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Link Adaptation Based on Adaptive Modulation and Coding for Multiple-Antenna OFDM System

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Abstract—In this paper, we study the problem of link adaptation based on adaptive modulation and coding for multiple-antenna OFDM system in slow fading channel. Based on the extrinsic information transfer analysis, we give an accurate packet error rate prediction with channel estimation errors. This method uses Gaussian approximation to characterize the output of the detector and decoder. We also discuss approaches for searching and selecting the best modulation and coding scheme for the link adaptation algorithm. Finally, the performance of the proposed link adaptation algorithm is studied for the IEEE 802.11n multiple-antenna OFDM system. Good system throughput are achieved using the proposed method, compared to the SNR based algorithm

Index Terms—MIMO-OFDM, adaptive modulation and coding, Gaussian approximation, PER prediction.

I. INTRODUCTION

THE BASIC idea of link adaptation is to adapt the link efficiently in the actual channel conditions by varying certain transmission parameters. Transmission power, symbol rate, constellation size and coding scheme can be dynamically adapted in response to the time-varying channel. With selection of these transmission parameters, the system makes the most out of a time varying channel, instead of fixing the parameters for a worst-case channel. The trade off involves minimizing the error probability for robustness and maximizing the instantaneous throughput for bandwidth efficiency.

Adaptive modulation and coding (AMC) is one of the adaptive techniques to counteract fading and enhance the performance of wireless system [1, 2]. It selects an optimal combination of modulation and coding scheme (MCS) to maximize bandwidth efficiency. The decision is based on the channel state information (CSI). Each MCS is associated with a coding rate and constellation size, which has a given bit rate. A Quality of Service (QoS) constraint on delivery delay is usually imposed. It requires that the packet error rate (PER) experienced in the transmission is less than a given target, so as to avoid frequent retransmission which subsequently affects both throughput and delivery delay. A typical value for the target PER is a few percent. For instance, imposing $PER_{\text{target}} \leq 0.1$ results in a residual PER below 10^{-5} after 4 retransmissions.

The key element of the AMC depends on the quality of PER prediction. Perfect PER prediction leads to optimum MCS selection and improved bandwidth efficiency. On the other hand, unreliable PER prediction can result in suboptimum performance or link failure. To overcome this problem, safety margins are added to impose a more conservative MCS selection. More robust MCS is selected to reduce the QoS outage probability:

$$P_{\text{outage}} = \Pr(PER > PER_{\text{target}}). \quad (1)$$

For a given MCS, neglecting the signaling overhead introduced by the Medium Access Control (MAC) protocol, the link throughput ρ_{MCS} is

$$\rho_{\text{MCS}} = r_{\text{MCS}}(1 - PER_{\text{MCS}}), \quad (2)$$

where r_{MCS} and PER_{MCS} are the rate and PER of the MCS, respectively. An AMC algorithm selects the MCS with the maximum throughput while meeting the PER constraint. Mathematically, it is given by

$$\begin{aligned} (P1) \quad & \max r_{\text{MCS}}(1 - PER_{\text{MCS}}) \\ & \text{s.t. } \Pr(PER_{\text{MCS}} > PER_{\text{target}}) \leq 0.05 \\ & r_{\text{MCS}} \in \text{MCS}_{\text{set}} \end{aligned}$$

Here, the outage probability is set to be less than 5%.

The prediction of the PER depends on the channel coherence time and estimation reliability. The PER is a function given by

$$PER = f(\text{MCS}, N_0, \mathbf{H}, L), \quad (3)$$

where N_0 is the noise variance, $\mathbf{H}$ is the channel realization and L is the packet length in number of information bits. To reduce the complexity of the PER prediction, a common approach is to map these parameters onto a single link quality metric (LQM) [3–7] which could be associated to the PER by means of a look-up table. For each MCS, it is possible to define a range of LQM values over which the MCS maximizes throughput. However, this approach depends heavily on the assumed channel model and could be problematic in practice.

The most common LQM used is the instantaneous signal-to-noise ratio (SNR) [3, 4]. For a multiple-antenna orthogonal frequency division multiplexing (OFDM) system [4], it is defined as the average of the ratio of the squared modulus of the complex channel coefficients to the noise variance over all transmit antennas, receive antennas, and subcarriers. However, the PER of a given MCS varies significantly for different channel realizations with the same instantaneous SNR. There

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will exist some bad channels in which the AMC selects a MCS which has a much higher PER than the target PER. This leads to a broken link for the duration which depends on the the channel coherence time. A solution to this problem is to shift the SNR thresholds with a safety margin for a more robust MCS selection. This, however, results in a reduction in throughput of the system.

