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Bayesian Learning based Rate Adaptation in IEEE 802.11ax WLANs with a Target PER

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Abstract: The optimal modulation and coding scheme (MCS) selection in wireless transmission depends on the dynamically evolving channel state. Hence, *Rate adaptation* in a wireless channel relies on periodically reported channel quality indicator (CQI) values to select the optimal MCS. The latest 802.11ax, with a HE-sounding protocol, supports an explicit feedback mechanism where the client sends back a transformed estimate of the channel state information (CSI) in the HE CQI Report field. When generated more frequently, these reports can be expensive as they introduce unnecessary computational and protocol overhead. Also, the CSI feedback information is quantized, delayed, and noisy. To reduce the frequent CSI feedback (receiver to the transmitter) overhead, in our work, we obtain CSI statistically at the transmitter through Bayesian Learning (BL). Further, we propose a Bayesian Learning based Rate Adaptation (BLbRA) scheme at the transmitter. BLbRA throughput performance is consistent even with *reduced feedback overhead*. BLbRA can be implemented without any change in the standard frame format, and therefore, it is suitable for practical deployment.

Keywords: Rate adaptation, 802.11ax, Bayesian learning, channel gain, RBIR, Gamma distribution.

1. Introduction

One of the critical features in Radio Resource Management (RRM) for 802.11ax networks is deciding the Modulation and Coding Scheme (MCS) for packet transmissions. This is known as "Rate adaptation" since the choice of MCS impacts the rate of data transfer (throughput) achieved. Higher MCS would be suitable for improved throughput, but there is also a higher chance of packet errors. We study this trade-off. Ideally, one would like an algorithm that achieves maximum throughput while complying with application-imposed target Packet Error Rate (PER) values.

The Rate adaptation algorithms (RAA) at the transmitter depend on the feedback from the receiver to assess the impact of MCS choices. Many widely deployed RAA-s use only *implicit* feedback, observing MAC-layer acknowledgments [1–3]. Positive acks cause the transmitter to choose a higher MCS, while the absence of acks results in a lower MCS. This inherently reactive approach leads to slow adaptation to changing channel conditions, leading to a burst of packet errors and unsatisfactory throughput.

A natural approach is to consider not only MAC-layer feedback but also PHY-layer feedback – the latter provides direct information about channel conditions. While this idea has been pursued in the literature, proposed schemes require changes in packet formats to convey the PHY layer feedback. Because of this, available solutions cannot be implemented at scale [4,5]. We seek a *standards-compliant* way of including PHY layer feedback so that the transmitter can access both MAC and PHY information to choose the MCS code for the next packet.

Explicit feedback rate adaptation techniques rely on periodically reported channel quality indicator (CQI) values to dynamically adjust the MCS for transmitting physical-layer transport blocks [4–6]. The IEEE WLAN 802.11ax standard has a HE-sounding protocol to determine channel quality. The HE CQI report field carries an array of received per-RU average SNRs for each space-time stream. Each per-RU average SNR in dB is the arithmetic mean of the SNR computed over a 26-tone RU [7].

The signal-to-noise ratio (SNR) at the receiver is a good measure of the channel conditions and provides very useful PHY layer feedback [6]. We propose an efficient and fast offline link model-based Bayesian update scheme to refine the channel SNR probability distribution model. We explore how Bayesian learning can gradually gauge the prevailing channel conditions and thereby help judicious MCS selection. To the best of our knowledge, we are the first to propose the Bayesian Learning based channel feedback framework to update the SNR probability distribution.

A mixture gamma (MG) distribution is a more accurate model for composite fading, and it is a versatile approximation for any type of fading SNR. The SNR in a Nakagami-1 fading channel is modeled with a mixture having a single gamma density [8, 9]. We verified this fact by repeated simulations for different channel input parameters using the WLAN TGax channel model of MathWorks's WLAN Toolbox. We found the empirical distribution of the channel fading coefficient to be Nakagami-1 or Rayleigh distributed and empirically observed packet SNR at the receiver to match the gamma distribution closely.

