Cross-layer link adaptation for IEEE 802.11n

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Abstract—This paper considers the use of cross-layer MIMO fast link adaption (FLA) algorithms in the context of IEEE 802.11n. An FLA technique based on packet error rate (PER) that makes use of the exponential effective SNR mapping (EESM) is proposed. Additionally, a bit error rate (BER) based FLA scheme is proposed that simplifies the calibration procedure without any significant performance degradation. Results show that both, PER- and BER-based, FLA techniques select the modulation and coding scheme (MCS) in a close to optimum fashion in the sense of maximising the data throughput while satisfying a prescribed packet error rate (PER) target. Channel estimation errors have also been considered, revealing the importance of good channel estimators in order for FLA strategies to work satisfactorily.

I. INTRODUCTION

Last years have witnessed an explosive growth in the deployment of wireless local area networks (WLANs), which has made the concept of nomadic computing a reality. Most of these networks are based on the IEEE 802.11a/g standards. In order to counteract the frequency and time selectivity of the wireless channel, the physical layer of these standards employ: 1) orthogonal frequency division multiplexing (OFDM) with guard interval (GI), and 2) adaptive modulation and coding (AMC) based on bit interleaved coded modulation (BICM). Ideally, and based on some form of channel state information (CSI), AMC strategies are used to select a combination of modulation and coding scheme (MCS) aiming at the optimization of spectral efficiency subject to quality of service (QoS) constraints such as, for instance, a maximum average packet error rate (PER) outage probability, \( P_{\text{out}} \), for a given target PER, \( PER_0 \). Mathematically, the instantaneous PER of MCS \( m \in \mathcal{M} \), where \( \mathcal{M} \) denotes the set of MCSs, can be expressed as

\[
P_m = F_m (\text{SNR}, L, H),
\]

where SNR is the received average signal to noise ratio, \( L \) is the packet length in number of information bits and \( H \) denotes the channel realization and, thus, optimum MCS selection process can be formulated as

\[
m^* = \arg \max_{m \in \mathcal{M}} \eta_m = \arg \max_{m \in \mathcal{M}} T_m (1 - P_m)
\]

subject to \( Pr \{ \text{PER} > PER_0 \} \leq P_{\text{out}} \),

where \( \eta_m \) and \( T_m \) denote the instantaneous throughput and transmission rate of MCS \( m \), respectively. This optimization process, usually known as fast link adaptation (FLA), clearly shows a close interaction between the physical layer (PHY) and the medium access control (MAC) layer and claims for a PHY-MAC cross-layer design. Despite this claim, legacy WLAN standards only specify which MCSs are allowed for which types of MAC frames, but not how and when to switch between the permitted rates. Furthermore, there is no signaling mechanism specified which would allow a receiver to inform the transmitter about the actual link quality or the rate to be used. The AutoRate Fallback (ARF) link adaptation protocol [1] and its modifications [2], [3], [4], [5] have been widely used in legacy WLANs. They consists of an automatic method for switching between transmission rates in which the PHY layer automatically switches to a lower rate after two consecutive transmission errors (missed ACKs) and switches to a higher rate either after ten successful transmissions (ACK reception) or after a time out. The rationale behind these approaches is that for the MCS set used in legacy systems and for a given SNR, a higher transmission rate in the MCS implies a higher instantaneous PER. The main advantage of these algorithms is their simplicity for implementation. The disadvantages are their suboptimality and their inaccuracy when there are collisions [6].

