LEARNING BASED LINK ADAPTATION IN MULTIUSER MIMO-OFDM

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ABSTRACT

Link adaptation in multiple user multiple-input multiple-output orthogonal frequency division multiplexing communication systems is challenging because of the coupling between user selection, mode selection, precoding, and equalization. In this paper, we present a methodology to perform link adaptation under this multiuser setting, focusing on the capabilities of IEEE 802.11ac. We propose to use a machine learning classifier to solve the problem of selecting a proper modulation and coding scheme, combined with a greedy algorithm that performs user and spatial mode selection. We observe that our solution offers good performance in the case of perfect channel state information or high feedback rate, while those scenarios with less feedback suffer some degradation due to inter-user interference.

***Index Terms*—** Multiuser MIMO-OFDM, Link Adaptation, Machine Learning

1. INTRODUCTION

Link adaptation (LA) is the process of selecting transmission parameters (usually modulation and coding scheme - MCS) in a wireless link to maximize some throughput metric while meeting some reliability constraints, usually expressed in terms of frame error rates (FER). In multiple-input-multiple-output (MIMO) orthogonal frequency division multiplexing (OFDM) systems, this adaptation is challenging because of the difficulty of predicting the FER performance as a function of the channel state information (CSI). As data is jointly coded and interleaved across multiple carriers and substreams, each one experiencing a different signal to noise ratio (SNR), it is hard to calculate (with low complexity) the probability of unsuccessful decoding.

To enable practical LA, some FER prediction metrics have been proposed in the literature [1–3]. These metrics are usually based on a generalized average model that maps the set of all SNRs (one for each carrier and spatial stream) to one *effective SNR*. This SNR value is usually defined as the necessary SNR for an additive white Gaussian noise (AWGN) channel to experience the same FER as the fading channel under study. Unfortunately, these unidimensional metrics may not be able to fully characterize the channel and may not provide a good approximation to the actual FER of the system.

Machine learning is one mathematical tool that can be used to develop practical LA methods [4–6]. Using machine learning, the LA optimization is framed as a classification problem, with the class boundaries determined from performance related data. The learning process can be performed offline [4] or online [7]. As the system experiences different channel states and FER values, the learning algorithm incorporates this information into its performance database, and is able to infer the FER value for the future channel states. A general benefit of using learning is that the impact of practical impairments that may be not explicitly modeled, e.g., non-Gaussian noise or non-linearities, can still be incorporated [8]. Prior work provided several approaches for LA in single user MIMO-OFDM communication links. Multiuser MIMO (MU-MIMO) communication, as used in emerging commercial wireless systems like IEEE 802.11ac [9], was not considered.

In this paper, we present a LA algorithm suitable for MU-MIMO communication focusing on the capabilities of IEEE 802.11ac. The MU scenario is more challenging due to the coupling between user selection, spatial mode selection, precoding and MCS selection. We propose to use a machine learning classifier for MCS selection, a greedy algorithm for user and mode selection, and exploit limited feedback information to perform block diagonalization (BD) precoding to remove inter-user interference. In our approach, this classifier is trained offline; online implementation is a subject of our current research. We explore insights from MU-MIMO precoding with scheduling [10] and LA in MIMO-OFDM systems [4] to develop our solution. We also explore the effect of limited feedback CSI, and conclude that the selection of a convenient feedback rate, specially in high SNR environments, is critical for a good performance of the proposed algorithm. Our approach is different from prior work in several ways. LA methods in single-user MIMO [4] require running the LA algorithm for different number of spatial streams, selecting afterwards the mode leading to a higher throughput. In the more general MU-MIMO case, this procedure degenerates into an exhaustive search for the number of spatial streams for every user, which is not practical. In [11] some solutions to the problems of dealing with multiple users were proposed by exploring the linkage between linear precoding (or beamforming) with limited feedback and MCS selection. In this case, the results were limited to a multicast scenario. Our paper considers MU-MIMO unlike [4] and deals with the broadcast setting unlike [11].