1.1. Contributions

We make the following primary contributions in this paper: (i) the design of a Bayesian Learning based Rate Adaptation (BLbRA) scheme that models the probability density function (pdf) of the channel SNR as a gamma distribution, (ii) the choice of the optimal MCS based on the SNR point estimates, obtained by

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sampling the posterior SNR pdf. The optimal MCS is chosen to maximize the throughput while keeping the average PER below a target value, (iii) Implementation and evaluation of the BLbRA scheme using standards-compliant MATLAB WLAN Toolbox, generating 802.11ax PHY layer waveforms, passing through the Indoor TGax channel model [7, 16] with LDPC channel coding and OFDMA receiver processing.

Other novel features included in packet processing much closer to real-time processing are as follows:

- In receiver processing, we do realistic Least squares (LS) channel estimation and perform time and frequency synchronization over the TGax frequency selective channel instead of the oversimplified ideal channel and synchronization assumptions. Channel estimation and synchronization are the unique features in our implementation compared to previous works and open TGax technical documents [11,20], wherein they assume perfect CSI and synchronization.
- The L-LTF and HE-LTF training fields of the packet preamble are used to estimate the channel gains, and these estimated channel gains are used to equalize the channel effects and decode the packet.
- PHY impairments such as carrier frequency offset (CFO) and symbol timing offset are considered to simulate more realistic situations. After packet detection, coarse CFO correction, timing synchronization, and fine CFO correction are done in the front-end processing of the receiver. This is yet another vital feature in the implementation of our algorithm. None of the earlier works considered these PHY impairments while evaluating their rate adaptation algorithms (RAA).

1.2. Organization

The rest of the paper is organized as follows. Section 2 presents the theoretical analysis of average SNR's probability distribution across a resource unit (RU) and the simulation settings. Section 3 lists the key implementation challenges and describes our proposed BLbRA algorithm. We evaluate BLbRA and compare its throughput with our earlier proposed Hybrid Channel-Dependent Rate Adaptation (HCDRA) algorithm [15] in Section 4. Finally, we conclude the paper in Section 5 and discuss future research directions.

2. System Model and Methodology

We consider packetized data transmission over an IEEE 802.11ax wireless link. Maximizing link throughput in a time-varying propagation channel due to multipath fading or movement of the surrounding objects requires a dynamic variation of MCS. At every transmission instant $t = 1, 2 \ldots$, the wireless transmitter selects a MCS $m(t) \epsilon \{1, 2 \ldots M\}$. With MCS index $m(t)$, bits are packed into a transport block, then encoded with the forward error-correcting code and bit-interleaved to protect against stochastic noise and channel fading effects [10]. The encoded bits are mapped onto complex-valued modulation symbols prescribed by the MCS. The sequence of modulated symbols is either zero-padded or truncated to fill the time-frequency resources allocated for transmission. The channel estimation at the receiver is done using the known High-Efficiency Long Training Fields (HE-LTF) of the packet preamble to equalize the channel effects. The IEEE 802.11 standard does not provide any specification for a rate-adaptation scheme. However, the rate adaptation strategy must allow transmissions at rates that can be successfully decoded at the receiver [7].

2.1. SNR Per Packet

For a SISO system, the received SNR for the i^{th} sub-carrier is given [11] by

$$SNR_i = \frac{P_{tx}}{N\sigma_i^2}|H_i|^2 = \frac{P_{tx}}{P_n}|H_i|^2, \tag{1}$$

where $\sigma_i^2 = kB_{sc}T$ with $B_{sc} = 78.125$ KHz, sub-channel bandwidth in 802.11ax, k is the Boltzmann's constant, and T is the temperature in Kelvin. N is the total number sub-carriers in a bandwidth B, $|H_i|^2$ is the channel gain at i^{th} sub-carrier, P_n is the total noise power, and P_{tx} is the total transmit power across bandwidth 'B'. Considering the Rayleigh fading channel, the channel gain for each sub-carrier $|H_i|^2$ is exponentially distributed [12], as depicted in Figure 1a. Here, the subcarrier index ($i = 75$) is picked randomly. A histogram plot of 20,000 samples corresponding to 20,000 channel realizations follows the exponential distribution. We have $|H_i|^2 \sim \exp(\lambda_1)$. From Equation (1), with the total transmit power $P_{tx} = 1W$ across 20 MHz operating bandwidth, $SNR_i \sim \exp(P_n\lambda_1)$.