At present, the standardization of what should be the next step, named IEEE 802.11n, is being pursued by the IEEE 802.11 High Throughput Task Group committee [7]. The new standard will support much higher transmission rates thanks to the use of multiple-input multiple-output (MIMO) antenna technology and other enhancements such as the possibility of operating on a 40 MHz bandwidth (employing more subcarriers) and transmission modes using a reduced guard interval. Moreover, the MAC layer incorporates new mechanisms to feedback information regarding MCS selection, thus making FLA a feasible option. In MIMO systems, in addition to MCS selection, link adaption algorithms face another challenge, the MIMO mode selection. MIMO can work in either space-time block-coding (STBC), cyclic delay diversity (CDD) or spatial division multiplexing (SDM) mode or even a combination of them. In this case, a higher transmission rate in the MCS does no longer imply a higher instantaneous PER and thus, the traditional link adaptation algorithms used in single-input multiple-output (SIMO) legacy systems become hardly effective. This motivates the development of cross-layer link adaptation algorithms based on AMC for MIMO-OFDM systems. As stated by (2), the key elements of the FLA optimization process are, on one hand, a high quality instantaneous PER prediction tool at the PHY layer for all possible MCS/MIMO modes, packet lengths and channel realizations, and, on the other hand, a MCS/MIMO mode selection methodology at the MAC layer that ensures the fulfilment of QoS constraints. There is no simple and systematic approach for predicting PER assuming arbitrary MCS/MIMO modes,
packet sizes, and channel realizations in frequency selective channels with arbitrary channel correlations. Nevertheless, in this paper we propose PHY abstraction techniques that enable accurate PER prediction based on frame-by-frame bit error rate (BER) prediction. Abstraction techniques are based on a common approach that maps system parameters like the selected MCS/MIMO operation mode, packet length and channel realization onto a link quality metric (LQM) which can be associated to the PER by means of simple look-up-tables [8]. Appropriate LQMs are derived for each MIMO detection strategy used at the receiver side. Moreover, this paper also presents an MCS selection approach that fulfills the optimization constraint on the PER outage probability. Furthermore, we also present a study on the impact of channel estimation errors on the performance of FLA techniques on IEEE 802.11n networks.

II. SYSTEM MODEL

A. Transmitter

Our study focuses on the IEEE 802.11n Draft proposal [7] whose physical layer transmitter structure is shown in Fig. 1. Information bits \( \{b_1, b_2, \ldots, b_L\} \) are first encoded with rate \( R = \frac{1}{3} \) convolutional encoder and subsequently punctured to one of the possible coding rates \( R_m \in \{1/2, 2/3, 3/4, 5/6\} \). Depending on the selected MIMO configuration, the resulting bits are demultiplexed into \( N_s \) spatial streams that are subsequently processed independently. For each stream, the coded bits are interleaved and then mapped to symbols from one of the allowed constellations (BPSK, QPSK, 16-QAM or 64-QAM). In accordance with the selected MIMO configuration, the symbols are then either STBC encoded or antenna mapped on the available \( N_T \) transmit antennas. The resulting symbols are then supplied to a conventional OFDM modulator consisting of an IFFT and the addition of full guard interval.

For simplicity of exhibition, this paper focuses on a \( 2 \times 2 \) MIMO system \( (N_T = 2 \) and \( N_s = 2) \), implying that MCS with \( N_s = 1 \) and \( N_s = 2 \) spatial streams employ STBC [9] and SDM [10], respectively. CDD is not applied.

B. Receiver

A generic receiver block diagram is depicted in Fig. 2. Reception begins by inverting the OFDM modulation (e.g. GI removal and FFT processing) to recover the received baseband samples, which for the \( k \)th subcarrier can be expressed as

- SDM

\[
r_t[k] = H_t[k] s_t[k] + \eta_t[k]
\]

- STBC

\[
r_t[k] = H_t[k] \begin{bmatrix} s_{t,1}[k] \\ s_{t,2}[k] \end{bmatrix} + \eta_t[k]
\]

\[
r_{t+1}[k] = H_{t+1}[k] \begin{bmatrix} -s_{t,2}^*[k] \\ s_{t,1}^*[k] \end{bmatrix} + \eta_{t+1}[k]
\]

where \( H_t[k] \) denotes the \( N_R \times N_T \) MIMO channel matrix affecting subcarrier \( k \), \( s_t[k] = [s_{t,1}[k], s_{t,2}[k]]^T \) is the \( N_T \times 1 \) vector of transmitted symbols with \( E\{s_t[k] s_t^*[k]\} = \frac{P_T}{N_T} I_{N_T} \), \( I_{N_T} \) is the \( N_T \times N_T \) identity matrix and \( \eta_t[k] \) is the \( N_R \times 1 \) thermal noise vector characterized as a zero-mean additive white Gaussian noise (AWGN) with \( E\{\eta_t[k] \eta_t^*[k]\} = \sigma^2 I_{N_R} \).

