical MCSs.



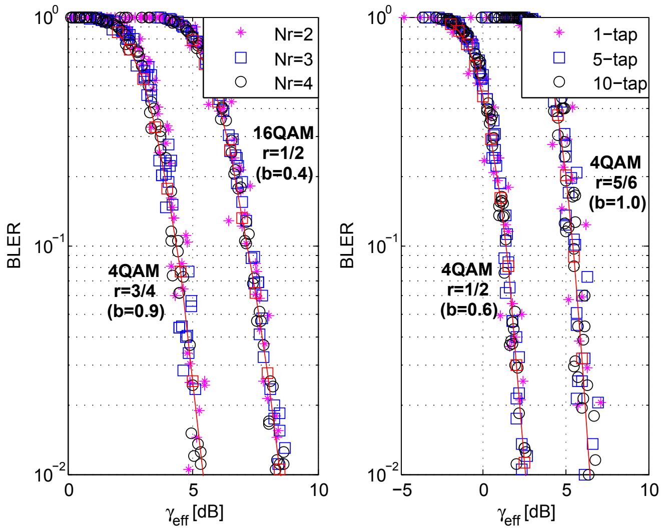
(a) 2×2 systems (b) 3×3 systems

Fig. 2. Link prediction accuracy for 2×2 and 3×3 horizontal encoding systems with non-identical MCSs.

In Figure 2, the horizontal encoding with different MCS levels over streams are plotted in 2×2 and 3×3 systems. In these simulations, the offset parameters $(\Delta\beta_1, \Delta\beta_2) = (-0.3, 0.7)$ and $(\Delta\beta_1, \Delta\beta_2, \Delta\beta_3) = (-0.8, 0.3, 1.2)$ are applied to each stream for $N_t = 2$ and 3, respectively, according to Table II. Similar to Figure 1, we find that high prediction accuracy is achieved at all data streams. From the figures, we can conclude that the proposed link error prediction method is very suitable for MIMO MLD systems.

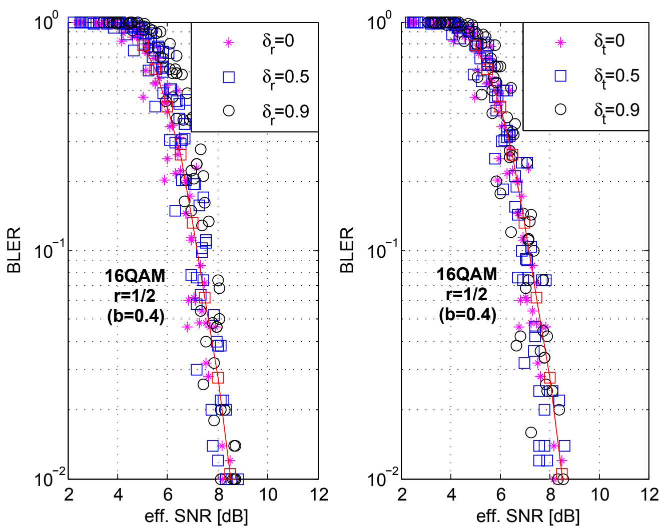
Next, we examine the property of the system parameter β discussed in Section IV-B. Since the vertical encoding systems exhibit better estimation accuracy overall as can be seen in Figure 1, only the results with the horizontal encoding

[3]This may not look intuitive because in general, channel estimation errors degrade the system performance. However, regardless of whether the receiver performance is degraded or not, the proposed scheme is able to maintain the estimation accuracy.



(a) (b)

Fig. 3. Link prediction accuracy with horizontal encoding in terms of (a) the number of receive antennas with $N_t = 2$ (b) the number of channel taps for 2×2 systems.



(a) receive correlation (b) transmit correlation

Fig. 4. Link prediction accuracy with different transmit and receive antenna correlation for 2×2 horizontal encoding systems with the channel estimation error $\sigma_e^2 = \frac{1}{1+P_s}$.

will be given in the following. In Figure 3, we show the PHY abstraction performance for various numbers of receive antennas and channel taps, respectively. As a representative example, we plot the results for $N_t = 2$ systems with 4-QAM and 16-QAM modulations. From the results, we observe that for each MCS, a single fixed value of β in Table I is well fitted for all cases of $N_r = 2, 3$ and 4 and 1-tap, 5-tap and 10-tap delay channels. Although not shown here, we have confirmed that $\Delta\beta$ in Table II also does not depend on the number of channel taps. This robustness is certainly a great merit for implementation of practical AMC schemes.