Notation: $\mathbf{A}^*$ denotes the Hermitian transpose of matrix $\mathbf{A}$, $\mathbf{A}^T$ denotes the transpose of matrix $\mathbf{A}$, $[\mathbf{A}]_{ij}$ denotes the element in the i-th row and j-th column of matrix $\mathbf{A}$, $\mathbf{I}_K$ denotes the $K \times K$ identity matrix, $\mathbf{0}_{K\times N}$ denotes the zero matrix of size $K \times N$, $\mathbf{A} \circ \mathbf{B}$ denotes the (entrywise) Hadamard product between matrices $\mathbf{A}$ and $\mathbf{B}$, $|\mathcal{A}|$ denotes the number of elements in set $\mathcal{A}$, $\mathbb{C}^K$ denotes the set of

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column vectors with K complex entries, and $\mathbb{C}^{K\times N}$ denotes the set of $K \times N$ matrices with complex entries.

2. SYSTEM MODEL

Consider an N-carrier OFDM wireless network where a transmitter equipped with N_{tx} antennas communicates with U users, $\mathcal{U} = \{1 \dots U\}$ where the u-th user has $N_{\text{rx},u}$ receive antennas. At a given time instant, the transmitter conveys information to a subset of the users $\mathcal{T} \subseteq \mathcal{U}$. We will denote $T = |\mathcal{T}|$ for the sake of simplicity. In a given time slot, as in IEEE 802.11ac, only the spatial multiplexing strategy can be adapted; the concept of *resource block* present in other standards like 3GPP long term evolution, which allows allocating subsets of subcarriers to different users [12], is not supported.

We restrict our analysis to transmitters employing linear precoders and receivers with linear equalizers. For a given carrier n, $\mathbf{s}_u[n] \in \mathcal{M}_u^{L_u}$ is the L_u spatial streams modulated signal containing the information for the u-th user (with $L_u \le \min\{N_{\text{tx}}, N_{\text{rx,u}}\}$), being $\mathcal{M}_u = \{m_1 \dots m_M\}$ the modulation for the u-th user (assumed to be constant over all the spatial streams[1]), $\mathbf{F}_u[n] \in \mathbb{C}^{N_{\text{tx}} \times L_u}$ is the transmit precoding matrix for the u-th user, $\mathbf{H}_u[n] \in \mathbb{C}^{N_{\text{rx},u} \times N_{\text{tx}}}$ is the flat fading MIMO channel from the transmitter to the u-th receiver, and $\mathbf{B}_u[n] \in \mathbb{C}^{L_u \times N_{\text{rx},u}}$ and $\mathbf{G}_u[n] \in \mathbb{C}^{L_u \times L_u}$ are the interference removal matrix and the linear equalizer applied at the u-th receiver. We divided the receive processing into two different matrices for simplicity in the treatment of the multiuser precoding: the objective of $\mathbf{B}_u[n]$ is to reject the inter-user interference, while the equalizer $\mathbf{G}_u[n]$ removes the intra-user interference. Finally, $\mathbf{n}_u[n] \sim \mathcal{CN}\left(\mathbf{0}, \sigma^2\mathbf{I}\right)$ denotes the received noise vector at the u-th receiver. With this, the post-processed signal at the u-th receiver $\mathbf{y}_u[n] \in \mathbb{C}^{L_u}$ is

$$\begin{aligned}\mathbf{y}_u[n] \quad = \quad & \mathbf{G}_u[n]\mathbf{B}_u[n]\mathbf{H}_u[n]\sum_{i\in\mathcal{T}} \frac{1}{\sqrt{P[n]}}\mathbf{F}_i[n]\mathbf{s}_i \\ & + \mathbf{G}_u[k]\mathbf{B}_u[n]\mathbf{n}_u[n]\end{aligned} \tag{1}$$

with

$$P[n] \triangleq \sum_{u\in\mathcal{T}} \text{tr}\left(\mathbf{F}_u[n]\mathbf{F}_u^*[n]\right), \tag{2}$$

the power normalization factor, and $\mathbb{E}\left(\mathbf{s}_u[n]\mathbf{s}_u^*[n]\right) = \mathbf{I}_{L_u}$. For the sake of clarity, we define

$$\hat{\mathbf{H}}_{u,i}[n] \triangleq \frac{1}{\sqrt{P[n]}}\mathbf{G}_u[n]\mathbf{B}_u[n]\mathbf{H}_u[n]\mathbf{F}_i[n],$$

and $\mathbf{w}_u[n] \triangleq \mathbf{G}_u[n]\mathbf{B}_u[n]\mathbf{n}_u[n]$, so

$$\mathbf{y}_u[n] = \hat{\mathbf{H}}_{u,u}[n]\mathbf{s}_u[n] + \sum_{i\in\mathcal{T}\setminus\{u\}} \hat{\mathbf{H}}_{u,i}[n]\mathbf{s}_i[n] + \mathbf{w}_u[n] \tag{3}$$

where it can be seen that the second and third terms correspond to inter-user interference and noise, respectively.

