Evaluating the Impact of Channel Feedback Quantization and Grouping in IEEE 802.11 MIMO Wi-Fi Networks

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***Abstract*—In this letter, we shed light on the impact of multiple-input, multiple-output (MIMO) beamforming feedback quantization and orthogonal frequency-division multiplexing (OFDM) sub-channel grouping on communication performance, for IEEE 802.11ac/ax Wi-Fi networks. We performed an extensive data collection campaign with commercial Wi-Fi devices deployed in different propagation environments considering several network configurations. Our objective is to provide a benchmark for research on efficient feedback compression mechanisms and to enable further analysis. As such, we pledge to share the datasets we collected and the emulation framework we developed.**

***Index Terms*—Multiple-input multiple-output (MIMO), precoding, channel sounding.**

I. Introduction

THE EFFICIENT use of radio spectrum resources is becoming paramount due to the increasing number of users requiring wireless connectivity and the continuous demand for supporting connectivity-hungry applications such as the Metaverse [1]. In this context, MIMO became key to increase the spectrum efficiency. MIMO leverages spatial diversity to enable a device to transmit multiple data streams concurrently, to one (single-user MIMO (SU-MIMO)) or more (multi-user MIMO (MU-MIMO)) connected devices, reusing the time and frequency resources for multiple transmissions. MIMO transmission is performed by combining all the streams at each transmitter antenna through specific precoding weights that compensate for wireless channel impairments and reduce interference among the transmitted streams. This requires the receiver devices to carry out a *channel sounding* phase before the actual MIMO transmission to obtain an estimate of the channel frequency response (CFR) that is then fed back to the transmitter (access point (AP)) [2]. At the AP, the precoding weights are designed such that each precoded stream is orthogonal to the channels associated with all the other data streams to be transmitted. This would lead to perfect stream separation at the receiver devices in ideal conditions. However, to save spectrum resources, *the beamforming feedback is compressed* before transmission through frequency sub-channel grouping and quantization. Such compression introduces a reconstruction error at the transmitter when recovering the CFR for precoding weight computation, thus making the weights slightly deviate from the ones that provide perfect orthogonality with the other involved links. The non-orthogonality causes inter-stream interference that negatively impacts communication performance.

Designing proper feedback compression schemes is a fundamental challenge of MIMO, especially when considering large-scale systems that allow increasing the network capacity. While compression is key to reduce the feedback overhead that increases with the number of antennas, inadequate compression can ultimately reduce the benefits of large antenna arrays. Recent research proposes to substitute the deterministic procedure currently in use by IEEE 802.11 devices (see Section II) with a learning-based architecture that compresses the CFR at the station (STA) and reconstructs it at the AP [3], [4]. However, also this approach can introduce errors in the CFR recovery that negatively impact the communication performance [5].

In this letter, we present a Wi-Fi network emulator – based on real channel measurements – for the evaluation of the impact of feedback compression on the bit error rate (BER). The emulator we developed aims to serve as a general framework for performance assessment of the different compression strategies that are being proposed by the research community. In this letter, we use the emulator to analyze the compression strategies currently implemented on IEEE 802.11ac/ax-compliant devices. The results show that adopting the higher quantization and grouping level for IEEE 802.11 devices only slightly increases the BER while reducing the number of bits to be transmitted by a factor of 689 for SU-MIMO. Our objective is to provide a tool to evaluate the accuracy–complexity trade-off of feedback compression approaches and provide a solid benchmark for further research in advanced techniques for feedback compression. This is key to properly designing advanced MIMO procedures for next-generation Wi-Fi networks. For example, operating in the newly opened 6 GHz band requires increasing the spectrum efficiency and avoiding interference to allow the coexistence of different technologies [6]. MIMO is one of the technologies that can help in this. However, the orthogonality propriety at the basis of MIMO is only enforced for the users inside the networks. Hence, other wireless devices in the surroundings not part of the network can experience interference from MIMO transmissions. To mitigate interference, some contributions in the literature proposed to enable coexistence by forcing a "null" in the direction of a device outside the considered system (see, e.g., [7]). The idea is to make the transmitted signals orthogonal to the link between the transmitter and the unintended receivers. This requires the precoding to accurately match the CFR of the different links.