In what follows, we present the simulation results under the realistic channel model (19) addressed in Section V. We adopt the exponential correlation model where the (i, j)-th

TABLE III
MCS TABLE FOR SIMULATIONS

Index	Code rate	Modulation	Index	Code rate	Modulation
1	1/2	4-QAM	8	3/4	16-QAM
2	2/3	4-QAM	9	5/6	16-QAM
3	3/4	4-QAM	10	7/8	16-QAM
4	5/6	4-QAM	11	2/3	64-QAM
5	7/8	4-QAM	12	3/4	64-QAM
6	1/2	16-QAM	13	5/6	64-QAM
7	2/3	16-QAM	14	7/8	64-QAM

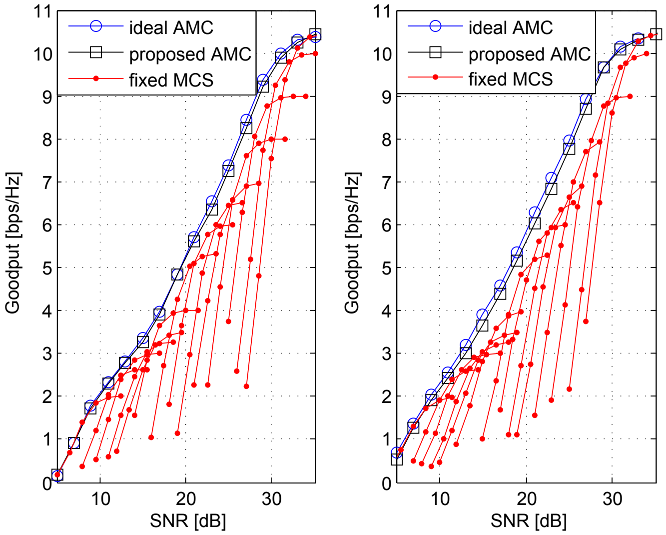
component of $\mathbf{R}_t$ and $\mathbf{R}_r$ equals $\delta_t^{|i-j|}$ and $\delta_r^{|i-j|}$ with δ_t and δ_r denoting the correlation coefficient, respectively [31]. Figure 4 shows the estimation performance of the proposed scheme for 2×2 horizontal MIMO-MLD systems in the presence of the receive and the transmit antenna correlation, respectively. In both two plots, the variance of the channel estimation error is modeled as $\sigma_e^2 = \frac{1}{1+P_s}$ so as to be inversely proportional to the SNR [34]. First, comparing Figure 4 (a) with the same case in Figure 3 (a), we learn that the channel estimation error without spatial correlation ($\delta_r = 0$) does not affect our estimation accuracy. This result is consistent with the previous discussion in Section V. Furthermore, the overall graphs in Figure 4 confirm that the proposed method is highly robust to both the transmit and the receive antenna correlation.

Lastly, we observe the throughput performance of adaptive MIMO-OFDM systems with the AMC scheme based on the proposed PHY abstraction technique. Here we adopt the "goodput" [35] to measure the actual data rate of a link. The goodput G is evaluated by counting the information bits in decoded frames with correct cyclic redundancy check (CRC) as

$$G = \frac{1}{T}\sum_{i=1}^{T}\frac{N_{b,i}}{N_{s,i}}$$

where T denotes the number of transmissions, and $N_{b,i}$ and $N_{s,i}$ represent the number of information bits in a frame with correct CRC and the number of symbols per frame at the i-th transmission, respectively. The MCS table used in simulations is listed in Table III.