If \( N_s = 1 \), STBC is applied at the transmitter side. This technique relies on an orthogonal combination of two consecutive OFDM symbols (STBC block) that allows optimal detection at the receiver by means of maximal ratio combining (MRC), which is implemented by a linear combination of received samples on two consecutive OFDM symbols. Thus, assuming ideal CSI and that coherence time is long enough to ensure that \( H_{t+1}[k] = H_t[k] \), the MRC estimate can be obtained as

\[
y^{\text{STBC}}[k] = \Gamma_k s[k] + \tilde{\eta}[k]
\]

where \( \Gamma_k = \sum_{n=1}^{N_s} (|h_{1,n}[k]|^2 + |h_{2,n}[k]|^2) \) with \( h_{n_1,n_r}[k] \) denoting the channel coefficient linking Tx antenna \( n_t \) with Rx antenna \( n_r \), and \( \tilde{\eta}[k] \) is a zero-mean AWGN vector with \( E\{\tilde{\eta}[k] \tilde{\eta}^*[k]\} = \Gamma_k \sigma^2 I_2 \). The output SNR corresponding to transmitted symbol \( j \) can then be calculated as

\[
SNR_j[k] = \frac{P_T \Gamma_k}{N_T \sigma^2}.
\]

Alternatively, if \( N_s = 2 \) a linear MMSE detector is applied on the received samples in order to decouple the two streams. That is, the MMSE symbol estimation can be written as

\[
y^{\text{SDM}}[k] = W[k] r[k]
\]

where the MMSE filter matrix \( W[k] \) is given by

\[
W[k] = \left( H^H[k] H[k] + N_T \sigma^2 I_{N_T} \right)^{-1} H^H[k].
\]

The post-MMSE equalizer SNR of transmitted symbol \( j \) is given by

\[
SNR_j[k] = \frac{1}{\left( \frac{P_T}{N_T \sigma^2} H^H[k] H[k] + I_{N_T} \right)^{-1}}.
\]

Based on [11], the LLR for the in-phase bit on the \( p \)th position of the transmitted symbol \( j \) can be obtained as

\[
LLR(s_j[k], b_{I,p}[k]) = SNR_j[k] D_{I,p}[k]
\]

where \( SNR_j[k] \) is determined according to the transmission scheme used (SDM or STBC) and \( D_{I,p}[k] \) is defined in Table I with \( y_t[k] = \text{Re}\{y_j[k]\} \). The LLRs for the quadrature bits are computed using an analogous procedure.

<table>
<thead>
<tr>
<th>Modulation</th>
<th>( D_{I,1}[k] )</th>
<th>( D_{I,2}[k] )</th>
<th>( D_{I,3}[k] )</th>
</tr>
</thead>
<tbody>
<tr>
<td>BPSK</td>
<td>( y_1[k] )</td>
<td>( Y_1[k] )</td>
<td>( Y_2[k] )</td>
</tr>
<tr>
<td>QPSK</td>
<td>( y_1[k] )</td>
<td>( Y_1[k] )</td>
<td>( Y_2[k] )</td>
</tr>
<tr>
<td>16QAM</td>
<td>( y_1[k] )</td>
<td>(</td>
<td>y_1[k]</td>
</tr>
<tr>
<td>64QAM</td>
<td>( y_1[k] )</td>
<td>(</td>
<td>y_1[k]</td>
</tr>
</tbody>
</table>

**Table I**

**Auxiliary Table for LLR Computation.**

\( (P_T/N_T) I_{N_T}, I_{N_T} \) is the \( N_T \times N_T \) identity matrix and \( \eta_t[k] \) is the \( N_R \times 1 \) thermal noise vector characterized as a zero-mean additive white Gaussian noise (AWGN) with \( E\{\eta_t[k] \eta_t^*[k]\} = \sigma^2 I_{N_R} \).
fading channel realization, which can be expressed as

\[
\text{SNR} = \frac{P}{N_0}
\]

to attain the same PER obtained over the frequency selective channel realizations. Using these performance predictions, an MCS/MIMO mode selection methodology can then be implemented at the MAC layer in order to ensure the fulfilment of QoS constraints.