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In this regard, the CFR estimate compression may lead to inaccurate precoding weights, making the nulling ineffective.

II. IEEE 802.11ac/ax System Model

The MIMO transmitter (also referred to as *beamformer* in the following) pre-codes the data packets by linearly combining the signals to be simultaneously transmitted to the different receivers (beamformees). To do so, the beamformer uses a precoding matrix $\mathbf{W}$ derived from the CFR $\mathbf{H}$, which describes how the environment modifies the irradiated signals in their path to the receiver. The CFR is estimated by each receiver and fed back – after compression and quantization – to the transmitter to allow proper precoding. The process is named *channel sounding* and is summarized in the following. Interested readers can find a more detailed explanation in [8].

A. Channel Frequency Response Estimation

The beamformer periodically broadcasts null data packet (NDP) frames to estimate the MIMO channel between itself and the connected beamformees. The NDP contains sequences of bits (named long training fields (LTFs)) the decoded version of which is known to the beamformees. Each beamformee receives and decodes the NDP to estimate the CFR $\mathbf{H}$ over each pair of the transmitter (TX) and receiver (RX) antennas, for every OFDM sub-channels. This generates a $K \times M \times N$ matrix $\mathbf{H}$ for each beamformee, where K, M and N respectively indicate the numbers of data OFDM sub-channels and TX and RX antennas. The CFR for the control sub-channels is not reported.

B. Channel Frequency Response Compression

To reduce the channel sounding airtime overhead, the IEEE 802.11ac/ax standard defines *grouping* strategies to transmit the feedback for a sub-set $\tilde{K} \leq K$ of the OFDM sub-channels instead of feeding back the CFR computed for all of them. An evenly-spaced sampling approach is adopted to select the $\tilde{K}$ sub-channels. Depending on the Wi-Fi standard (IEEE 802.11ac/ax), different sampling factors N_g can be used as detailed in Table I. The grouping does not depend on the number of antennas or spatial streams. Note that an 802.11ax OFDM transmission uses four times the sub-channels used by an 802.11ac system with the same operating bandwidth B. Indeed, the sub-channel spacing is $\Delta_f = 312.5$ KHz in 802.11ac, while it reduces to $\Delta_f = 78.125$ KHz in 802.11ax. The number of sub-channel is obtained as $K = B/\Delta_f$.

Using $\mathbf{H}_k$ to identify the $M \times N$ sub-matrix of $\mathbf{H}$ containing the CFR samples related to sub-channel $k \in \{0, \dots, \tilde{K}-1\}$, the *compressed beamforming feedback* is hence obtained as follows ([2], Chapter 13). First, $\mathbf{H}_k$ is decomposed through singular value decomposition (SVD) as $\mathbf{H}_k^T = \mathbf{U}_k \mathbf{S}_k \mathbf{Z}_k^\dagger$ where $\mathbf{U}_k$ and $\mathbf{Z}_k$ are, respectively, $N \times N$ and $M \times M$ unitary matrices which columns are the left and right singular vectors respectively, while the singular values are collected in the $N \times M$ diagonal matrix $\mathbf{S}_k$. Using this decomposition, the complex-valued beamforming matrix $\mathbf{V}_k$ is defined by collecting the first $N_{\text{SS}} \leq N$ columns of $\mathbf{Z}_k$. Such a matrix is used by the beamformer to compute the pre-coding weights for the N_{SS} spatial streams directed to the beamformee. Before transmission, $\mathbf{V}_k$ is further compressed by applying some geometrical transformations called *Givens rotations*. Specifically, $\mathbf{V}_k$ is rewritten as