Figure 5 presents the average goodput of 2×2 vertical and horizontal MIMO-MLD systems under the realistic channel model with $\delta_t = \delta_r = 0.5$ and $\sigma_e^2 = \frac{1}{1+P_s}$. The results for other configurations are not included due to space limitations. The goodput results of the ideal AMC are obtained by exhaustive search where the receiver selects the best MCS which yields the highest goodput by simulations over all possible combinations (14 cases for vertical encoding and 14^{N_t} cases for horizontal encoding), which is too complex to be implemented in practice. In contrast, by applying the proposed PSSR technique, the MCS levels proper to the channel condition can be easily chosen at each transmission. Moreover, from the figure, we can see that the performance based on the proposed AMC scheme is very close to the optimum performance obtained by the exhaustive search for both encoding structures. Therefore, we can conclude that the proposed link error prediction for MIMO-MLD is quite effective in achieving the optimum throughput performance with much reduced complexity.



(a) vertical encoding (b) horizontal encoding

Fig. 5. Average goodput for 2×2 systems with the antenna correlation $\delta_t = \delta_r = 0.5$ and the channel estimation error $\sigma_e^2 = \frac{1}{1+P_s}$.

VII. Conclusions

In this paper, we have proposed an accurate link abstraction technique for MIMO-OFDM systems with ML receiver. By employing our proposed PSSR method, exact link error prediction has been made for both vertical and horizontal MIMO-MLD systems. The proposed scheme is computationally efficient and also allows simple parameter search compared to conventional MIMO ESM methods. From simulations, we have confirmed that the proposed method provides superior accuracy with various antenna configurations and channel environments, and also exhibits robust performance over a practical channel model including the channel estimation error and the spatial correlation.

Appendix

A. Proof for the inequality $C_{MMSE} \leq C_{open} \leq C_{PIC}$

Since $\mathbf{H}^H\mathbf{H}$ is non-negative definite, applying Hadamard's inequality directly proves

$$
\begin{aligned}
C_{\text{open}} &= \log_2 \det\left(\mathbf{I}_{N_t} + \rho \mathbf{H}^H \mathbf{H}\right) \\
&\leq \log_2 \prod_{n=1}^{N_t} \left(1 + \rho \|\mathbf{h}_n\|^2\right) = C_{\text{PIC}}
\end{aligned}
$$

where the equality holds when $\mathbf{H}^H\mathbf{H}$ is diagonal, i.e., all columns of $\mathbf{H}$ are orthogonal.

On the other hand, it is known that the optimal MMSE-SIC receiver assuming no error propagation achieves the MIMO channel capacity C_{open} regardless of its decoder order. Letting the decoding order be $\pi_n = n$ for $\forall n$, the effective channel model for the n-th decoding stage is given by

$$
\mathbf{y}^{(n)} = \mathbf{h}_n x_n + \sum_{j>n}^{N_t} \mathbf{h}_j x_j + \mathbf{n}_n,
$$

and the resultant SINR for the n-th stream is

$$
\gamma_n^{\text{MMSE-SIC}} = \mathbf{h}_n^H \left(\sum_{j>n}^{N_t} \mathbf{h}_j \mathbf{h}_j^H + \frac{1}{\rho} \mathbf{I}_{N_r} \right)^{-1} \mathbf{h}_n \triangleq \mathbf{h}_n^H \mathbf{B}^{-1} \mathbf{h}_n.
$$

where we define $\mathbf{B} \triangleq \sum_{j>n}^{N_t} \mathbf{h}_j \mathbf{h}_j^H + \frac{1}{\rho}\mathbf{I}_{N_r}$.

Since (5) is alternatively represented as

$$
\gamma_n^{\text{MMSE}} = \mathbf{h}_n^H \left(\mathbf{B} + \sum_{i=1}^{n-1} \mathbf{h}_i \mathbf{h}_i^H \right)^{-1} \mathbf{h}_n, \tag{24}
$$

by applying the matrix inversion lemma to (24), we can show that $\gamma_n^{\text{MMSE}} \leq \gamma_n^{\text{MMSE-SIC}}$. Therefore, we have

$$
\begin{aligned}
C_{\text{open}} &= \sum_{n=1}^{N_t} \log_2\left(1 + \gamma_n^{\text{MMSE-SIC}}\right) \\
&\geq \sum_{n=1}^{N_t} \log_2\left(1 + \gamma_n^{\text{MMSE}}\right) = C_{\text{MMSE}}
\end{aligned}
$$

where the equality holds also when $\mathbf{h}_1, \cdots, \mathbf{h}_{N_t}$ are orthogonal to each other.

