Method for Multi-Antenna Networking Through Multi-path Feedback Extraction and Reporting

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Abstract

In this technical report, we present a new mechanism for channel sounding feedback in wireless multiple-input, multiple-output (MIMO) networks that significantly reduces feedback overhead while not degrading communication performance. Our new approach consists of using the multi-path representation of the wireless propagation as an antenna- and bandwidth-independent—and thus scalable—feedback instance instead of relying on the channel frequency response (CFR) which should be fed back for each transmitter and receiver antenna pair over the entire operational bandwidth. Previous approaches propose to compress the CFR with heuristic or learning-based approaches for efficient feedback. Yet, the resulting feedback does not scale with the number of antennas in the MIMO system and the operational bandwidth. Thanks to the sparse nature of wireless multi-path channels, our approach provides a highly compressed representation of the CFR. Indeed, the number of multi-path components is less than 30 in typical indoor environments. Moreover, we show that the overhead can be further reduced by transmitting only the dominant multi-path components. Our preliminary evaluation demonstrates that the proposed multi-path parameter-based feedback allows maintaining near-optimal performance with minimal bit error rate (BER) degradation compared to CFR feedback, while drastically reducing the feedback spectrum usage. This scalable approach addresses the critical feedback overhead bottleneck of MIMO wireless networks. This will enable the use of more antennas and wider bandwidths, thus improving spectrum efficiency and enhancing multi-user performance in next-generation scenarios where channel resources are expected to be scarce due to the growing number of connected users.

1 Introduction

Multiple-input, multiple-output (MIMO) technology employs multiple antennas at both transmitter and receiver sides to create parallel spatial channels that can carry independent data streams simultaneously over the same time-frequency resources [5]. By exploiting multi-path propagation rather than mitigating it, MIMO systems achieve spatial multiplexing gains that theoretically scale linearly with the minimum number of transmit and receive antennas, dramatically increasing channel capacity without requiring additional bandwidth. However, realizing these gains requires accurate channel frequency response (CFR) at the transmitter to perform crucial operations such as spatial precoding, beamforming, and multi-user interference management.

The CFR is usually acquired at the receiver device to avoid channel compensation issues linked with the use of channel reciprocity properties when estimating the channel at the transmitter. Hence, the receiver is required to feed back the estimated CFR to the transmitter. However, the CFR should be obtained for each transmitter–receiver antenna pair, making the CFR feedback mechanism a fundamental bottleneck to achieving the theoretical capacity gain of MIMO. The challenge is further exacerbated by the frequency-selective nature of wideband channels [1]. As bandwidth increases, the channel exhibits greater frequency selectivity, requiring fine-grained CFR across all subcarriers to capture the channel's frequency-domain variations. Each additional subcarrier in a multi-carrier system (such as orthogonal frequency-division multiplexing (OFDM)) requires separate channel estimates for every antenna pair, which leads to a direct linear increase in feedback overhead with bandwidth. When combined with the quadratic scaling from MIMO antenna pairs, the feedback size exhibits cubic growth with system scale—a fundamentally unsustainable trajectory that calls for alternative approaches. Indeed, the evolution of Wi-Fi and cellular network standards reveals a clear trend toward wider bandwidths and higher-order MIMO configurations, imposing an exponential growth in feedback overhead [4, 13].

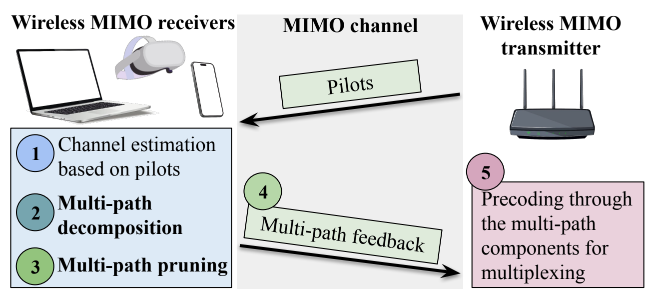


Figure 1. Proposed multi-path parameter-based feedback. Instead of transmitting the complete CFR, the MIMO receivers extract and feed back the multi-path components. The numbers indicate the steps in the procedure (Steps 2 and 3 are representing our proposed approach).