### III. Fast Link Adaptation

As stated in the introduction, FLA algorithms are used to select the MCS that maximizes the instantaneous throughput subject to a constraint on the maximum average PER outage probability, \( P_{\text{out}} \), for a given target PER, \( PER_0 \). Thus, a high quality instantaneous PER prediction tool is required at the PHY layer for all possible MCS/MIMO modes, packet lengths and channel realizations. Using these performance predictions, an MCS/MIMO mode selection methodology can then be implemented at the MAC layer in order to ensure the fulfillment of QoS constraints.

#### A. PER prediction

As shown in (1), the PER can be expressed as a function of MCS \( m \in \mathcal{M} \), the received SNR, the packet length \( L \) and the channel realization \( H \). In order to map these parameters onto a single link quality metric (LQM) which could be associated to the PER by means of look-up tables obtained by off-line simulations, different approaches have been proposed in the literature (see, e.g., [12], [8] and references therein). Among all the proposed prediction strategies, those based on a one-dimensional mapping between the LQM, called effective SNR, and the PER are particularly interesting [12] (and references therein). Given an MCS \( m \in \mathcal{M} \), the corresponding effective SNR can be defined as the SNR that would be required by this MCS on an AWGN channel to attain the same PER obtained over the frequency selective fading channel realization, which can be expressed as

\[
\text{SNR}_{\text{eff}}^{(m)} = \alpha_1^{(m)} J^{-1} \left( \frac{1}{N_S N_d} \sum_{j=1}^{N_S} \sum_{k=1}^{N_d} J \left( \frac{\text{SNR}_j[k]}{\alpha_2^{(m)}} \right) \right)
\]

where \( J(\cdot) \) is a model specific LQM function and \( J^{-1}(\cdot) \) is its inverse. The parameters \( \alpha_1^{(m)} \) and \( \alpha_2^{(m)} \) allow the model to be adapted to the characteristics of the corresponding MCS. The capacity effective SNR metric (CESM) is obtained with \( J(\gamma) = \log_2(1 + \gamma) \). The exponential effective SNR metric (EESM) corresponds to \( J(\gamma) = \exp(-\gamma) \). Other proposed metrics are, for instance, mutual information effective SNR metric (MIESM) obtained as \( J(\gamma) = I_m(\gamma) \), where \( I_m(\cdot) \) represents the mutual information of MCS \( m \), or the logarithmic effective SNR metric (LESM) characterized by \( J(\gamma) = \log_{10}(\gamma) \).

In this paper, without loss of generality, we focus on the EESM-based PER prediction strategy. The optimum values for the fitting parameters \( \alpha_1^{(m)} \) and \( \alpha_2^{(m)} \) in (12) are obtained off-line by an exhaustive search aimed at minimizing the \( \text{SNR}_{\text{eff}}^{(m)} \) estimation error averaged over a large set \( \mathcal{H} \) of independent channel realizations and an average error rate interval \( \mathcal{P} = [PER_{\text{min}}, PER_{\text{max}}] \), that is,

\[
(\alpha_1^{(m)}, \alpha_2^{(m)}) = \arg \min_{\alpha_1, \alpha_2} E_{\mathcal{H}, \mathcal{P}} \left\{ |\text{SNR}_{\text{eff}}^{(m)} - \text{SNR}_{\text{AWGN}}^{(m)}|^2 \right\}
\]

for all \( m \in \mathcal{M} \), where \( \text{SNR}_{\text{AWGN}}^{(m)} \) is the required SNR for mode \( m \) to obtain the same PER on the AWGN channel as on the current channel realization.