IEEE 802.11ax supports OFDMA, where multiple subcarriers are grouped to form a resource unit (RU). Each RU is assigned to a user for data packet transmission. Since packets are the entities we transmit and receive, SNR per packet is a quantity of interest. The WLAN channel varies slowly; hence, the SNR is assumed to be static over the entire packet duration. The SNR for each packet is computed using the channel and noise estimates at the receiver. The channel estimates are obtained using the HE-LTF samples of the packet preamble transmitted over N_d sub-carriers of the allotted RU. The average noise power is estimated using the pilot sub-carriers of the HE-data field. The SNR at the receiver over an RU of N_d sub-carriers with $P_{tx} = 1W$,

$$SNR_{RU} = \left(\frac{1}{N_d}\right)\sum_{i=1}^{N_d} SNR_i = \left(\frac{1}{N_d}\right)\sum_{i=1}^{N_d}\frac{|H_i|^2}{P_n}. \tag{2}$$

If sub-carrier SNRs, SNR_i, are ***iid***, since SNR_i are exponentially distributed, the average SNR over N_d sub-carriers of an RU (SNR per packet) is distributed according to a Gamma distribution [12, 13], $SNR_{RU} \sim$ Gamma $(N_d, N_d P_n \lambda_1)$. N_d is the number of sub-carriers in a RU, P_n is the noise power, and λ_1 is the parameter of the exponentially distributed channel gains at the i^{th} sub-carrier.

2.2. Simulation Settings

We simulate a scenario of an Access Point (AP) transmitting to a user in a 20 MHz Bandwidth channel (OFDMA) at a carrier frequency of 5.25GHz using WLAN High Efficiency (HE) multi-user (MU) format packets as specified in IEEE 802.11ax [7].

MATLAB WLAN Toolbox of MathWorks is used to model 802.11ax multi-user OFDMA downlink transmission over a TGax

Table 1.

Simulation parameters	
General Parameters	
Distance (d)	12 m (NLOS)
Noise power (Pn)	−90 dBm
Transmit power per packet (P_{tx})	1W
Packet size (P_b)	500 bytes
Number of packets processed	40,000
Signal flow	Downlink
Target PER	0.1
Specific for IEEE 802.11ax	
Mode of transmission	OFDMA
RU allocation index	192
Number of RUs	1
Number of users	1
RU size (N_d)	242
Channel parameters	
Channel Bandwidth	20 MHz
Carrier frequency	5.25 GHz
Delay profile	Channel model-D
Environmental speed	0.089 km/hr
Channel coding	LDPC
No. of penetration walls	2
Wall penetration loss	2.5 dB
Pathloss	74.62dB

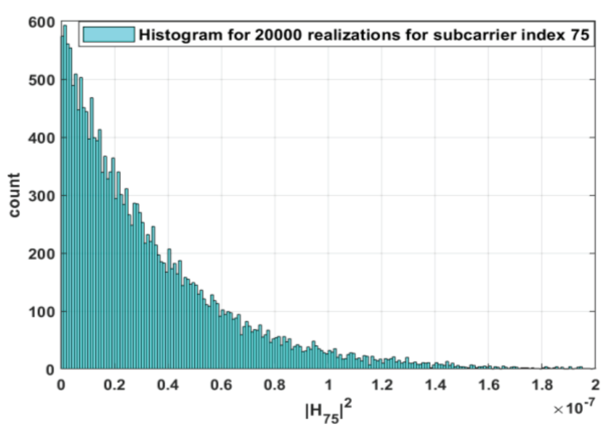

Figure 1a.
Histogram of a channel gain at i = 75, $|H_{75}|^2$.

indoor fading channel. Table 1 summarizes the simulation parameters to evaluate our proposed rate adaptation algorithm, BLbRA, and HCDRA algorithm.

The RU allocation index property defines the number of RUs, the size of each RU, and the number of users assigned to each RU. The AP transmits a burst of 40,000 packets, and the client demodulates and decodes the packets. An evolving TGax indoor Rayleigh fading channel with AWGN is modeled between the AP and client device.