The transmit signal for each of the T scheduled receivers is the result of performing coding, interleaving and constellation mapping operations on a stream of source bits. The MCS for the u-th user c_u is selected from a finite set of MCS $\mathcal{C}$. The selected number of spatial streams and MCS for the u-th user has an associated rate of $\eta\left(c_u, L_u\right)$ bps.

[1]Although in IEEE 802.11n the use of different modulations in each spatial stream was allowed, it was apparently not implemented in most commercial devices, and finally discarded for 802.11ac.

In general, the probability that a frame is not correctly decoded at the u-th receiver (i.e., the FER), depends on the transmit power, channel matrices, number of scheduled users, selected MCS for the u-th user, selected modulation for the interfering users, etc. Treating the noise and residual multi-user interference as Gaussian, and assuming a linear receiver, it is reasonable to write the FER of the u-th user p_u as a function of the the selected MCS c_u and the post-processing SNR values $\boldsymbol{\gamma}_u = \left[\gamma_{u,1}\left[1\right], \dots \gamma_{u,L_u}\left[1\right], \dots \gamma_{u,L_u}\left[N\right]\right]^T$, where

$$p_u = \text{FER}\left(\boldsymbol{\gamma}_u, c_u\right), \tag{4}$$

and the post processing SNR of the u-th user in the i-th spatial stream and n-th carrier defined as

$$\gamma_{u,i}[n] = \frac{\left|\left[\mathbf{D}_{u,u}\left[n\right]\right]_{ii}\right|^2}{\left[\mathbf{R}_u[n]\right]_{ii}} \tag{5}$$

with

$$\begin{aligned}\mathbf{R}_u[n] = & \left(\hat{\mathbf{H}}_{u,u}[n] - \mathbf{D}_{u,u}[n]\right)\left(\hat{\mathbf{H}}_{u,u}[n] - \mathbf{D}_{u,u}[n]\right)^* + \\ & + \sum_{j\in\mathcal{T}\setminus\{u\}} \hat{\mathbf{H}}_{u,j}[n]\hat{\mathbf{H}}_{u,j}^*[n] + \sigma^2\mathbf{G}_u[n]\mathbf{B}_u[n]\mathbf{B}_u^*[n]\mathbf{G}_u^*[n]\end{aligned} \tag{6}$$

the covariance matrix of interference plus noise, and $\mathbf{D}_{u,u} \triangleq \hat{\mathbf{H}}_{u,u} \circ \mathbf{I}_{L_u}$. Based on the rate η and the FER p, we can define the throughput of user u as

$$t_u = \left(1 - p_u\right)\eta\left(c_u, L_u\right). \tag{7}$$

3. PROPOSED LINK ADAPTATION ALGORITHM

The LA problem in the multiuser scenario is different from the single-user scenario. In the single user case, the usual objective of LA is to maximize the (unique) link throughput subject to a constraint on the FER. In the MU-MIMO case, each user has a different rate, so the objective might be to maximize a function of the rates, subject to a FER constraint $p_0 > 0$ (assumed to be equal for all receivers). We consider the sum rate as the performance objective in this paper. In general, if we denote by $\mathbf{t} = [t_1 \dots t_U]$ the vector containing the throughput of all users, and by $\nu\left(\mathbf{t}\right) \triangleq \sum_{u=1}^{U} t_u$ the sum rate, the LA problem can be stated as

$$\begin{array}{ll} \text{maximize} & \nu\left(\mathbf{t}\right) \\ \text{subject to} & p_u \le p_0 \qquad u = 1 \dots U. \end{array} \tag{8}$$

We will assume $t_u = 0$, $p_u = 0$ if $u \notin \mathcal{T}$ to be consistent with our approach, which involves scheduling a subset of the users. Note that the LA problem can be modified to maximize other utility metric than the sum rate just by defining $\nu\left(\mathbf{t}\right)$ accordingly.