B. Procedure of finding β

The search for the optimal values of β is based on the link level simulation of the proposed PHY abstraction model. For each MCS, the optimal β is chosen to provide the best fitting accuracy between the measured BLER vs. effective SNR curves and the AWGN reference curve within its range $0 \leq \beta \leq 1$. The curve fitting accuracy can be mathematically written in a mean-square error sense similar to [23] and [25] as

$$
\hat{\beta} = \arg \min_{0 \leq \beta \leq 1} \sum_{t=1}^{T} \left| \gamma_{\text{AWGN}} - \hat{\gamma}(\beta, \mathbf{H}_k(t)) \right|^2 \tag{25}
$$

where $\hat{\gamma}(\beta, \mathbf{H}_k(t))$ represents the effective SNR in dB provided by the proposed algorithm in Section IV-D for channel realization $\mathbf{H}_k(t)$ at time slot t when the parameter β is applied in (11), and γ_{AWGN} denotes the corresponding SNR in dB to meet the same target BLER at the AWGN channel. We can choose $\hat{\beta}$ which satisfies (25) over a sufficiently large number of channel realizations T. Note that since β has a small range of $0 \leq \beta \leq 1$, the search is quite simple.

References

[1] I. E. Telatar, "Capacity of multi-antenna Gaussian channels," *Eur. Trans. Telecommun.*, vol. 10, pp. 585–595, Nov. 1999.

[2] G. J. Foschini and M. Gans, "On limits of wireless communications in a fading environment when using multiple antennas," *Wireless Personal Commun.*, vol. 6, pp. 311–335, Mar. 1998.

[3] R. V. Nee and R. Prasad, *OFDM for Wireless Multimedia Communications*. Artech House Publishers, 2000.

[4] G. Caire, G. Taricco, and E. Biglieri, "Bit-interleaved coded modulation," *IEEE Trans. Inf. Theory*, vol. 44, pp. 927–946, May 1998.

[5] I. Lee, A. Chan, and C.-E. W. Sundberg, "Space-time bit-interleaved coded modulation for OFDM systems," *IEEE Trans. Signal Process.*, vol. 52, pp. 820–825, Mar. 2004.

[6] H. Lee, B. Lee, and I. Lee, "Iterative detection and decoding with an improved V-BLAST for MIMO-OFDM systems," *IEEE J. Sel. Areas Commun.*, vol. 24, pp. 504–513, Mar. 2006.

[7] H. Lee and I. Lee, "New approach for error compensation in coded V-BLAST OFDM systems," *IEEE Trans. Commun.*, vol. 55, pp. 345–355, Feb. 2007.

[8] 3rd Generation Partnership Project (3GPP) TS 36.913; Technical Specification Group Radio Access Network; E-UTRA; Physical Channels and Modulation (Release 10), Mar. 2011.

[9] IEEE Standard for Local and Metropolitan Area Networks, Part 16: Air Interface for Fixed and Mobile Broadband Wireless Access Systems; Advanced Air Interface (Working Document), June 2009.

[10] W. T. Webb and R. Steele, "Variable rate QAM for mobile radio," *IEEE Trans. Commun.*, vol. 43, pp. 2223–2230, July 1995.

[11] A. J. Goldsmith and S.-G. Chua, "Adaptive coded modulation for fading channels," *IEEE Trans. Inf. Theory*, vol. 46, pp. 595–602, May 1998.

[12] S. T. Chung and A. J. Goldsmith, "Degrees of freedom in adaptive modulation: a unified view," *IEEE Trans. Commun.*, vol. 49, pp. 1561–1571, Sep. 2001.

[13] A. Conti, M. Z. Win, and M. Chiani, "Slow adaptive M-QAM with diversity in fast fading and shadowing," *IEEE Trans. Commun.*, vol. 55, pp. 895–905, May 2007.