TABLE I

Sampling Factor (N_g) for the IEEE 802.11 Sub-Channel Grouping (Left Table) and Number of Quantization Bits for b_ϕ and b_ψ for Different Codebooks (Right Table)

	802.11ac	**802.11ax**
G 0	$N_g = 1$	$N_g = 4$
G 1	$N_g = 2$	$N_g = 16$
G 2	$N_g = 4$	—

	SU-MIMO		**MU-MIMO**	
	b_ϕ	b_ψ	b_ϕ	b_ψ
CB 0	4	2	7	5
CB 1	6	4	9	7

$$\mathbf{V}_k = \tilde{\mathbf{D}}_k \prod_{i=1}^{\min(N_{\text{SS}}, M-1)} \left(\mathbf{D}_{k,i} \prod_{l=i+1}^{M} \mathbf{G}_{k,l,i}^T \right) \mathbb{I}_{M \times N_{\text{SS}}}, \quad (1)$$

where $\tilde{\mathbf{D}}_k$, $\mathbf{D}_{k,i}$ and $\mathbf{G}_{k,l,i}$ are rotational matrices whose entries are sinusoidal functions of quantities referred to as *beamforming feedback angles* and identified as ϕ and ψ. We refer interested readers to [9] for the specific structure of $\tilde{\mathbf{D}}_k$, $\mathbf{D}_{k,i}$ and $\mathbf{G}_{k,l,i}$. The number of ϕ and ψ angles depends on the specific network configuration, i.e., the number of transmitter antennas and the number of spatial streams requested by the reporting beamformee, as detailed in the standard. For example, two angles per sub-channel are used for a 2 × 1 or a 2 × 2 MIMO setup while 12 angles per sub-channel are required for a 4 × 4 MIMO configuration. Using this transformation, the beamformee is only required to transmit the beamforming feedback angles to the beamformer as they allow reconstructing $\mathbf{V}_k$ precisely.

C. Beamforming Feedback Angles Quantization

To further reduce the channel occupancy, the angles ϕ and ψ are quantized into q_ϕ and q_ψ using b_ϕ bits for ϕ and $b_\psi = b_\phi - 2$ bits for ψ, as follows:

$$[q_\phi, q_\psi] = \left[2^{b_\phi - 1} \left(\frac{\phi}{\pi} - \frac{1}{2^{b_\phi}} \right), 2^{b_\psi + 1} \left(\frac{\psi}{\pi} - \frac{1}{2^{b_\psi + 2}} \right) \right]. \quad (2)$$

The possible values of b_ϕ and b_ψ for single user (SU) and multi user (MU) are summarized in Table I.

The quantized feedback angles – $q_\phi \in \{0, \dots, 2^{b_\phi} - 1\}$ and $q_\psi \in \{0, \dots, 2^{b_\psi} - 1\}$ – are packed into the *compressed beamforming frame* that is transmitted to the beamformer. Such frame also entails a *MIMO control field* that includes several sub-fields, among which the "Grouping" (G) and the "Codebook Information" (CB), that respectively define the sampling factor N_g and the number of quantization bits (Table I).

D. Beamforming Feedback Airtime Overhead

The beamforming feedback angles (BFAs) frame airtime overhead varies with the sub-channel grouping mode and the angle quantization level. Specifically, the lower is $\tilde{K}$, the lower the computation complexity and transmission overhead is, as the number of OFDM sub-channels for which the beamforming feedback is sent decreases. Likewise, the transmission overhead is proportional to the number of quantization bits (b_ϕ and b_ψ bits). Overall, without quantization and grouping, the channel overhead associated with the feedback is $M \cdot N_{SS} \cdot b_b \cdot K$ bits, where b_b is the number of bits required to represent a complex number (usually $b_b = 128$ bits). When compressing the feedback through quantization and grouping, the overhead reduces to $\left[\sum_{\ell=1}^{\min(N_{\mathrm{ss},i},M-1)}(M-\ell)\right]\cdot(b_\phi+b_\psi)\cdot\tilde{K}$ bits.