In order to reduce this safety margin, the PER-indicator [5] and the exponential effective SNR mapping (Exp-ESM) methods [4, 6, 7] are proposed to predict the PER performance. In both cases, a scalar is computed based on the knowledge of CSI. The PER-indicator method is based on the observation that the PER curves of all the channel realizations are nearly parallel. An indicator is computed which is then mapped to the corresponding distance (in dB) from the PER performance in an additive white Gaussian noise (AWGN) channel. This mapping is done by curve fitting for each combination of the code rate, the modulation and the information block size. For the Exp-ESM method, it consists of deriving a scalar LQM called exponential effective SNR, which is the required SNR on an AWGN channel for the wireless system studied to obtain the same PER. This effective SNR is to fit the model over a large-enough number of independent channel realizations according to certain criterion [4].

In general, it is difficult to characterize the PER performance by a scalar parameter. Multiple parameters have been used to predict the PER performance [8, 9]. In [8], a method based on the post-detection SNRs has been proposed to predict PER performance in multiple-antenna OFDM system where each spatial stream is encoded separately. The effective SNR for each stream is then mapped to the corresponding PER which is used in predicting the overall PER. In [9], a simple SNR metric per spatial stream is used together with bound to compute the combined BER from the OFDM subcarriers. The coded PER at the decoder output is then modeled as a function of the decoder-input BER (uncoded BER from the detector) and code rate. The polynomial curves for the coded PER of the decoder against the uncoded BER of the detector are obtained by simulations, which require a fixed packet length.

Recently, there has been a lot of emphasis on joint detection and decoding of coded wireless systems by the iterative decoding which is based on the Turbo principle [10]. It is an efficient and powerful method for decoding wireless systems as it approaches the limit of the optimum decoder. It has been applied to wireless systems with intersymbol interference, multiple antennas, multicarrier and multiple users. Such systems are essentially serial concatenation schemes [11]. For any particular channel realization, it is possible to characterize the BER performance of the iterative decoding using extrinsic information transfer (EXIT) functions [12]. In [13], AMC is implemented in multiple-antenna system using iterative decoding with linear receivers and perfect CSI. The approximation of the BER performance of the linear receivers is based on the EXIT analysis carried out in [14]. The PER is then approximated from the BER by assuming that the BER is uncorrelated. However, for coded system, the BER is usually correlated.

In this work, we propose a link adaptation algorithm for slow fading multiple-antenna OFDM systems with and with-

out eigen-beamforming. Using EXIT functions, we give an accurate PER prediction in the presence of channel estimation error. Accurate PER prediction allows its negative impact on AMC to be minimized. The advantages of the MCS selection described in this paper over the other LQM based algorithms [3–7] are as follows. The LQM based algorithm is implemented using tables, which can result in lower complexity. However, each channel type must have its own table. Hence, the detection of channel type is required before a suitable table is identified for the MCS selection. Joint implementation of one table for different channel type will degrade the throughput performance as the worst LQM switching is always used. Moreover, the tables are constructed using fixed packet length, whereas the PER prediction algorithm in Section III can work with various packet lengths. Hence, the proposed MCS selection algorithm is more flexible. In addition, the implementation of the LQM based algorithm requires the full channel matrix ($N_r \times N_t$) for computing the LQM which selects the MCS. Sounding of the full channel is therefore required unless the received packet has the full channel matrix, i.e., the MCS of the received packet contains the maximum number of supported spatial streams. If not, the receiver only has the effective channel matrix ($N_r \times N_{ss}$), which is insufficient for the selection of MCS. Unlike other non LQM based algorithm like [9, 14], the MCS set we considered includes MCS of different number of spatial streams, leading to improvement in throughput performance. The MCS selection algorithm is based on each channel realization, but can be designed to be independent of the channel types and antenna configurations.

The remainder of this paper is organized as follows. In Section II, the system model and the corresponding link adaptation algorithms are described. The PER prediction by EXIT functions is shown in Section III and the MCS selection algorithm is described in Section IV. Numerical results are presented in Section V and concluding remarks are summarized in Section VI.

II. SYSTEM MODELING

For a multiple-antenna OFDM system with N_t transmit and N_r receive antennas transmitting N_{ss} independent data streams, the received $N_r \times 1$ symbol vector $\mathbf{r}$ on a given subcarrier is modeled as

$$\mathbf{r} = \mathbf{H}\mathbf{s} + \mathbf{n}, \quad (4)$$

where $\mathbf{s} = [s_1, s_2, \dots, s_{N_{ss}}]^T$ is the $N_{ss} \times 1$ vector of transmitted symbols with $\mathbb{E}[\mathbf{s}\mathbf{s}^H] = \mathbf{I}_{N_{ss}}/N_{ss}$, $\mathbf{I}_{N_{ss}}$ is an identity matrix with dimension $N_{ss} \times N_{ss}$ and $\mathbf{n}$ is the thermal noise vector with $\mathbb{E}[\mathbf{n}\mathbf{n}^H] = N_0\mathbf{I}_{N_r}$. $\mathbf{H}$ is the equivalent channel matrix with dimension $N_r \times N_{ss}$ which depends the channel impulse response and the transmitter spatial mapping (or beamforming) matrices.