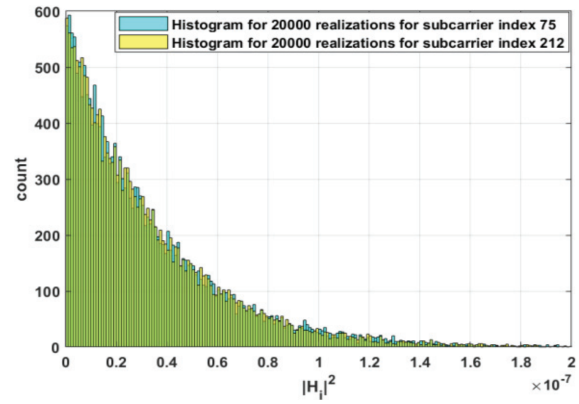

Figure 1b.
Histogram overlap of $|H_{75}|^2$ and $|H_{212}|^2$.

3. Key Implementation Challenges and Bayesian Learning

We mention some *challenges faced* during the experimentation, and the directions followed to overcome them.

- The initial plan was to use N_d, the number of subcarriers in an RU, as the shape parameter (α) of the SNR probability distribution and learn the rate parameter 'R' from the observed SNR measurements at the receiver. However, experiments showed that the learned distribution did not match the empirically observed SNR distribution. This resulted in overestimating the packet SNR, as shown in Figure 2.
- This observation made us suspect that the ***iid*** property among subcarriers could be assumed. We obtained the histogram plots of channel gains $|H_i|^2$ at sub-carrier indices $i = 75, j = 212$, as shown in Figure 1b. We further chose closely spaced sub-carrier indices to $i = 75, j = 72$ to obtain their histogram plots and then concluded that the sub-carriers are *identically* distributed.

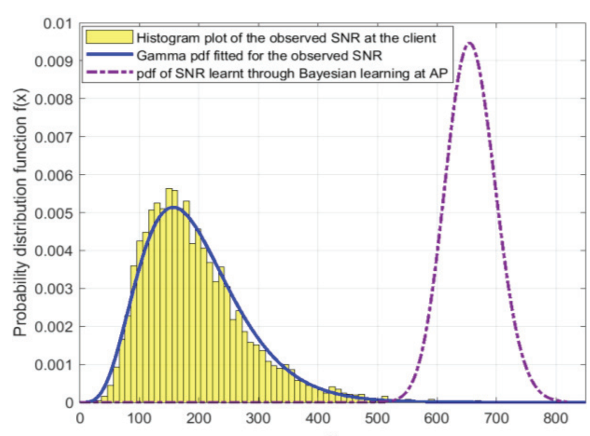

Figure 2.
Histogram plot and Gamma pdf fit of the observed SNR at the client, SNR pdf learned through Bayesian learning by fixing the shape parameter, α = 242.

Table 2.

Experimental data to check for the independence of channel gains at sub-carrier indices 75 and 212

(A1, B1)	(A2, B2)	W	N1	N2	N3	P (X AND Y)	P(X)	P(Y)	P(X) P(Y)
[0.2e-7, 0.21e-7]	[0.6e-7, 0.61e-7]	0.01e-7	3	339	107	**1.50e-04**	0.01695	0.00535	**0.9069e-04**
[0.2e-7, 0.22e-7]	[0.6e-7, 0.62e-7]	0.02e-7	7	656	202	**3.50e-04**	0.03280	0.01010	**3.3128e-04**
[0.2e-7, 0.23e-7]	[0.6e-7, 0.63e-7]	0.03e-7	11	967	304	**5.50e-04**	0.04835	0.01520	**7.3492e-04**
[0.2e-7, 0.24e-7]	[0.6e-7, 0.64e-7]	0.04e-7	19	1273	386	**9.50e-04**	0.06365	0.01930	**12.2845e-04**

- To check the independence of channel gains over sub-carriers, we define two events for sub-carrier indices $i \neq j$. Event $X = \{|H_i|^2$ falling in the interval (A1, B1)} and Event $Y = \{|H_j|^2$ falling in the interval (A2, B2)}. Let N1 = Number of occurrences of the joint event X AND Y, N2 = Number of occurrences of event X, and N3 = Number of occurrences of event Y, W = width of an interval. We check for the probability condition for the two events X and Y to be independent, P (X and Y) = P(X) P(Y). Table 2 summarizes the observed values.
- The experimentation suggested that subcarrier SNRs, SNR_i are not independent. This is because the channel gains at any two sub-carriers are *not independent*. The channel gains of sub-carriers are significantly correlated due to the channel coherence bandwidth. Therefore, multipath propagation has an impact on the channel gain or SNR statistics.