#### B. MCS selection process

In order to fulfill the optimization constraint on the average PER outage, an effective SNR threshold \( \text{SNR}_{\text{TH}}^{(m)} \) is obtained for each \( m \in \mathcal{M} \) in such a way that

\[
\Pr \left\{ \text{PER}_{\text{AWGN}}^{(m)} \left( \text{SNR}_{\text{eff}}^{(m)} > \text{PER}_0 \right) \leq P_{\text{out}} \right\} \leq P_{\text{out}} \tag{13}
\]

whenever \( \text{SNR}_{\text{eff}}^{(m)} \geq \text{SNR}_{\text{TH}}^{(m)} \). The \( \text{SNR}_{\text{TH}}^{(m)} \) is computed as the \( \text{SNR}_{\text{eff}}^{(m)} \) satisfying (13) with equality. This probability is computed numerically using all realizations over the set \( \mathcal{H} \). When determining the optimum MCS for a given channel realization, the FLA algorithm evaluates the effective SNR for the different MCSs in descending throughput order. During the evaluation of a given MCS, two situations may occur: if the effective SNR of the MCS is above the corresponding \( \text{SNR}_{\text{TH}}^{(m)} \), the evaluated MCS is selected as a possible transmission mode;
otherwise, the considered MCS is deemed unsuitable. This iterative procedure continues until one MCS is selected or all have been discarded, in which case, the no transmission mode is selected. Some throughputs may be achieved using either SDM or STBC, in such cases, both MCSs are evaluated and if both are found suitable for transmission, the STBC-based one is selected due to their higher spectral efficiency at low SNR regimes [9].

C. BER-based PER prediction

Previously, it has been stated that PER prediction methods depend on the particular packet length \( L \), leading to an individual calibration/prediction procedure for each \( L \). That is, a set of look-up tables would be required for each packet length. In order to avoid this situation, a novel solution is presented that relies on BER, rather than PER, thus making the FLA strategy independent of \( L \). The basic assumption for this strategy is that for long enough packets, the BER is independent of \( L \) and consequently, if BER and PER can be related by means of a closed-form expression, PER prediction can be made on the basis of BER.

The BER-based estimation relies on the EESM technique introduced earlier though modifying some of its characteristics. It determines the \( SNR_{\text{eff}}^{(m)} \) for each channel realization, using (12) with \( \alpha_1^{(m)} \) and \( \alpha_2^{(m)} \) obtained from a calibration where the PER curves have been replaced by BER curves. Correspondingly, a \( SNR_{\text{eff}}^{(m)} \) is determined for each \( m \in M \) in such a way that \( P \{ BER_{\text{AWGN}}(SNR_{\text{eff}}^{(m)}) > BER_0^{(m)} \} \leq P_{\text{out}} \) whenever \( SNR_{\text{eff}}^{(m)} \geq SNR_{\text{th}}^{(m)} \), where, as it is later shown, the target BER for each MCS, namely \( BER_0^{(m)} \), can be obtained from \( PER_0 \). Obviously, the search algorithm is not modified.

The error event probability for a convolutionally encoded packet using MCS \( m \) can be approximated by

\[
P_e^{(m)} \approx P_b^{(m)}/d_f, \tag{14}\]

where \( d_f \) is the free distance of the convolutional code and \( P_b^{(m)} \) is the uncoded bit error probability of MCS \( m \). This is based on the assumption that the number of bit errors per error event is approximately equal to the free distance. Using \( P_e \), the PER of MCS \( m \) can be approximated as

\[
PER^{(m)} \approx 1 - \left( 1 - P_e^{(m)} \right)^{\frac{1}{R_m}} \tag{15}\]

where \( R_m \) is the MCS code rate. This approximation is based on the assumption that an error-free packet is due to the absence of error events in each possible transition along the convolutional code trellis. Using (14) and (15), \( BER_0^{(m)} \) for all \( m \in M \) can be obtained as a function of \( PER_0 \) as

\[
BER_0^{(m)} = \left( 1 - (1 - PER_0)^{\frac{d_f}{R_m}} \right) d_f. \tag{16}\]