We assume per-subcarrier least-squares (LS) channel estimation and minimum mean square estimation (MMSE) detection of $\mathbf{s}$ in this paper. The results of this work, however, can also be extended to other channel estimation and multiple-antenna detection approaches.

For channel estimation, a training sequence of N_{ss} OFDM symbols is used. The training sequence on a given subcarrier

$\mathbf{X}$ is an $N_{ss} \times N_{ss}$ unitary matrix that satisfies $\mathbf{X}\mathbf{X}^H = \mathbf{I}_{N_{ss}}$. On each subcarrier, the $N_r \times N_{ss}$ received signal $\mathbf{R}$ is

$$\mathbf{R} = \mathbf{H}\mathbf{X} + \mathbf{N}, \quad (5)$$

where $\mathbf{N}$ is the noise matrix. The LS channel estimate is then obtained by $\hat{\mathbf{H}} = \mathbf{R}\mathbf{X}^H = \mathbf{H} + \mathbf{N}\mathbf{X}^H$. The MMSE detection [15] is given by multiplying the received vector $\mathbf{r}$ with a matrix $\mathbf{W}^H$,

$$\mathbf{W} = \left(\hat{\mathbf{H}}\hat{\mathbf{H}}^H + N_0 N_{ss} \mathbf{I} \right)^{-1} \hat{\mathbf{H}}, \quad (6)$$

where $\hat{\mathbf{H}}$ is the channel estimate of $\mathbf{H}$. The MMSE detector generates the log-likelihood ratios (LLRs) which can be used by Viterbi or belief-propagation decoding. Iterative decoding [14, 16, 17] is not considered, but it can be incorporated easily into the model.

As shown in Fig.1, link adaptation involves the sequence of MCS selection which is classified into transmitter-based and receiver-based. For the transmitter based MCS selection, MCS feedback is not required at the receiver. This method exploits the reciprocal property of the channel in the time division duplex (TDD) mode to select a MCS at the transmitter. The downlink channel is used to select a MCS for the uplink channel and vice versa. Access point (AP) transmits data frame using MCS A at time t_0 . At time t_1 , station (STA) receives the data frame and selects MCS B using the receiving data frame. At time t_2 , STA transmits the data frame using MCS B. Here, STA uses the downlink channel to select a MCS for the uplink channel. At time t_3 , AP receives the uplink data frame and select MCS C for its downlink transmission using the receiving frame. At time t_4 , MCS C is used for the downlink data transmission.

For the receiver based MCS selection, the channel is not required to be reciprocal, since the MCS selection is done in the receiver. AP transmits data frame using MCS X and included feedback (FB) rate of MCS X. This FB rate is the MCS index recommended for data transmission at the STA. At time t_1 , STA receives the data frame and selects MCS Y for the downlink transmission. At time t_2 , STA transmits the data frame using MCS X that is informed by AP in the previous data frame. The feedback rate MCS Y is also embedded in the FB field. At time t_3 , AP receives the data frame and starts the MCS selection for the uplink transmission. At time t_4 , the FB rate in the previous frame is used for the downlink transmission.

III. PER ESTIMATION OF CODED MULTIPLE-ANTENNA OFDM TRANSMISSION

We consider a slow time-varying multipath fading channel, where all OFDM symbols in one packet experience approximately the same channel. One practical example of such channel model is the 802.11n [18] high-throughput wireless LAN system.

A. Computation of SNR for Each Spatial Stream for MMSE Detection

The output of the MMSE detector can be expressed as

$$y_i = \mathbf{w}_i^H \mathbf{r}, \quad \text{for } i = 1, \dots, N_{ss},$$

where $\mathbf{w}_i = \left(\hat{\mathbf{H}}\hat{\mathbf{H}}^H + N_0 N_{ss} \mathbf{I} \right)^{-1} \hat{\mathbf{H}} \mathbf{e}_i$ and $\mathbf{e}_i$ is a $N_{ss} \times 1$ vector of all zeros, except for its i th element which is one. In practice, the knowledge of CSI can never be perfect. Thus [19],

$$\mathbf{H} = \hat{\mathbf{H}} + \mathbf{\Xi}, \quad (7)$$

where $\mathbf{\Xi}$ is the estimation error matrix. $\hat{\mathbf{H}}$ and $\mathbf{\Xi}$ are uncorrelated due to the orthogonality principle [20]. Each element of $\mathbf{\Xi}$ is i.i.d. with a Gaussian distribution of zero mean and variance $\sigma_\epsilon^2 = \mathbb{E}[|H_{i,j} - \hat{H}_{i,j}|^2]$.