III. Experimental Setup

Commercial Wi-Fi devices operating as STAs set the codebook, i.e., the number of bits used for feedback angle quantization, based on an implementation-dependent procedure. The codebook information is then communicated to the AP by transmitting it in the MIMO control field of the compressed beamforming report (see Section II-C). This information is used by the AP to obtain the unquantized version of the angles and, in turn, compute the precoding weights. As it is not possible to change the codebook selected by the STA from the user interface, to perform our analysis, we emulated the different quantization levels by developing an emulation framework based on Python and MATLAB. The program uses *real channel data* collected from commercial Wi-Fi devices operating with the IEEE 802.11ac/ax standards on channels with 40 and 80 MHz of bandwidth.

Specifically, we set up two different Wi-Fi networks operating in SU-MIMO mode on channel 36 with center frequency $f_c = 5.18$ GHz following the IEEE 802.11ac and IEEE 802.11ax standards respectively. We used an Asus RT-AC86U router as the IEEE 802.11ac AP while an Asus RT-AX86U router served as AP for the IEEE 802.11ax configuration. A commercial-off-the-shelf (COTS) AX200 network interface card (NIC) – connected to the IEEE 802.11ac or the IEEE 802.11ax AP depending on the experimental campaign – was used as the station. We have conducted an extensive data collection campaign in three different environments – an anechoic chamber, a classroom, and an office room – as depicted in Figure 1. The data in the classroom and office room were collected when people were freely moving in the environment thus ensuring the representativeness of data for real environments. The data in the anechoic chamber were collected in static conditions. During the data collection campaigns, we simultaneously collected both the CFR and the BFAs of the wireless link between the AP and the STA. We leveraged the PicoScenes tool [10] for CFR collection and the Wi-BFI tool [8] for BFAs extraction. UDP data streams were sent from the AP to the STA in the downlink direction to trigger the channel sounding. We recorded the CFR and BFAs for 2 minutes for each of the setups, i.e., different bandwidths (40, 80 MHz), different frame type (very high throughput (VHT), high-efficiency (HE)), and different environment (anechoic chamber, classroom, office room). The datasets for different bandwidths and frame types were collected in a sequential manner without any change in the environment.

We used the MATLAB Communications and WLAN Toolboxes to emulate the IEEE 802.11ac/ax Wi-Fi networks. For this, we first derived the multi-path parameters characterizing the physical environment by processing the CFR matrices through the mD-Track algorithm implemented in Python (see [11]). Hence, we used the multi-path parameters to configure a `comm.MIMOChannel` System object in MATLAB that generates a model for the real MIMO multi-path fading channel. The complete procedure for Wi-Fi signal transmission and reception has been implemented in the emulator. This includes the channel sounding where the number of bits used for feedback angle quantization

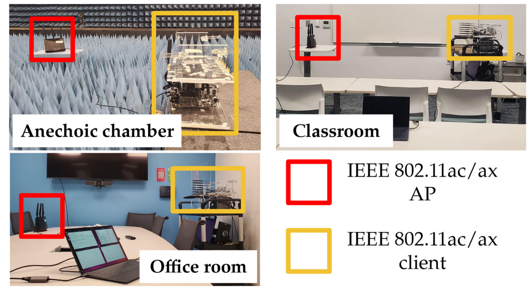


Fig. 1. Experimental setup at three different environments.

(CB) and sub-channel grouping (G) are hyperparameters that were changed to evaluate their impact on the overall system performance (the values are reported in Section IV for each of the evaluations).

In addition to the results using real channel data at 40 and 80 MHz, we simulated an IEEE 802.11ax network working on a 160 MHz channel. The simulation has been performed in MATLAB following the same procedure adopted for the emulations and leveraging the MATLAB implementation of the TGax channel model (Model-B).