Trying to solve this problem directly is computationally intractable. Besides the difficulty of obtaining a mathematical model that maps the CSI to the FER p_u, the number of design variables is quite large and difficult to handle. For example, the set of active users $\mathcal{T}$, the streams per each active user L_u, the precoding matrices $\mathbf{F}_u[n]$, the interference removal matrices $\mathbf{B}_u[n]$, equalizers $\mathbf{G}_u[n]$ and MCS c_u. We propose to divide this general problem into three different operational blocks: *MCS selection*, *Precoding/Equalization* and *User and Mode Selection* [2].

[2]Due to space constraints, some of the details of the link adaptation procedure are omitted. For further details see [13].

3.1. MCS selection

The MCS selection block consists of a function μ that takes as input the set of post-processing SNR values of user u, and number of spatial streams L_u, and computes the higher MCS that meets the FER constraint for those SNR values:

$$\mu\left(\boldsymbol{\gamma}_u, L_u\right) = \arg\max_{c\in\mathcal{J}} \eta\left(c, L_u\right) \text{ s.t. } \mathrm{FER}\left(\boldsymbol{\gamma}_u, c_u\right) \leq p_0. \quad (9)$$

We use a machine learning inspired approach to solve (9). Essentially, we classify features derived from the channel into the highest MCS that meets the target FER constraint. Note that this is slightly different from conventional machine learning in that we have a target average error rate, whereas machine learning usually involves avoiding classification errors altogether. We will follow a supervised learning approach to solve this problem, which includes two separated tasks: feature extraction and classification.

Feature extraction: In machine learning, there is a well-known curse of dimensionality associated with larger dimensions feature vectors requiring exponentially more training data [14]. Consequently there are benefits to reducing the dimensionality of $\boldsymbol{\gamma}_u$. To reduce dimensionality of the feature space, we exploit insights made in [4] about performance in coded bit interleaved MIMO-OFDM systems. In particular, it was recognized that performance was invariant to subcarrier ordering and thus a reduced dimension feature vector derived from certain post-processing SNRs is sufficient to reliably predict performance. Therefore, we define $\tilde{\boldsymbol{\gamma}}_u = \left[\tilde{\gamma}_{u,1} \ \cdots \ \tilde{\gamma}_{u,NL_u}\right]^T$ as a vector formed by ordering $\boldsymbol{\gamma}_u$ in ascending order, from which we obtain our feature vector $\mathbf{f} = \alpha\left(\tilde{\boldsymbol{\gamma}}_u\right)$ by selecting a subset of the entries of $\tilde{\boldsymbol{\gamma}}_u$.

Classification: The objective of the classification task is to estimate the highest MCS supported by the channel characterized by the feature vector $\mathbf{f}$. Following a similar approach as in [7], we have a set of classifiers $\delta_{c,L}(\mathbf{f})$ that discriminate whether the current channel, characterized by $\mathbf{f}$, is going to support the transmission with MCS c and L spatial layers while meeting the FER constraint. That is, we have two classes: -1: MCS not supported, 1: MCS supported, so our classifier is a function of the feature vector $\mathbf{f}$ that maps

$$\delta_{c,L}: \ \mathbf{f} \rightarrow \{-1, 1\}.$$

For a given number of layers L, the overall classifier chooses the MCS with a higher rate among those predicted to meet the FER constraint[3]. In other words, the selected MCS is

$$\mu\left(\boldsymbol{\gamma}_u, L_u\right) = \arg\max_{c} \left\{\eta\left(c, L_u\right)\right\} \text{ s.t. } \delta_{c,L}(\mathbf{f}) = 1 \quad (10)$$

with $\mathbf{f} = \alpha\left(\tilde{\boldsymbol{\gamma}}_u\right)$ the feature vector representing the SNR values $\boldsymbol{\gamma}_u$.

The classifiers $\delta_{c,L}$ are built following a data driven approach as follows: for each pair (c, L) we have a set of training samples $\{(\mathbf{f}_1, v_1), (\mathbf{f}_2, v_2) \ldots (\mathbf{f}_M, v_M)\}$ such that the correct class for the feature vector $\mathbf{f}_i$ is $v_i \in \{-1, 1\}$. The classifier is trained offline with these samples so it can learn to classify other feature vectors. The extension to online training and classification is a subject of future work.