The output of the i th filter is then approximated by an equivalent AWGN channel having $\tilde{s}_i$ as its input symbol, where $\mathbb{E}[|\tilde{s}_i|^2] = 1$. This equivalent channel is represented as

$$y_i = a_i \tilde{s}_i + b_i, \quad (8)$$

where a_i is the equivalent amplitude of the signal and the noise term b_i is a Gaussian random variable with zero mean and variance $\sigma_{b_i}^2$. The amplitude a_i is computed as follows:

$$\begin{aligned} a_i &= \mathbb{E}[\tilde{s}_i^* y_i] \\ &= \mathbf{w}_i^H \hat{\mathbf{H}} \mathbf{e}_i / \sqrt{N_{ss}}. \end{aligned} \quad (9)$$

The variance $\sigma_{b_i}^2$ is obtained from $\mathbb{E}[y_i^* y_i]$ which is given by

$$\begin{aligned} \mathbb{E}[y_i^* y_i] &= \mathbb{E}[\mathbf{w}_i^H \mathbf{r} \mathbf{r}^H \mathbf{w}_i] \\ &= a_i / \sqrt{N_{ss}} + N_t \sigma_\epsilon^2 \mathbf{w}_i^H \mathbf{w}_i / N_{ss}, \end{aligned} \quad (10)$$

where N_t is the number of transmit antennas and σ_ϵ^2 is the variance of the channel estimation error. The variance $\sigma_{b_i}^2$ is given by

$$\sigma_{b_i}^2 = a_i / \sqrt{N_{ss}} + N_t \sigma_\epsilon^2 \mathbf{w}_i^H \mathbf{w}_i / N_{ss} - a_i^2, \quad (11)$$

The parameter a_i and $\sigma_{b_i}^2$ can be obtained from the multiple-antenna detection module. If σ_ϵ^2 is not given, a safety margin is added to account for the channel estimation error. The SNR [dB] of this equivalent channel is then

$$\gamma_i = 10 \log_{10} \frac{a_i^2}{a_i / \sqrt{N_{ss}} + N_t \sigma_\epsilon^2 \mathbf{w}_i^H \mathbf{w}_i / N_{ss} - a_i^2} \quad (12)$$

Note that $\{\gamma_i\}$ are the SNRs for all the spatial streams on a given subcarrier.

B. Computation of SNR for Each Spatial Stream for Eigen-Beamforming

The estimated $N_r \times N_t$ channel matrix $\hat{\mathbf{H}}$ for each subcarrier can be diagonalized by singular value decomposition (SVD) as $\hat{\mathbf{H}} = \hat{\mathbf{U}} \hat{\mathbf{D}} \hat{\mathbf{V}}^H$, where $\hat{\mathbf{U}}$ and $\hat{\mathbf{V}}$ are the unitary matrices, and $\hat{\mathbf{D}}$ is a diagonal matrix whose elements are the ordered singular values of the channel.

With SVD based multiple-antenna OFDM systems, we transform the symbol vector $\mathbf{s}$ by multiplying it with the matrix $\hat{\mathbf{V}}$. Due to the orthonormality of $\hat{\mathbf{U}}^H$, the noise vector $\mathbf{z}$ remains Gaussian with mean $\mathbf{0}$ and variance $N_0 \mathbf{I}$. Each element of the received signal is given by

$$y_i = (\sqrt{\hat{\lambda}_i} + \hat{\Xi}_{i,i}) s_i + \sum_{j \neq i} \hat{\Xi}_{j,i} s_j + z_i, \quad (13)$$

Fig. 1. Link adaptation for transmitter and receiver based MCS selection.

for $i = 1, \dots, N_{ss}$. With perfect CSI, (13) shows that the transmission takes place on a set of N_{ss} parallel equivalent channels. However, in the presence of imperfect CSI, these channels are no longer independent due to the fact that $\hat{\mathbf{D}} + \hat{\mathbf{\Xi}}$ is not diagonal. In other words, there exists not only AWGN, but also cochannel interference (CCI) from other channels. The SNR γ_i [dB] of the equivalent channel is given by

$$\gamma_i = 10 \log_{10} \frac{\hat{\lambda}_i / N_{ss}}{N_0 + \sigma_e^2}. \quad (14)$$