[14] K.-B. Song, A. Ekbal, S. T. Chung, and J. M. Cioffi, "Adaptive modulation and coding (AMC) for bit-interleaved coded OFDM (BIC-OFDM)," *IEEE Trans. Wireless Commun.*, vol. 5, pp. 1685–1694, July 2006.

[15] H. S. Abdel-Ghaffar and S. Pasupathy, "Asymptotical performance of M-ary and binary signals over multipath/multichannel Rayleigh and Rician fading," *IEEE Trans. Veh. Technol.*, vol. 43, pp. 2721–2731, Nov. 1995.

[16] A. Conti, W. M. Gifford, M. Z. Win, and M. Chiani, "Optimized simple bounds for diversity systems," *IEEE Trans. Commun.*, vol. 57, pp. 2674–2685, Sep. 2009.

[17] A. Conti, D. Panchenko, S. Sidenko, and V. Tralli, "Log-concavity property of the error probability with application to local bounds for wireless communications," *IEEE Trans. Inf. Theory*, vol. 55, pp. 2766–2775, June 2009.

[18] N. Gresset, L. Brunel, and J. J. Boutros, "Space-time coding techniques with bit-interleaved coded modulations for MIMO block-fading channels," *IEEE Trans. Inf. Theory*, vol. 54, pp. 2156–2178, May 2008.

[19] V. Tralli, A. Conti, and M. Chiani, "Pragmatic space-time trellis codes: GTF-based design for block fading channels," *IEEE Trans. Signal Process.*, vol. 59, pp. 2809–2823, June 2011.

[20] C. K. Sung, S.-Y. Chung, J. Heo, and I. Lee, "Adaptive bit-interleaved coded OFDM with reduced feedback information," *IEEE Trans. Commun.*, vol. 55, pp. 1649–1655, Sep. 2007.

[21] Ericsson, "System-level evaluation of OFDM−further considerations," TSG-RAN WG1 #35, R1-031303, Nov. 2003.

[22] K. Sayana, J. Zhuang, and K. Stewart, "Link performance abstraction based on mean mutual information per bit (MMIB) of the LLR channel," IEEE C802.16m-07/097, May 2007.

[23] H. Zheng and *et al.*, "Link performance abstraction for ML receivers based on RBIR metrics," IEEE C802.16m-08/119, Mar. 2008.

[24] K. Sayana, J. Zhuang, and K. Stewart, "Short term link performance modeling for ML receivers with mutual information per bit metrics," in *Proc. 2008 IEEE Globecom*.

[25] IEEE 802.16m Evaluation Methodology Document (EMD), Jan. 2009.

[26] J. Kim, K.-J. Lee, C. K. Sung, and I. Lee, "A simple SNR representation method for AMC schemes of MIMO systems with ML detector," *IEEE Trans. Commun.*, vol. 57, pp. 2971–2976, Oct. 2009.

[27] J. Kim, S.-H. Moon, C. K. Sung, and I. Lee, "A new SNR prediction method for MIMO-OFDM systems with maximum likelihood detector," in *Proc. 2011 IEEE ICC*.

[28] Z. Pan, Y. Zhou, and C. I, "Bit-wise exponential ESM (BE-ESM) methods for accurate link level performance evaluation," in *Proc. 2009 IEEE ICC*.

[29] R. W. Heath, S. Sandhu, and A. J. Paulraj, "Antenna selection for spatial multiplexing systems with linear receivers," *IEEE Commun. Lett.*, vol. 5, pp. 142–144, Apr. 2001.

[30] K. Sayana, J. Zhuang, and K. Stewart, "Comparison of link performance abstraction for ML receivers with MMIB and RBIR metrics," IEEE C802.16m-08/073, Jan. 2007.

[31] D.-S. Shiu, G. J. Foschini, M. J. Gans, and J. M. Kahn, "Fading correlation and its effect on the capacity of multielement antenna systems," *IEEE Trans. Commun.*, vol. 48, pp. 502–513, Mar. 2000.