3.2. Precoding / Equalization

Given the subset of active users $\mathcal{T}$ and the number of streams per user L_u, the problem of selecting the precoders $\mathbf{F}_u$, interference removal matrices $\mathbf{B}_u$ and equalizers $\mathbf{G}_u$ is not trivial. As the design of precoders is independent for each carrier, we will drop the index $[n]$ in this section. For the sake of simplicity, we assume that the precoders $\mathbf{F}_u$ and interference removal matrices $\mathbf{B}_u$ are obtained using the BD technique [15] modified as in [16]. This low complexity precoding removes the interference between the different users but not the interference between streams associated to the same user. The equalizers $\mathbf{G}_u$ can be chosen independently of $\mathbf{B}_u$, and can be obtained following a zero forcing or minimum mean squared error design. This procedure is chosen for its simplicity with respect to capacity-achieving non-linear techniques, and for its small gap with respect to capacity when used in conjunction with user selection algorithms [10]. Let $\mathbf{H}_u = \mathbf{U}_u\boldsymbol{\Sigma}_u\mathbf{V}_u^*$ be the singular value decomposition of $\mathbf{H}_u$ with the singular values in $\boldsymbol{\Sigma}_u$ arranged in decreasing order. Note that $\mathbf{U}_u \in \mathbb{C}^{N_{\mathrm{rx},u}\times N_{\mathrm{rx},u}}$, $\boldsymbol{\Sigma}_u \in \mathbb{R}^{N_{\mathrm{rx},u}\times N_{\mathrm{tx}}}$ and $\mathbf{V}_u \in \mathbb{C}^{N_{\mathrm{tx}}\times N_{\mathrm{tx}}}$. The matrix $\mathbf{B}_u$ is formed by taking the first L_u columns of $\mathbf{U}_u$ (i.e., the left singular vectors associated with the largest singular values). Let us denote $\tilde{\mathbf{H}}_u \triangleq \mathbf{B}_u\mathbf{H}_u$, and

$$\bar{\mathbf{H}}_u \triangleq \left[\begin{array}{cccccc} \tilde{\mathbf{H}}_1^T & \cdots & \tilde{\mathbf{H}}_{u-1}^T & \tilde{\mathbf{H}}_{u+1}^T & \cdots & \tilde{\mathbf{H}}_T^T \end{array}\right]^T. \quad (11)$$

BD forces to choose precoders such that $\bar{\mathbf{H}}_u\mathbf{F}_u = \mathbf{0}_{K,L_u}\ \forall u$ with $K = \sum_{i\in\mathcal{T}, i\neq u} L_i$.

The set of precoders meeting this constraint can be written as $\mathbf{N}_u\mathbf{P}_u$, with $\mathbf{N}_u$ a basis for the nullspace of $\bar{\mathbf{H}}_u$. We choose $\mathbf{F}_u$ as the matrix containing the singular vectors associated to the largest singular values of $\tilde{\mathbf{H}}_u\mathbf{N}_u$. Note that if the system is fully loaded ($\sum_{u=1}^{U} L_u = N_{\mathrm{tx}}$) then the nullspace of $\bar{\mathbf{H}}_u$ will have dimension L_u and, therefore, $\mathbf{P}_u$ will be a square matrix. With this precoding technique, the resulting MIMO channel is

$$\mathbf{y}_u = \mathbf{G}_u\mathbf{B}_u\mathbf{H}_u\mathbf{F}_u\mathbf{s}_u + \mathbf{w}_u. \quad (12)$$

Although we followed this precoding approach in our simulations, other precoding designs could be used in the adaptation framework.

If we follow the feedback scheme proposed for IEEE 802.11ac, the transmitter has only knowledge of a quantized version of the first L_u right singular vectors of the channel, which are the preferred transmit beamformers for L_u spatial streams, and the associated singular values. This information, however, suffices to calculate the BD precoders and the corresponding SNR values.