C. Approximation of PER for Each MCS

For the MMSE detection and eigen-beamforming, the SNR $\{\gamma_i\}$ are given in (12) and (14), respectively. To reduce the complexity of PER prediction, their average $\bar{\gamma}_i$ across all subcarriers for each spatial stream is used. For even modulation where all the spatial streams use the same modulation scheme, the SNR are first sorted for each subcarrier and then averaged over all subcarriers. If the spatial streams employ different modulation schemes, sorting is not required. Safety margins are added for various impairments. Note that for transmitter based link adaptation, safety margins are also required when the number of transmit and receive antennas is different. This is to account for the using of the uplink channel for MCS selection of the downlink channel and vice versa. For example, in a system where the AP has 4 antennas and the STA has 3 antennas, the uplink will experience receive diversity, whilst the downlink experiences transmit diversity. Safety margins are required for the difference in diversity.

The output of the detector is modeled as multiple virtual additive white Gaussian noise (AWGN) channels with SNR given by $\bar{\gamma}_i$. To describe the input-output relation of these channels, we use the EXIT function [12] to associate the input and output log-likelihood ratios (LLRs) via a single

parameter. Several possible choices for this parameter are possible [21]. In this work, we are concerned about the mutual information between the coded bit $c \in \{\pm 1\}$ and its LLR Λ . The LLR is well approximated by a conditional normal random variable whose probability density function $p(\Lambda|c)$ satisfies the consistency condition $\Lambda|c \sim \mathcal{N}(c\sigma^2/2, \sigma^2)$. Its mutual information is given by

$$J(\sigma^2) = 1 - \int \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(z - \sigma^2/2)^2}{2\sigma^2}\right] \times \log_2 [1 + \exp(-z)] dz. \quad (15)$$

If $p(\Lambda|c)$ is unknown, we still assume that $\log \frac{p(\Lambda|c)}{p(\Lambda|-c)} \approx c\Lambda$ and the mutual information $I(c; \Lambda)$ is approximated as [22]

$$I(c; \Lambda) \approx 1 - \frac{1}{n} \sum_{i=1}^n \log_2 [1 + \exp(-c_i \Lambda_i)], \quad (16)$$

where Λ_i are independent samples of the random variable Λ corresponding to input value c_i .

The EXIT functions of these channels describing the behavior of the detector depend on the modulation scheme of a MCS and the demapper used. Since there is no closed-form expression, they are usually obtained by Monte-Carlo simulations. For a fixed modulation scheme and demapper, we perform the following process for a range of SNR values. We first generate samples of c_i randomly and map them into the modulated symbols, which are then transmitted across with the AWGN channel for the given SNR value. Note that these coded bits are considered to be independent of one another due to the interleaver. The mutual information $I(c; \Lambda)$ at the output of the demapper is then approximated using (16). Curving fitting is then used to generate the mapping function for the extrinsic mutual information of the demapper as a function of SNR. The mapping function used in this work is a 3rd order

polynomial of the form

$$ca_i = p_3\bar{\gamma}_i^3 + p_2\bar{\gamma}_i^2 + p_1\bar{\gamma}_i + p_0, \quad (17)$$

where $\{p_i\}$ are predetermined coefficients. Note that the value of $\bar{\gamma}_i$ is given in dB. The mutual information $\{ca_i\}$ mapped from their corresponding $\{\bar{\gamma}_i\}$ are then averaged again over the spatial streams to give a mean value $\bar{ca}$.

The behavior of the decoder is also modeled by the EXIT function. The EXIT function takes the extrinsic information $\bar{ca}$ and maps it to the performance of the decoder. Each code has its own EXIT function and it is also dependent on the type of decoder used. For a given code and a range of extrinsic information $\bar{ca}$, the following procedure is carried out to evaluate its performance. We first generate coded bits from randomly chosen equiprobable binary information. The corresponding conditional *a priori* LLRs are then generated according to the consistent Gaussian distribution given by a preset value of the mutual information $\bar{ca}$. The variance of this distribution σ^2 is determined by taking the inverse mapping of (15) on $\bar{ca}$. We then run Monte-Carlo simulations to evaluate the performance of the decoder. The performance of interest are coded bit error rate of convolutional code and PER of LDPC code with fixed block length. Similarly, curving fitting is used to approximate the function for mapping $\bar{ca}$ to the performance of the code.