To ease the replicability of the evaluation and enable further analysis, we released the collected datasets and the code.[1]

IV. Experimental Evaluations

We evaluate the error in the reconstruction of the feedback matrix at the transmitter and its impact on the BER at the receiver, considering both quantization and grouping using the parameters detailed in Table I. As a reference, we also evaluate the performance when the quantization and grouping are not applied, i.e., the feedback is transmitted without compression. The case without quantization is hereafter identified as CB inf and we indicate with G inf the case when no grouping is applied with 802.11ax (possibility not envisioned by the standard, see Table I). We analyze both IEEE 802.11ac and 802.11ax setups with different SU-MIMO configurations, operating bandwidth (40, 80 and 160 MHz) and MCS codes (3 and 4). For 40 and 80 MHz the results are obtained through emulations using the real channel data collected in the three different environments as detailed in Section III. We run the emulation for each considered setup using 1400 different channel realizations obtained from the experimental data collection campaigns to obtain statistically significant results. While in this letter we report the results for some of the scenarios in the dataset we collected, our emulator allows researchers to obtain the results for all the configurations.1footnotemark The results at 160 MHz are from simulated CFR traces and obtained averaging 2400 simulation results each, where for each simulation we changed the TGax channel model initialization.

A. Reconstruction Error on the Feedback Matrix

In Figure 2, we show the error in reconstructing the beamforming feedback matrix at the beamformer, obtained as an average of the error on all the OFDM sub-channels. We report in the figure the results for the "Anechoic" and "Classroom" scenarios using IEEE 802.11ac/ax data. Similar results have been obtained for all the other configurations. The results

[1] https://github.com/francescamen/MIMO_feedback_quantization_grouping

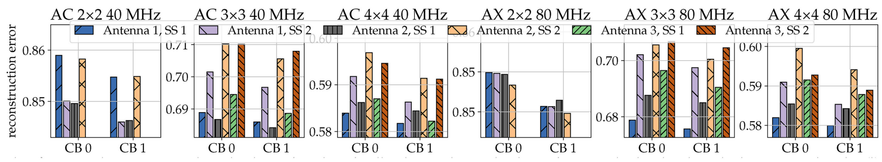


Fig. 2. Error in reconstructing the beamforming feedback matrix at the beamformer obtained using devices operating in (i) IEEE 802.11ac mode on a 40 MHz channel, in the "Anechoic" scenario (three leftmost plots), and (ii) IEEE 802.11ax mode on a 80 MHz channel, in the "Classroom" scenario (three rightmost plots). 'SS' stands for spatial stream.

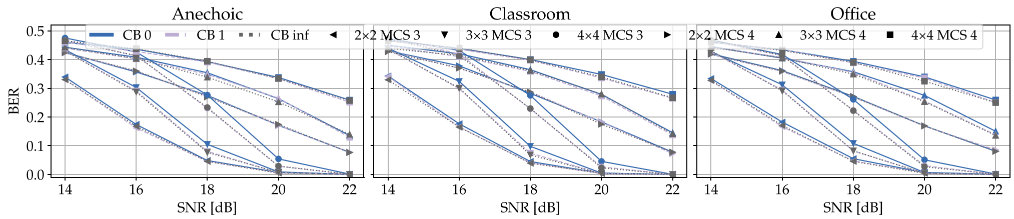
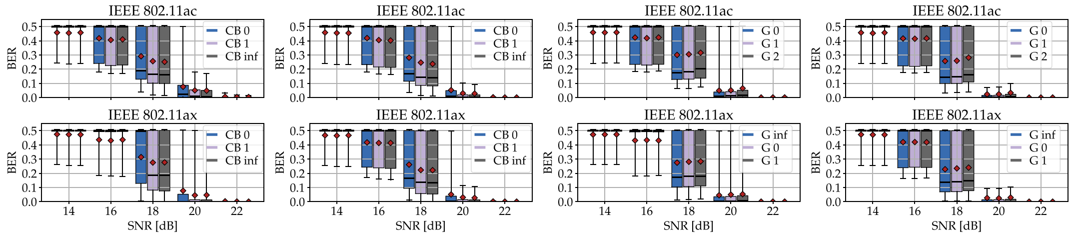