IV. RESULTS

The simulated system follows the specifications of the current draft for IEEE 802.11n (see Fig. 1) [7]. The system is configured to use full GI, \( N_c = 64 \) subcarriers over a 20 MHz bandwidth on the 5.25 GHz carrier frequency with \( N_d = 52 \) data subcarriers (rest of subcarriers are pilots or nulls). Rayleigh fading channel realizations have been created by a MIMO channel model generator tool [13] using \( 3m \) distance between transmitter and receiver, \( \lambda \) Tx antenna spacing and 0.5\( \lambda \) Rx antenna spacing, where \( \lambda \) is the wavelength. In order to determine \( \alpha_1^{(m)} \) and \( \alpha_2^{(m)} \), the calibration set \( H \) has been defined by a mixture of 200 channel realizations from Channel profiles B and E and over the PER interval \( P = [0.01, 0.95] \). The PER target has been set to \( PER_0 = 0.1 \) and the maximum PER outage probability has been fixed to \( P_{\text{out}} = 0.05 \).

Imperfect channel estimation has been modelled by corrupting each channel frequency coefficient with a zero-mean AWGN with variance modelled as the mean square error (MSE) correspondingly to the maximum performance bound of the MIMO-multicarrier channel estimator specified in [14]

\[
MSE = \frac{T_0}{T_{\text{OFDM}}} \sigma^2 \]

where \( T_{\text{OFDM}} \) is the OFDM symbol period and \( T_0 \) is the largest delay introduced by the channel.

Figures 3a and 3b depict throughput results using ideal channel estimation for fixed mode transmission, FLA and performance bounds algorithm (PBA) when using packets of length \( L = 1664 \) bits. The PBA is an ideal FLA algorithm that for any channel realization is able to select the MCS with maximum throughput while guaranteeing zero transmission errors [15]. The EESM FLA clearly outperforms the fixed MCS and remains within 1.5 dB of the PBA. Furthermore, EESM fulfills the QoS constraints by keeping the PER well below the \( PER_0 \) (see Figs. 3d and 3e). The large difference in actual PER and \( PER_0 \), resulting in an overly pessimistic system, is basically due to the absence of power control.

As it can be observed in Fig. 3c, for Channel E imperfect CSI causes degradation in the throughput performance of around 1.5dB for any considered transmission technique. Additionally, note that the system PER constraint is not fulfilled (see Fig. 3e). The reason for this misbehavior has to be sought in the large maximum delay of this channel, which causes a large MSE in the channel estimation process. We note that for Channel B, and owing to its low maximum delay, imperfect CSI barely harms performance (see Fig. 3d).

Fig. 4 shows results obtained by using BER-based PER prediction methods with \( L \) as parameter. The calibration process has been performed using BER performance realizations for a packet length of \( L = 1664 \) bits. These results have then been extrapolated to predict the PER performance for packet lengths ranging from \( L = 416 \) bits to \( L = 3328 \) bits. As it can be observed this approach leads to almost identical performance results (Fig. 4a) as the PER-based approach, thus validating the BER-prediction accuracy for practical values of packet length. Logically, the shortest packet length achieves always the best performance results. The channel imperfection affects in the same manner all \( L \), being the average degradation around 1.5dBs, similar to what was observed in FLA PER-based systems. System performance in channel E is not capable of
meeting the QoS constraints (see Fig. 4b). For the channel B, there are no differences between ideal and imperfect channel estimation results, and the $P_E R_{95}$ constraint is fulfilled.

V. CONCLUSIONS

This paper has addressed cross-layer FLA techniques within the framework of IEEE 802.11n networks. Single and double stream MCS are considered, using STBC and SDM, respectively. It has been shown that PER prediction EESM-based FLA with ideal channel estimation meets the PER requirements while performing very close ($1.5$ dB) to the PBA. When channel estimation errors are present in high diversity channels, the performance of the studied FLA algorithms in terms of throughput is significantly affected, reducing the whole performance in $\approx 1.5$ dB for any methodology. Moreover, the instantaneous PER occasionally goes above the target. A new variant of FLA algorithm has been introduced that is based on BER prediction (rather than PER) using EESM. This technique performs almost identically to its PER-based counterpart while simplifying the costly calibration/prediction procedure.

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