For each convolutional code with a given code rate, we first obtain its coded bit error rate as a function of $\bar{ca}$, using the method described above. This function is approximated in the form

$$CBER = \frac{1}{2} \exp(3\text{rd order polynomial function of } \bar{ca}). \quad (18)$$

The coefficients of the polynomial function are determined using a curve fitting algorithm. The PER is then approximated by

$$PER \approx 1 - (1 - CBER)^{L/\nu}. \quad (19)$$

When approximating the PER in (19), we only consider the error events with constraint length ν . There are L/ν such events in a codeword. The probability of such an event not occurring is $(1 - CBER)$, which is also the probability that the first coded bit of the corresponding sequence is correct. Assuming that these events are independent, the probability that the codeword is decoded correctly is given by $(1 - CBER)^{L/\nu}$, which results in the PER given in (19). Note that this approach is different from the more common way of using $PER = 1 - (1 - BER)^L$, where the BER of each bit is assumed to be conditionally independent. However, for convolutional coded systems, the BER is correlated. Simulations showed that (19) is a better approximation. For block code like LDPC, the PER is approximated by

$$PER \approx 1 - (1 - PER_B)^{L/k}, \quad (20)$$

where PER_B is the PER of the block code used, and k is the length of the information bits of the LDPC code. There are L/k codewords in each packet and the probability that all these codewords are decoded correctly is $(1 - PER_B)^{L/k}$. Hence, we can approximate the PER as (20). Similarly,

TABLE I
MODULATION SCHEMES AND CODE RATES AVAILABLE FOR EACH SPATIAL STREAM.

Modulation	Code rate
BPSK	1/2
QPSK	1/2
QPSK	3/4
16QAM	1/2
16QAM	3/4
64QAM	1/2
64QAM	2/3
64QAM	3/4

PER_B is also related to $\bar{ca}$ by a 3rd order polynomial function.

The MCS set considered in the work is taken from the IEEE 802.11n [23] wireless LAN standard. For each spatial stream, modulation schemes and code rates available are listed in Table I. In a 4×4 system, the maximum number of spatial streams supported is 4 and hence there are 32 MCSs to choose from even modulation. To summarize, the approximated PER of a given MCS is computed as follows.

- 1) The average SNR $\bar{\gamma}_i$ of each spatial stream from the received packet is first computed using (12) or (14), depending on the type of system employed.
- 2) With the modulation scheme of the MCS and $\bar{\gamma}_i$, the mean mutual information $\bar{ca}$ is computed using (17).
- 3) Next, the $CBER$ or the PER_B can be computed using $\bar{ca}$ and the code rate of the MCS. Finally, the PER of the MCS can be approximated using (19) or (20). Note that the EXIT functions (17), (19) and (20) are predetermined and easy to generate. Hence, the system can accommodate various modulation schemes and different types of code.

IV. MCS SELECTION

With the method of approximating the PER of a MCS described in the previous sections, we can now proceed to the steps of the MCS selection algorithm. The purpose of the MCS selection algorithm is to solve the optimization problem (P1). Upon receiving the packet, the station compute the average SNR $\bar{\gamma}_i$ of each spatial stream. The number of spatial streams available depends on the number of spatial streams used in the received packet. This would limit the size of the MCS set which can be searched. All the MCSs in this set has to have the same number of spatial streams.

Given a MCS set, several different approaches can be implemented to search for a suitable MCS which also satisfies the outage constraint. The trivial one is exhaustive search if the table is small. Following the direction of search, every entry in the MCS table is tested with the PER prediction algorithm described in Section III. The algorithm stops when a suitable choice is found. One simplification is to arrange the MCSs such that their throughput are in descending order. The search is started from the middle entry of the table or the previous selected MCS.

The number of spatial streams of the chosen MCS is determined by the MCS of the received packet as stated

Fig. 2. Throughput vs Average SNR, 4 by 4 system, 20 MHz, for different MCS selection algorithms.

previously. For example, in a 4X4 system, the maximum number of spatial streams supported is 4. If the MCS of the received packet has only 3 spatial streams, the chosen MCS will also have 3 spatial streams. In order to further increase the throughput performance, the chosen MCS might be replaced by another one with a different number of spatial streams.

The switching of the MCS is implemented by a look-up table. To obtain this table, the throughput performance curves are first generated for all the MCSs with different number of spatial streams. With a switching table implemented, we can choose a MCS with fewer or more spatial streams than the received packet, which result in a better throughput. For example, for certain cases, a MCS with lesser number of spatial streams might have a better throughput due to its higher spatial diversity. In such cases, with a switching table, we can switch to this lower stream MCS without re-estimating the PER of this MCS. On the other hand, a MCS of higher number of spatial streams might be used instead for improving the throughput performance if the PER of the chosen MCS is very small.

With switching, the size of the MCS search is smaller and the complexity is reduced because it is no longer required to estimate the PER performance of multiple number of spatial streams. The MCS selected after this switching process is then the output of the MCS selection algorithm.