3.1. Probabilistic SNR Model

However, we found the empirical distribution of observed packet SNR at the receiver to match the Gamma distribution closely, as shown in Figure 2. Then, we wondered if the Gamma distribution could be "tuned" to match observed histograms by adjusting its parameters. Ideally, both parameters should be learned. However, the literature indicates that learning both parameters is hard. The conjugate prior for the Gamma rate parameter is known to be Gamma distributed, but no standard distribution behaves as the prior for the shape parameter [14]. So, we decided to keep the shape parameter, α, fixed and learn the rate parameter (R) through Bayesian learning.

The next question that arose was, what value to be chosen for α. We use the range of desirable SNR from past channel measurements as a piece of prior information to choose the shape parameter's value. We had two criteria: (i) we wanted the SNR pdf to cover the full range of possible SNR values from 0 to 28dB, modeling all possible channel conditions. (ii) we wanted the shape of the pdf not to become symmetric around its mean value. We did some experiments to study the effect of the shape parameter, α, on the gamma pdf by fixing the scale parameter β = 10, 20, 30, 40 and 50. The pdf spread is smaller than the desired range for lower values of α, up to 5. For larger values of α beyond 7, the mean of the distribution shifts towards the right, and the support of the distribution does not include lower values of observed SNR. Also, higher values of α, beyond 15, resulted in a more concentrated distribution around its mean. So, we prefer to choose $\alpha = 6$ and estimate R (=1/β) through Bayesian learning. This method yielded an excellent match with the experimentally observed receiver SNR histogram and the gamma distribution learned by Bayesian learning.

Bayesian Learning (BL) of the Rate Parameter of the Gamma Distribution

To find the posterior probability of the Gamma distributed rate parameter R, we use the Bayes rule,

$$p(R|\gamma) = \frac{p(\gamma|R)p(R)}{p(\gamma)}, \tag{3}$$

where $\gamma = \{\gamma_1, \ldots, \gamma_n\}$ is a positive vector of observed SNR per packet. Since the denominator only depends on observed data, the posterior is proportional to the likelihood multiplied by the prior

$$p(R|\gamma) \propto p(\gamma|R)p(R). \tag{4}$$

Obtaining analytical solutions for the rate parameter R requires using conjugate priors. A prior is called conjugate with a likelihood function if the prior functional form remains unchanged after multiplication by the likelihood distribution [14]. A well-known conjugate prior for the rate parameter R of the Gamma distribution is a Gamma distribution parameterized using shape d and rate e,

$$p(R) = \text{gamma}(R|d, e). \tag{5}$$

Given the observation vector γ, and multiplying its Gamma likelihood by the prior on the rate (5), we get its posterior [14], $q(R) = \text{gamma}(R|\widehat{d}, \widehat{e})$ with

$$\widehat{d} = d + n \propto \quad \text{and} \quad \hat{e} = e + \sum_{k=1}^{n} \gamma_k, \tag{6}$$

where $\propto$ is the shape parameter of the Gamma likelihood distribution of the SNR per packet ($\alpha = 6$), γ_k is the measured SNR of the k^{th} packet, and n is the number of SNR observations. We call 'n' as the *rate parameter update window*.

3.2. SNR Point Estimates and Posterior SNR Distribution

Let the SNR probability density function (pdf) at the transmission time $t = 0$ be denoted by $P_{\gamma(t=0)}(\theta) = gamma(6, R_0)$. The initial rate parameter, R_0, is chosen based on past measurements from the expectation of the likelihood distribution of average SNR, γ. Initially, we generate an SNR sample using SNR pdf $P_{\gamma(t=0)}(\theta)$. Though several sampling techniques exist [10], we describe one such technique called *inverse CDF sampling*. It is computationally efficient and easily implementable.