3.3. User and mode selection

Performing optimal user and mode selection requires an exhaustive search over all possible combinations of users and number of streams per user. To overcome this issue, we propose a greedy approach, similar to [17], where the layers are added one by one until the utility function $\nu\left(\mathbf{t}\right)$ does not increase. This algorithm has a complexity of $\mathrm{O}\big(N_{\mathrm{tx}}U\big)$, while the exhaustive search complexity is $\mathrm{O}\big(N_{\mathrm{tx}}^U\big)$. The greedy user and mode selection algorithm is described in Algorithm 1.

4. SIMULATION RESULTS

We have simulated the proposed LA algorithm using the IEEE 802.11ac reference physical layer [9] in a 20MHz channel with 800ns guard interval, zero forcing receive equalizers, FER constraint $p_0 = 0.1$, a 4-antenna transmitter and three 2-antenna receivers. Perfect CSI was assumed at the receiver, and different feedback rates were considered for CSI acquisition at the transmit side. The only CSI mismatch between transmitter and receiver is due to the finite

[3] Although in general this selection does not imply that the throughput is maximized, for usual values of p_0 and MCS granularity it does.

Algorithm 1 Link Adaptation Algorithm

$L_u = 0\ \forall u$
$\mathcal{R} \leftarrow 0$
while $\sum_{u=1}^{U} L_u < N_{\rm tx}$ **do**
  for Each user u with $L_u < N_{\rm rx,u}$ **do**
    Calculate matrices $\mathbf{F}_v[n]$, $\mathbf{G}_v[n]$, $\mathbf{B}_v[n]$ for all users v, for the spatial layers set $\{L_1, L_2 \ldots L_u + 1 \ldots L_K\}$ following the procedure in 3.2.
    Calculate post-processing SNR values $\boldsymbol{\gamma}_v \forall v$ as in (5).
    $c_v \leftarrow \mu(\gamma_v, L_v)\,\forall v$. {Calculate optimum MCS for all users}
    $t_v \leftarrow \eta(c_v, L_v)\,\forall v$ {Calculate the corresponding rate}
    $\mathcal{R}_u \leftarrow \nu(\mathbf{t})$ {Utility metric if we incremented L_u by 1}
  end for
  $j \leftarrow \arg\max_u \{\mathcal{R}_u\}$ {User whose increment in L_u leads to a higher rate}
  if $\mathcal{R}_j \geq \mathcal{R}$ **then**
    $L_j \leftarrow L_j + 1$
    $\mathcal{R} \leftarrow \mathcal{R}_j$
  else
    Stop algorithm.
  end if
end while

rate feedback channel, thus no time variation is assumed. In a realistic setting, this would imply that the time variation is negligible between the received feedback message and the actual transmission, but relatively large between different transmissions so the learning algorithm can explore different channel states. The training of the classifiers δ was performed as follows: for each MCS and L value we obtained training samples by simulating 200 different point-to-point MIMO-OFDM channels, generated in the time domain as a 3-tap MIMO filter (each one with entries generated independently following a $\mathcal{CN}(0,1)$ distribution), and for 30 different noise levels $-10\log_{10}(\sigma^2) = \{1, 2, \ldots 30\}$dB, so the complete training set size was 6000. The statistical distribution of the channel samples is not to critical for the link adaptation performance as long as both training and test samples follow the same distribution. We used a support vector machine (SVM) classifier with a radial basis function kernel; consequently the parameters of the kernal function C and γ are adapted. We followed the usual procedure and perform K-fold cross validation [18] with K=4 to obtain C and γ, and afterwards train the classifier with the whole training set. The SVM classifier was implemented using the `LIBSVM` library [19]. The feature vector $\mathbf{f}$ was obtained from the set of ordered SNR by selecting 4 equally spaced indexes, including the first and last ordered SNR values. In general, feature space selection is one of the key factors for the performance of classifiers, so determining whether the performance of the proposed scheme is sensitive to feature selection or not is a subject of future research.