V. NUMERICAL EXAMPLES

The system selected for the numerical examples is the IEEE 802.11n [23] wireless LAN. We simulated the proposed MCS selection over IEEE channel model B and D for system with four transmit and maximum four receive antennas. The speed of movement in the scattering environment is assumed to be 1.2km/h. This is equivalent to a doppler spread $f_d \approx 6$ Hz at 5.25GHz band. Channel B has a root mean square (rms) delay spread of 15ns while channel D has a rms delay spread of 50ns. No retransmission is employed. The system have

20MHz bandwidth and employs even modulation schemes (same modulation scheme for all the spatial streams) with convolutional code with generator $(133, 171)_8$. The MCS set consists of MCS of all the supported spatial streams. MMSE detection of the transmitted data is implemented. We assume perfect timing and frequency synchronization, but with least square channel estimation. The transmission nonlinearities such as RF impairments are also ignored. The data length is 1000 bytes per packet. For each SNR point, 10000 packets are transmitted over the channel. A target PER of 10% is selected and the outage probability is 5%. Transmitter based MCS selection is implemented to avoid feedback of MCS, although the link adaptation algorithm works for the receiver based MCS selection. We also assume perfect reciprocity of the channel.

The MCS selection (MS) algorithm is compared to the instantaneous SNR based error prediction method in Fig. 2 for a 4 by 4 system. MCS 24¹ (4 spatial streams of BPSK with rate 1/2 FEC code) is used for the initial data frame (see Fig. 1). The thin curves represent the downlink average throughput of each MCS without AMC and without any constraint on the outage probability. The ‘..’ lines correspond to the downlink throughput of the MCSs with 1 spatial stream without AMC, the ‘-.-’ lines correspond to the downlink throughput of the MCSs with 2 spatial streams without AMC, the ‘- -’ lines correspond to the downlink throughput of the MCSs with 3 spatial streams without AMC, and the ‘-’ lines correspond to the downlink throughput of the MCSs with 4 spatial streams without AMC. A good estimate on the desired throughput performance would be the convex hull of the throughput curves obtained for each MCS. The uplink throughput curves do not differ much from the downlink for the MS algorithm. The MS algorithm achieves higher throughput than the instantaneous SNR based algorithm for channel B, as shown in Fig. 2(a). The throughput performance is shown in 2(b) for channel

¹For the description of the other MCSs, the reader can refer to [23].

Fig. 3. Throughput vs Average SNR, 4 by 4 system, 20 MHz, for different updating frequencies.

D, which has more frequency selectivity. The MS algorithm performs better than the instantaneous SNR based algorithm at high SNR and worse at low SNR. This is because the MS algorithm is jointly optimized for both channel B and D. The loss in throughput performance in channel D at low SNR is mainly due to the fact that the selected MCS also needs to satisfy the outage probability criterion in channel B. With joint optimization, detection of channel type is not required, unlike the instantaneous SNR based algorithm.

In Fig. 3(a), the average throughput of MS algorithm is plotted against average SNR for a 4 by 4 system in channel B. It can be observed that the MS algorithm can be activated once every 50 packets (5 ms) without causing much deterioration in the throughput. Similar observation can be seen in Fig. 3(b) for channel D.

In Fig. 4(a), we consider an asymmetric case using a 4 by 3 system operating in 20 MHz channel B. MCS 16 (3 spatial streams of BPSK with rate 1/2 FEC code) is used for the initial data frame. For the transmitter based MCS selection, the downlink channel is used for selecting a MCS for the uplink channel and vice versa. A fixed safety margin is added to the uplink channel when selecting a MCS of the downlink channel. Other than this safety margin, the MS algorithm is precisely the same as the one used for the 4 by 4 system. Note that the performance of uplink channel is better than the downlink channel. The requirement for the outage constraint at high SNR leads to a floor on the throughput performance at low SNR. However, the uplink throughput performance remains unaffected. Similar throughput performance can be observed for channel D, as shown in Fig. 4(b).

VI. CONCLUSION

We have proposed a link adaptation algorithm that maximizes throughput with PER constraint. The EXIT analysis is used to predict the PER performance of the coded multiple-antenna OFDM systems with channel estimation error. With

this PER prediction, we have also illustrated a MCS selection algorithm which is independent of the type of channel models. The MCS set consists of MCSs of various number of spatial streams. Numerical examples are given to show the good throughput performance of the transmitter based link adaptation algorithm, which does not require MCS feedback.