- First, the cumulative distribution function (CDF) is calculated using (7).

$$F_{\gamma(t)}(\theta) = P(\gamma(t) \leq \theta) = \int_{x \leq \theta} P_{\gamma(t)}(x)dx. \tag{7}$$

- Generate a uniformly distributed random variable, $u[t] = \mathcal{U}(0,1)$.
- Finally, map $u[t]$ to an SNR sample through the inverse SNR CDF, $\tilde{\theta}[t] = F^{-1}_{\gamma(t)}(u[t])$, where $\tilde{\theta}[t]$ is the SNR sample or the SNR point estimate at the t^{th} transmission instant, and $\tilde{\theta}[t] \sim P_{\gamma(t)}$.

The sampling of the updated SNR pdf is done for every packet transmission, so the MCS is selected based on the sampled SNR. The selected MCS is used for the next packet transmission. The client device measures the SNR per packet using the channel and noise estimates and computes the sum of the measured average SNR for 'n' packets. The sum, $\sum_{k=1}^{n} \gamma_k$ is fed back to the AP using the standards-compliant HE-CQI report field. The rate parameter R's hyperparameters are updated using (6) after every 'n' packets (rate parameter update window). The posterior expectation of the rate parameter is calculated using the recently updated $(\widehat{\mathrm{d}}, \widehat{\mathrm{e}})$ pair. The updated value of R_i is further used to update the pdf of the average SNR ~ gamma (6, R_i).

3.3. Simulation Results

The Bayesian update channel SNR model simulation is done using the standards-compliant, credible link simulator MATLAB WLAN Toolbox of MathWorks. Fixing the shape parameter, α to 6, and learning the rate parameter, R, through Bayesian learning resulted in an excellent match with the experimentally observed receiver SNR histogram at the client and the SNR pdf learned through Bayesian learning at AP.

The pdf of SNR iteratively concentrates around the true channel SNR, i.e., assigns a higher probability density to the SNRs close to the true channel SNR. This is depicted in Figure 3a. Figure 3b shows the perfect overlap of the CDF of the observed SNR at the client and the CDF learned at AP through Bayesian learning.

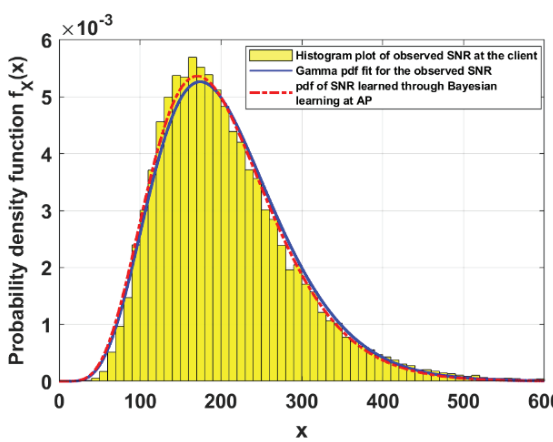

Figure 3a.

Histogram plot and Gamma pdf fit of the observed SNR at the client, and SNR pdf learned through Bayesian learning by fixing $\alpha = 6$.

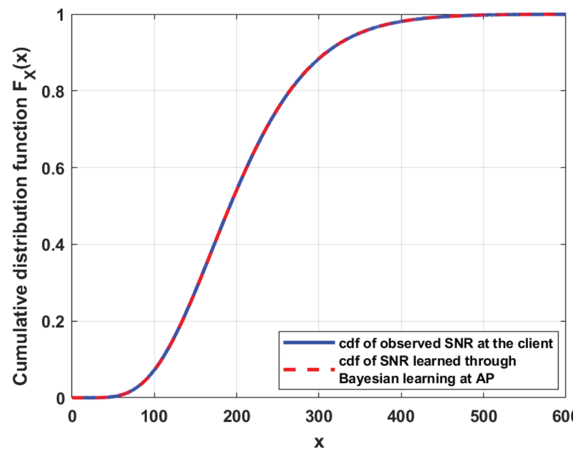

Figure 3b.

CDF of observed SNR and Learned SNR.