We evaluated the performance of the proposed user selection and link adaptation algorithm for different feedback rates present in the IEEE 802.11ac standard. The limited feedback scheme present in IEEE 802.11ac is based on the quantization of beamforming unitary matrices using a Givens decomposition [20], and afterwards quantizing the angles ψ and ϕ that characterize those matrices with b_ψ and b_ϕ bits, respectively. As precoding design is performed at the transmitter, the presence of limited feedback information is going to cause the BD precoder to *leak* some interference between users,

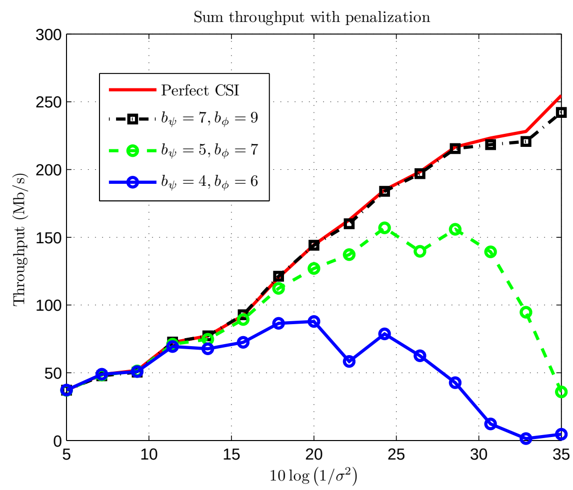

Fig. 1: Sum throughput as a function of the SNR for different feedback rates.

thus degrading the overall system performance. The effect of this leakage is twofold: on the one hand, in the noise limited regime, the SNR in every carrier is (almost surely) going to decrease, thus increasing the FER; on the other hand, in the interference limited regime, the transmitter is not going to be aware of the amount of inter-user interference, which causes him to overestimate the SNR values and, in consequence, select an MCS which is not convenient. The rate of each user was penalized and set to 0 in those cases where the actual FER was greater than p_0 to take into account these misclassified samples (i.e., the cases where a MCS is selected and turns out not to meet the FER constraint). Note that this effect creates even more degradation than the well-known ceiling for MU-MIMO capacity with constant feedback rate [21].

In Figure 1 we see that for the perfect CSI case the sum throughput increases as the SNR increases. The effect of imperfect CSI is an error floor in the high SNR regime: for the $(b_\psi, b_\phi) = (4, 6)$ case (which is intended for single user feedback) and $(b_\psi, b_\phi) = (5, 7)$ we see that the throughput even decreases with increasing SNR values due to the mismatch in MCS selection. For the highest feedback rate or lower SNR values the effect is much less noticeable, which shows the importance of selecting the feedback rate depending on the SNR operating region. In Figure 2 we see the evolution of the FER with the average SNR. In this case, both the perfect CSI and the highest rate feedback can be seen to meet the FER constraint, while the FER in the two other cases grows up to almost 1. Note that this growth in the FER is not caused by errors in the classifier, but by the mismatch between the feature set and the actual SNR values due to limited feedback precoding. In particular, the feature set did not incorporate the codebook size or account for quantization error; incorporating feedback explicitly is a topic of future work.

5. CONCLUSION

In this paper we proposed an adaptation algorithm for MU-MIMO-OFDM. In this case, the MCS selection problem is coupled with user selection, precoding and equalization, which makes this scenario specially challenging. We proposed a machine learning based algorithm to solve this problem, and evaluated its performance in a

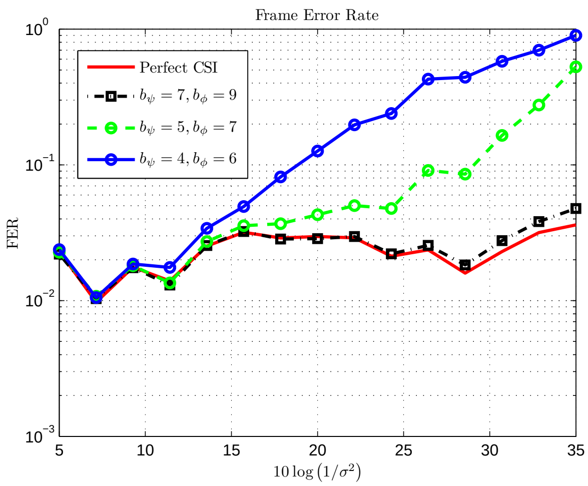

Fig. 2: Frame Error Rate as a function of the SNR for different feedback rates.

802.11ac with limited feedback. Future work includes modifying of the learning algorithm to take into account the degradation due to limited feedback precoding, studying the effect of time-varying channels, optimizing the feature set selection, and transforming the current learning scheme into an online procedure. Also, the development of a standard benchmark for comparison with other LA approaches remains a subject of future work.

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