REFERENCES

- [1] B. Vucetic, "An adaptive coding scheme for time-varying channels," *IEEE Trans. Commun.*, vol. 39, pp. 653–663, May 1991.
- [2] A. Goldsmith and S. G. Chua, "Adaptive coded modulation modulation for fading channel," *IEEE Trans. Commun.*, vol. 46, pp. 595–602, May 1998.
- [3] S. Simoens and D. Bartolome, "Optimum performance of link adaptation in HIPERLAN/2 system," in *Proc. Int. Conf. Veh. Technol.*, Rhodes, Greece, May 2001, pp. 1129–1133.
- [4] S. Simoens, S. Rouquette-Léveil, P. Sartori, Y. Blankenship, and B. Clas-son, "Error prediction for adaptive modulation and coding in multiple-antenna OFDM systems," *Signal Processing*, vol. 86, pp. 1911–1919, Aug. 2006.
- [5] M. Lampe and H. Rohling, "PER-prediction for PHY mode selection in OFDM communication systems," in *Proc. Global Telecommun. Conf.*, San Francisco, USA, Dec. 2003, pp. 25–29.
- [6] Ericsson, "System-level evaluation of OFDM - further considerations," *Technical Report, 3GPP, TSG-RAN WG1*, Nov. 2003.
- [7] Y. W. Blankenship, P. J. Sartori, B. K. Classon, V. Desai, and K. L. Baum, "Link error prediction methods for multicarrier systems," in *Proc. Int. Conf. Veh. Technol.*, Los Angeles, USA, Sep. 2004, pp. 4175–4179.
- [8] B. A. Bjerke, J. Ketchum, R. Walton, and S. Nanda, "Packet error probability prediction for system level simulations of MIMO-OFDM based 802.11n WLANs," in *Proc. IEEE Conf. Commun.*, Seoul, Korea, May 2005, pp. 2538–2542.
- [9] F. Peng, J. Zhang, and W. E. Ryan, "Adaptive modulation and coding for IEEE 802.11n," in *Proc. IEEE Wireless Comm. and Networking Conf.*, Hong Kong, Mar. 2007, pp. 293–298.
- [10] C. Berrou, A. Glavieux, and P. Thitimajshima, "Near Shannon limit error-correcting coding and decoding: Turbo-codes," in *Proc. IEEE Conf. Commun.*, Geneva, Switzerland, May 1993, pp. 1064–1070.
- [11] S. Benedetto, D. Divsalar, G. Montorsi, and F. Pollara, "Serial concatenation of interleaved codes: performance analysis, design, and iteration decoding," *IEEE Trans. Inform. Theory*, vol. 44, no. 3, pp. 909–926, May 1998.
- [12] S. ten Brink, "Convergence behavior of iteratively decoded parallel concatenated codes," *IEEE Trans. Commun.*, vol. 49, pp. 1727–1737, Oct. 2001.

Fig. 4. Throughput vs Average SNR, 4 by 3 system, 20 MHz, for different updating frequencies.

- [13] C. Hermosilla and L. Szczeciński, "Adaptive modulation and coding for turbo receivers in space-time bmc," in *Proc. IEEE Wireless Comm. and Networking Conf.*, Las Vegas, USA, Apr. 2006, pp. 1293–1298.
- [14] —, "Performance evaluation of linear turbo-receivers using analytical extrinsic information transfer functions," *EURASIP Journal on Applied Signal Processing*, vol. 6, pp. 892–905, May 2005.
- [15] X. Wang and H. V. Poor, "Iterative (turbo) soft interference cancellation and decoding for coded CDMA," *IEEE Trans. Commun.*, vol. 47, pp. 1046–1061, Jul. 1999.
- [16] M. Sellathurai and S. Haykin, "Turbo-BLAST for wireless communications: theory and experiments," *IEEE Trans. Signal Processing*, vol. 50, pp. 2538–2546, Oct. 2002.
- [17] D. Hochwald and S. ten Brink, "Achieving near-capacity on a multiple-antenna channel," *IEEE Trans. Commun.*, vol. 51, no. 3, pp. 389–399, Mar. 2003.
- [18] IEEE 802.11 TGn channel model special committee, "TGn channel models for IEEE 802.11 WLANs," *IEEE 802.11-03/940r4*, May 2004.
- [19] P. Xia, S. Zhou, and G. B. Giannakis, "Adaptive MIMO-OFDM based on partial channel state information," *IEEE Trans. Signal Processing*, vol. 52, pp. 202–213, Jan. 2004.
- [20] S. Haykin, *Adaptive filter theory*. Prentice-Hall, 2002.
- [21] M. Tüchler, S. ten Brink, and J. Hagenauer, "Measures for tracing convergence of iterative decoding algorithms," in *Proc. 4th IEEE/ITG Conference on Source and Channel Coding*, Berlin, Germany, Jan. 2002, pp. 53–60.
- [22] M. Tüchler and J. Hagenauer, "Exit charts of irregular codes," in *Proc. Conf. on Information Sciences and Systems (CISS)*, Princeton, U.S.A., Mar. 2002, pp. 153–158.
- [23] IEEE 802.11 working group, *IEEE P802.11n/D2.00*. IEEE Standards Department, Feb. 2007.

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