3.4. Optimal MCS Selection

The posterior SNR pdf learned through Bayesian learning is sampled for every packet transmission to get the SNR sample or the SNR point estimate. The SNR sample is mapped to the PER for all MCS (0–9) through a fast Received Bit Information Rate (RBIR) based offline link PLA model table lookup [15–17]. RBIR is described in detail in our previous work [15]. We select the highest MCS for which the estimated PER ≤ target PER (0.01).

For every successful packet transmission, there is some *link margin*. It is the difference between the instantaneous channel SNR (actual) and the minimum SNR (dependent on MCS) required for the successful decoding of the packet [18]. BLbRA addresses link margin by choosing the MCS for every packet transmission. BLbRA has lower computational complexity for computing the optimal MCS using RBIR table lookup and requires lower memory to store the SNR model. In our algorithm, the Access Point (AP) performs the Bayesian learning of the rate parameter of the SNR and decides the optimal MCS, taking off the computational load from the client device.

4. Throughput Performance Evaluation Using WLAN Toolbox

This section presents the throughput comparison of BLbRA and Hybrid Channel-Dependent Rate Adaptation (HCDRA), an algorithm we proposed earlier in [15]. Figures 4a, 4b and 4c show the throughput, PER and transmission time of both algorithms. For each presented results, we show the mean value over the 20 simulation runs with 95% confidence level.

HCDRA performs rate adaptation based on fresh channel estimates for every SNR feedback window. The per-RU average SNR derived from the channel estimates is fed back through HE Channel Quality Indicator (CQI) report field. The SNR feedback window (FBW) is set to 10, 50, and 100 packets. We observed that the throughput decreases in HCDRA as the FBW increases. This is because HCDRA uses the same MCS for all the packets transmitted for every SNR feedback window unless the probe

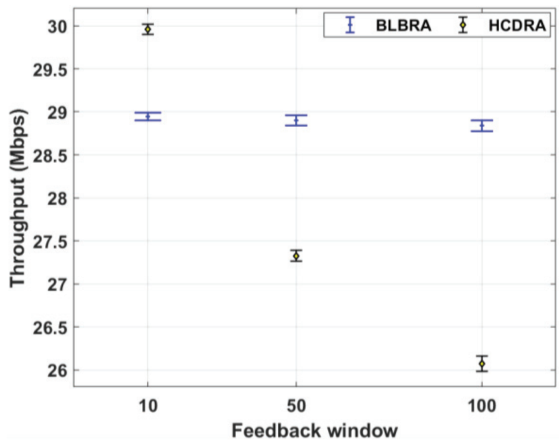

Figure 4a.

Throughput (Mbps) with 95% confidence level.

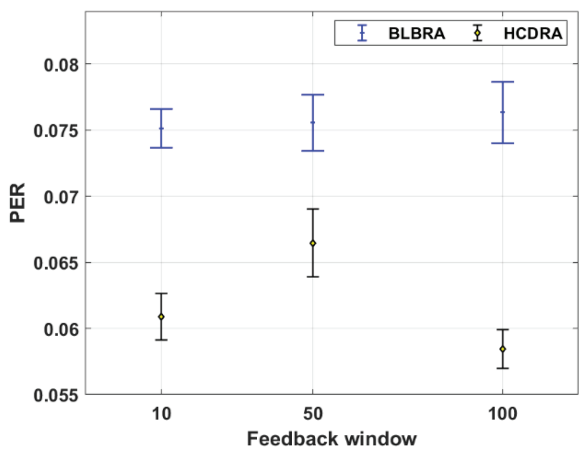

Figure 4b.

PER with 95% confidence level

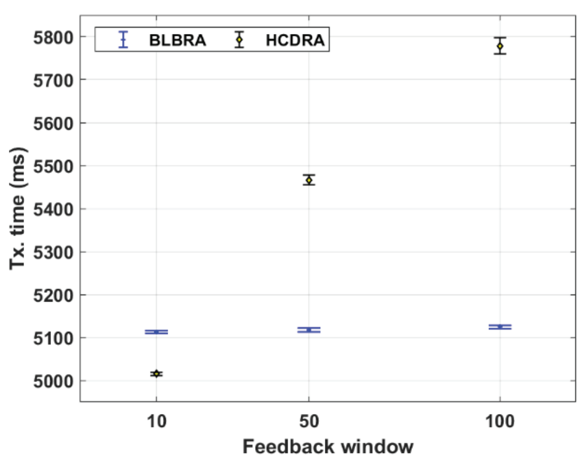

Figure 4c.