[32] C.-N. Chuah, D. N. C. Tse, J. M. Kahn, and R. A. Valenzuela, "Capacity scaling in MIMO wireless systems under correlated fading," *IEEE Trans. Inf. Theory*, vol. 48, pp. 637–650, Mar. 2002.

[33] J. Hagenauer, "Rate-compatible punctured convolutional codes (RCPC codes) and their applications," *IEEE Trans. Commun.*, vol. 36, pp. 389–400, Apr. 1988.

[34] T. Yoo and A. Goldsmith, "Capacity and power allocation for fading MIMO channels with channel estimation error," *IEEE Trans. Inf. Theory*, vol. 52, pp. 2203–2214, May 2006.

[35] R. Gozali, R. M. Buehrer, and B. D. Woerner, "On the performance of scheduling over space-time architectures," in *Proc. 2002 IEEE VTC*, vol. 1, pp. 415–419.

Sung-Hyun Moon (S'05-M'12) received the B.S., M.S., and Ph.D. degrees in electrical engineering from Korea University, Seoul, Korea, in 2005, 2007, and 2012, respectively. Since 2012, he has been with the Electronics and Telecommunications Research Institute (ETRI), Daejeon, Korea, as a research engineer. During spring 2009, he visited the University of Southern California (USC), Los Angeles, CA, as a visiting student. His current research interests include multiuser information theory and signal processing techniques for MIMO wireless cellular networks.

Kyoung-Jae Lee (S'06-M'11) received the B.S., M.S., and Ph.D. degrees in the School of Electrical Engineering from Korea University, Seoul, Korea, in 2005, 2007, and 2011, respectively. During the summer of 2009, he visited University of Southern California, Los Angeles, CA, USA as a Visiting Research Scholar. From March 2011 to September 2011, he was a Postdoctoral Researcher in Korea University. Since October 2011, he has been with the Wireless Networking and Communications Group (WNCG) at the University of Texas at Austin, Austin, TX, USA, where he is currently a Postdoctoral Fellow. His research interests are in information theory, signal processing, and applications for wireless communications and networking. He received the Gold Paper Award at IEEE Seoul Section Student Paper Contest in 2007, and the Best Paper Award at IEEE VTC Fall in 2009.

Jihoon Kim (S'04) received the B.S. and M.S. degrees in radio science and engineering from Korea University, Seoul, Korea, in 2003 and 2005, respectively, and the Ph.D. degree in the School of Electrical Engineering at Korea University, Seoul, Korea, in 2010. He has been with the Samsung Electronics, Suwon, Korea, as a research engineer in the Korea s/w R&D group, since 2010. His research interests include space-time coding, signal processing, and coding for wireless communications, with current emphasis on analysis of MIMO-OFDM techniques.

Inkyu Lee (S'92-M'95-SM'01) received the B.S. degree (Hon.) in control and instrumentation engineering from Seoul National University, Seoul, Korea, in 1990, and the M.S. and Ph.D. degrees in electrical engineering from Stanford University, Stanford, CA, in 1992 and 1995, respectively. From 1995 to 2001, he was a Member of Technical Staff at Bell Laboratories, Lucent Technologies, where he conducted research on high-speed wireless system designs. He later worked for Agere Systems (formerly Microelectronics Group of Lucent Technologies), Murray Hill, NJ, as a Distinguished Member of Technical Staff from 2001 to 2002. In September 2002, he joined the faculty of Korea University, Seoul, Korea, where he is currently a Professor in the School of Electrical Engineering. During 2009, he visited University of Southern California, LA, USA, as a visiting Professor. He has published around 70 journal papers in IEEE, and has 30 U.S. patents granted or pending. His research interests include digital communications and signal processing techniques applied for next generation wireless systems. Dr. Lee currently serves as an Associate Editor for IEEE TRANSACTION ON COMMUNICATIONS and the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS. Also, he has been a Chief Guest Editor for the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS (Special Issue on 4G Wireless Systems). He received the IT Young Engineer Award as the IEEE/IEEK joint award in 2006, and received the Best Paper Award at APCC in 2006 and IEEE VTC in 2009. Also he was a recipient of the Hae-Dong Best Research Award of the Korea Information and Communications Society (KICS) in 2011.