Fig. 3. BER in different environments obtained using devices operating in IEEE 802.11ax on a 80 MHz channel. The results for different MIMO settings and MCS are shown.

for three different MIMO configurations (2×2, 3×3 and 4×4) are shown for the two quantization levels CB 0 CB 1). We assumed that the compressed channel feedback is received by the transmitter without being corrupted by the wireless channel (the results for CB inf are not reported as the reconstruction error is zero without quantization). The bars are obtained by averaging the results for all the MCS and signal-to-noise ratio (SNR) values considered. The MCS has no impact on the reconstruction error because the NDP is transmitted with MCS 0. Instead, the SNR value has no impact on the error for the current evaluation as we assume that the feedback is received by the transmitter without errors associated with the over-the-air transmission. In the figures, we show the results for the first three transmitter antennas and the first two spatial streams (for 2×2 there is no third transmitter antenna). We observe that by increasing the number of bits used for quantization, i.e., using CB 1, the reconstruction error decreases in all the configurations. We can also note that the decrease looks systematic, i.e., in each configuration, the error for the different antenna/spatial streams decreases by a comparable amount from CB 0 to CB 1. Moreover, by comparing the three leftmost (802.11ac) with the three rightmost (802.11ax) plots in Figure 2, we see that the reconstruction error is not affected by the bandwidth and follows the same trend in different environments (anechoic chamber and classroom). This suggests that this error is strongly related not only to the number of quantization bits but also to the MIMO configuration itself. Moreover, for each transmitter antenna, the error of the second spatial stream is higher with respect to the first. This is probably linked to the error propagation in the feedback compression procedure, as highlighted in [9]. To conclude, we note that by increasing the number of antennas and spatial streams – from 2×2 to 4×4 MIMO – the reconstruction error on the single link (antenna-SS) is smaller in absolute value. However, the cumulative error increases and leads to a higher BER when increasing the MIMO cardinality, as discussed in Section IV-B.

B. Bit Error Rate at the Receiver With Perfect Feedback

Next, we evaluate the impact of the feedback matrix reconstruction error on the BER assuming that the compressed channel feedback is received by the transmitter without being corrupted by the wireless channel. In Figure 3 we report the BER obtained for the data collected in the three different environments using the IEEE 802.11ax devices. The plots compare the results for different MIMO configurations and feedback quantization codebooks. The results show that increasing the MIMO cardinality has a negative impact on the performance in terms of BER. The same happens when increasing the MCS index, i.e., when adopting less robust modulations. For each configuration, the lowest BER is achieved when obtaining the precoding from the original feedback, without quantization (CB inf). However, this leads to the highest airtime overhead for feedback transmission. For example, for 4×4 MIMO, the overhead would be 254.98 KB (see Section II-D with $\tilde{K} = K = 996$ for the 80 MHz channel without grouping applied). Instead, using CB 1 and CB 0, the overhead reduces to 9.96 KB and 5.98 KB respectively. Regarding the impact of quantization on the BER, the results in Figure 3 shows that the difference between CB inf and CB 1 is in general smaller than the gap with CB 0, suggesting that CB 1 can be considered a good option to reduce overhead in most cases while CB 0 should be considered when a slight increase in the BER is acceptable. These considerations are confirmed by the evaluation in Figures 4(a)-4(b), where we consider 4×4 802.11ac/ax MIMO configurations and show in detail the BER statistics when using MCS 3 and 40-80 MHz of bandwidth. The bars in the plots cover the 25-75 percentile interval, the horizontal line within each bar represents the median value, and the whiskers span over the 5-95 percentile interval. The mean values are identified by a red diamond. Comparing the upper and lower plots in Figures 4(a)-4(b), we note that 802.11ax performs slightly better on average but the improvement is small in both cases. Moreover, comparing Figure 4(a) with Figure 4(b) we see that increasing the bandwidth slightly reduces the BER. This suggests that the quantization error "spreads" in the bandwidth available thus reducing its impact on the communication performance. On the other hand, it also suggests that working with higher bandwidths allows tolerating a heavier quantization than working with smaller bandwidths. Figures 4(c)-4(d) depict the impact of the sub-channel grouping on the BER when using the two different quantization levels CB 0 and CB 1. The results show that the