Transmission time (ms) with 95% confidence level with increasing feedback window.

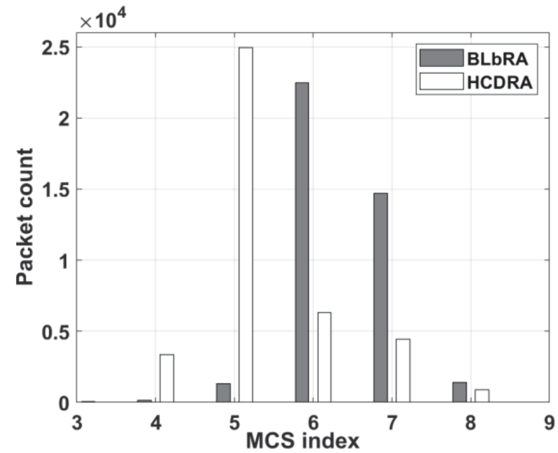

Figure 5.

Histogram of the MCS used in BLbRA (n=100) and HCDRA (FBW=100).

Table 3.

Performance of BLbRA (n = 100) within the window of N/4 packets				
Packet Number	**1 to N/4**	**N/4 to N/2**	**N/2 to 3N/4**	**3N/4 to N**
Throughput (Mbps)	28.7458	28.8675	28.8256	28.7661
PER	0.0775	0.0769	0.0773	0.0761
Transmission time (ms)	1282.32	1280.31	1281.49	1282.47

packet fails or if two consecutive packets fail within the FBW (refer to Step. 5a of [15]).

In BLbRA, the rate parameter update window 'n' (of Equation (6)) is set to 10, 50, and 100 packets to compare the throughput performance with HCDRA. Here the sum of per-RU average SNR for 'n' packets is fed back to the AP using the standards-compliant HE-CQI report field. With the rate parameter update window of n = 10 packets, BLbRA throughput performance is close to HCDRA with FBW of 10 packets. However, we observed that throughput and PER performance of BLbRA with increased rate parameter update window of n = 50 and n = 100 remains on par with n = 10 packets.

HCDRA has a lower PER than BLbRA. This is because HCDRA becomes very conservative as feedback window increases compromising on the throughput gain. Unlike HCDRA, the transmission time in BLbRA is consistently smaller for n = 50 and 100, emphasizing the fact that BLbRA chooses a higher MCS for most of the packet transmissions.

Figure 5 shows the histogram plot of MCS used in BLbRA and HCDRA for a feedback window of 100. It is evident that the BLbRA uses higher order MCS larger compared to HCDRA, leading to a throughput gain.

Table 3 shows the performance metric for BLbRA (n = 100) within the transmission window of N/4 packets, with N = 40K packets. The throughput and PER are consistent within each transmission window. This is because the MCS in BLbRA is obtained by mapping the SNR point estimate for every packet transmission, as explained in section 3D. The BLbRA addresses the link margin for every packet transmission, thus transmitting the higher-order MCS whenever the channel supports it.

5. Conclusion

We designed the Bayesian Learning based rate adaptation to decide on the MCS for the next packet by sampling the learned SNR distribution at the AP and pretending that the sampled value is the SNR that the next packet will see. To evaluate both algorithms, we modeled the end-to-end link-level SISO transmit-receive link with IEEE standard-defined channel models [7,16]. BLbRA learns from the observed SNR feedback (after every rate parameter update window) to obtain the SNR estimate; the estimates closely match the true channel SNR. The rate parameter update window is increased to see the effect on throughput. BLbRA continues to perform well even with the reduced feedback overhead.

BLbRA is eminently implementable using the feedback mechanism recommended by the IEEE 802.11ax standard. Therefore, no customized mechanisms are needed to implement our proposed algorithm. Further, we would like to extend Bayesian learning to explore the possibility of learning both the parameters of Gamma distributed SNR and evaluate the throughput and PER performance of the link adaptation algorithm.

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