In this work, we present a novel feedback strategy that exploits the inherent sparsity of wireless channels in the spatial-temporal domain by using a multi-path parameter-based feedback. By recognizing that the wireless channel, despite appearing complex in the frequency domain across hundreds of subcarriers and tens of antennas, is fundamentally characterized by less than 30 propagation paths in the spatial-temporal domain, our approach achieves substantial compression while preserving the essential information required for effective precoding and beamforming. Our approach is presented in Figure 1. Specifically, instead of feeding back CFR coefficients for every subcarrier and antenna pair, we extract and transmit only the parameters of the dominant multi-path components, drastically reducing feedback overhead. Our evaluation demonstrates that obtaining the precoding from the multi-path decomposition does not degrade communication performance, as the dominant multi-path components contain the essential channel information required for effective beamforming and interference management. Imperfect parameter estimation primarily affects weak multi-path components that contribute minimally to the overall precoding gain, allowing the system to maintain near-optimal spatial multiplexing performance despite the substantial feedback compression. This paradigm shift from a frequency-domain to a spatio-temporal-domain feedback representation breaks the direct coupling between feedback overhead and system dimensionality in terms of bandwidth and number of antennas, generating a fixed-size feedback. Our comprehensive evaluation demonstrates that this multi-path parameter-based approach maintains near-optimal MIMO performance while reducing feedback overhead by more than an order of magnitude, and enables practical deployment of next-generation MIMO-OFDM systems that would otherwise be constrained by prohibitive feedback overhead.

Summary of novel contributions

- We propose a new approach for channel feedback in wireless networks based on the multi-path decomposition of the CFR. While the CFR should be fed back for each pair of transmitter and receiver antennas and each sub-carrier, our feedback mechanism is antenna- and bandwidth-independent. This allows increasing the number of antennas and widening the bandwidth in MIMO systems without incurring in an increased feedback size.
- We show that it is sufficient to feed back the parameters of a limited number of multi-path components to maintain adequate communication performance. Indeed, weaker multi-path components contribute minimally to the precoding and, in turn, their transmission can be avoided, thus further reducing channel feedback overhead.
- We evaluated the proposed approach through simulations in Sionna and experimental evaluations with commercial devices, showing that the proposed constant-size feedback approach effectively reduces feedback overhead while not degrading communication performance.

2 Related Work

Channel sounding is essential to enable MIMO connectivity, as it provides the channel information needed to precode transmitted data and reliably decode received signals. Sounding can be performed *implicitly*, doing the estimation at the transmitter by exploiting channel reciprocity in Time Division Duplexing (TDD), or *explicitly*, where the receiver estimates the CFR and feeds it back to the transmitter. As implicit feedback requires accurate calibration to compensate for hardware impairments, explicit feedback is usually preferred in wireless networks. However, in the explicit feedback mode, the airtime/feedback overhead grows with the number of antennas and the signal bandwidth, which finally erodes the theoretical throughput gains of having large arrays in MIMO systems [9]. To address this challenge, two complementary directions have emerged: (i) sounding feedback compression, which maps the channel to a compact representation (e.g., codebooks, sparse angle–delay models, learned encoders, or path-parametric; and (ii) sounding rate adaptation, which reduces how often rich updates are sent by exploiting temporal correlation and long-term statistics. Our approach follows the first direction: we replace dense per-subcarrier CFR reports with a compact set of multipath parameters, tying payload to the number of dominant paths rather than to bandwidth or subcarrier count, while remaining compatible with standard wireless signal precoding strategies.

2.1 Sounding Feedback Compression

Sounding feedback compression reduces the size of the feedback frame by mapping the channel to a compact representation. Several deep neural network (DNN)-based methods have been proposed [13]. A convolutional neural network (CNN)-based autoencoder, CsiNet, compresses the estimated CFR at the receiver and reconstructs it at the transmitter for precoding [13]. An online learning framework leverages side information already present in 802.11 to train autoencoders and reduce feedback overhead while preserving compatibility with existing devices [10]. DeepMux focuses on IEEE 802.11ax multi-user MIMO (MU-MIMO) and orthogonal frequency-division multiple access (OFDMA): the station (STA) feeds back quantized CFR on a subset of subcarriers, and the access point (AP) reconstructs the full CFR with a DNN, jointly optimizing resource allocation via deep learning [11]. SplitBeam adopts a split-DNN with a bottleneck to shrink the feedback and lighten processing at the STA [2]. Other works refine quantization and training regimes, from dynamic bit allocation that balances accuracy and overhead [15] to data-efficient training with extrapolation and few-shot strategies [14]. Beyond Wi-Fi systems, parametric feedback has been explored in cellular networks. Ju et al. [7] proposed COMPaCT, which uses Transformer networks to compress mmWave massive MIMO channels into geometric parameters (angles, delays, path losses, phases), achieving over 90% feedback reduction by exploiting delay-domain sparsity. However, this approach targets cellular mmWave systems with different channel characteristics and has not been demonstrated on commercial hardware. These schemes effectively reduce control bits relative to the IEEE 802.11 baseline, but most operate directly on dense CFR tensors or learned latent codes, which remain largely context-agnostic and keep the payload coupled to bandwidth, array size, and model order.

In contrast, our approach performs compression in a *path-parametric* manner: we transform the estimated channel into the spatial-temporal domain, identify a small number of dominant multi-path components, and feed back only per-path parameters.