(a) "Office", 40 MHz, no group. (b) "Office", 80 MHz, no group. (c) "Classroom", 80 MHz, CB 0. (d) "Classroom", 80 MHz, CB 1.

Fig. 4. BER when varying the number of bits used for quantization (a, b) and the OFDM sub-channel grouping (c, d) (see Table I). The results are obtained for 4 × 4 MIMO and MCS 3.

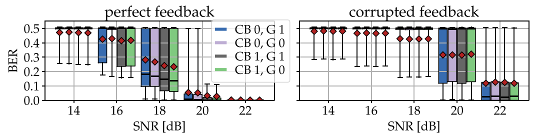


Fig. 5. IEEE 802.11ax, "Anechoic", 4 × 4 MIMO, 80 MHz, MCS 3, with perfect and corrupted feedback.

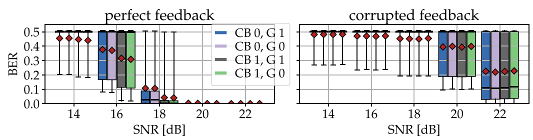


Fig. 6. IEEE 802.11ax simulations, 4 × 4 MIMO, 160 MHz, MCS 3, with perfect and corrupted feedback.

BER only slightly increases when increasing the grouping factor N_g while largely reducing the airtime overhead. Considering 802.11ax, as in the numerical example above, and CB 1, the overhead would be 9.96 KB without grouping and reduces to 2.49 KB and 0.62 KB with G 0 and G 1 respectively. This makes grouping key in reducing the airtime overhead. Combining the higher quantization and grouping levels (i.e., CB 0 and G 1) allows further reducing the overhead to 0.37 KB.

C. Bit Error Rate at the Receiver With Corrupted Feedback

In Figure 5 we evaluate the impact of the different combinations of quantization and grouping parameters CB and G in Table I when also accounting for the corruption of the feedback associated with its wireless transmission from the beamformee to the beamformer. The results suggest that the corruption linked with the feedback transmission has a higher impact on the BER than the feedback compression. For example, the 4 × 4 MIMO network operating at a SNR of 20, has a BER below 0.1 with perfect feedback while the BER increases to 0.3 when accounting for the feedback transmission. In Figure 6 we show the results obtained from the MATLAB simulation using the TGax channel model, operating at 160 MHz with MCS 3 and considering the corruption associated with the feedback transmission. Also in this case, we note that the channel impairments strongly impact the communication performance and make the impact of the different compression mechanisms comparable. Hence, the choice of the compression strategy should account for the wireless channel conditions as it may happen that the compression error is negligible compared to the channel impairments.

V. Concluding Remarks

In this letter, we experimentally evaluated the impact of the beamforming feedback quantization and grouping on the BER of MIMO Wi-Fi networks. We showed that using the highest compression allows reaching a BER comparable to the one achievable without compression, with the advantage of reducing the airtime overhead for feedback transmission by a factor of 689. Our analysis will serve as a benchmark for channel feedback compression research. New techniques can be easily integrated within the emulation framework we developed, enabling their performance assessment using the dataset of real channel measurements we collected. Our hope is that this letter will speed up the research on efficient sounding procedures that will enable large-scale Wi-Fi MIMO.

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