2.2 Sounding Rate Adaptation

Few approaches have been proposed in the literature for sounding rate adaptation in Wi-Fi networks. Bejerano et al. [3] proposed MUTE, an algorithm where the AP decides which STAs have to feed back an updated channel estimate based on the statistics of the wireless channel. Specifically, the AP estimates how much each new channel measurement has degraded with respect to the previous estimates. This provides a hint on the variability of the channel. The AP computes the variance of the channel differences and triggers the sounding for the STAs for which the channel variance exceeds a threshold. Hence, MUTE performs opportunistic sounding rounds during idle downlink periods to sound as many users as possible from the set of users that need to be sounded. The algorithm has been implemented on a WARP software-defined radios (SDRs). A combination of real-world data and emulation has been used for performance evaluation. Ma et al. [8] proposed a dynamic sounding approach that relies on the estimate of the throughput at the STA, which is performed by the AP and is based on the estimation of the successfully transmitted frames. Channel sounding is triggered when the estimated throughput starts degrading. The validation has been performed through a custom IEEE 802.11ac emulator using measured channel data. Finally, Su et al. [12] developed a K-nearest neighbors model to estimate the throughput at the AP. Specifically, the AP computes the correlation between two subsequent channel measurements and finds the best match in a dataset consisting of channel correlation and the associated throughput. The authors also introduced an algorithm to jointly optimize the sounding period, the number of spatial streams assigned to each user, and the client grouping. The approach has been evaluated through emulations using experimental data.

In stark contrast to these approaches that treat channel impulse response (CIR) extraction and quantization as separate processes, our proposed method jointly optimizes parameter extraction and compression. Previous approaches rely on traditional signal processing techniques like inverse discrete Fourier transform (IDFT) for CIR extraction followed by separate quantization stages, which may not be optimal for the end-to-end feedback task. Our approach instead learns the complete mapping from received pilots to compressed multi-path component (MPC), allowing the network to discover the most efficient representation for feedback. This enables our method to adapt to varying channel conditions and achieve superior compression rates across diverse propagation environments. Moreover, for the first time, we demonstrate the practical implementation of multi-path parameter-based feedback on commercial MIMO-OFDM hardware. Conversely, prior approaches only rely on simulations, analytical studies, or custom testbeds that do not capture the full complexity of practical systems.

3 System Model

This section presents the mathematical framework and theoretical foundations for our multi-path parameter-based feedback approach in MIMO-OFDM systems. We consider a single user MIMO-OFDM system with N_t transmit antennas and N_r receive antennas, operating over N_c subcarriers with bandwidth B and subcarrier spacing $\Delta f = B/N_c$. The transmitted signal at the k-th subcarrier, $k \in \{0, 1, \ldots, N_c - 1\}$, is represented as $\mathbf{x}[k] \in \mathbb{C}^{N_t \times 1}$. The multi-user case can be derived as a simple extension of this model.

The frequency-domain channel matrix at subcarrier k is hereafter denoted as $\mathbf{H}[k] \in \mathbb{C}^{N_r \times N_t}$, where element $H_{\ell,r}[k]$ represents the complex channel gain from transmit antenna ℓ to receive antenna r. The received signal at subcarrier k is given by:

$$\mathbf{y}[k] = \mathbf{H}[k]\mathbf{x}[k] + \mathbf{n}[k] \tag{1}$$

where $\mathbf{n}[k] \sim \mathcal{CN}(\mathbf{0}, \sigma_n^2 \mathbf{I}_{N_r})$ represents additive white gaussian noise (AWGN) with variance σ_n^2 per complex dimension.

3.1 Multi-path Channel Model

The wireless propagation environment can be characterized by P discrete multi-path components, where each path $p \in \{0, 1, \ldots, P - 1\}$ is defined by its complex amplitude $A_p(n)$, propagation delay $\tau_p(n)$, angle of departure (AoD) $\theta_p(n)$, angle of arrival (AoA) $\gamma_p(n)$, and Doppler shift characterized by $D_p(n)$. The frequency-domain channel response for transmit antenna ℓ, receive antenna r, and subcarrier k at time index n is expressed as:

$$\begin{aligned} H_{\ell,r,k}(n) = \sum_{p=0}^{P-1} A_p(n) \exp \Big\{ - j\pi \big[2(f_c + \Delta f k)\tau_p(n) \\ + \ \ell \sin(\theta_p(n)) \ + \ r \sin(\gamma_p(n)) \\ - \ 2 f_c D_p(n) n T_c / c \big] \Big\}, \end{aligned} \tag{2}$$

where f_c is the carrier frequency, Δf is the subcarrier spacing, T_c is the sampling time, and c is the speed of light. This comprehensive model captures delay spread, angular spread, and Doppler effects in the channel. Equation 2 reveals that the number of multi-path parameters does not depend on the MIMO configuration, i.e., the number of antennas in the system and the bandwidth. Hence, using these P multi-path components described by 4 values each as the feedback allows reducing the overhead with respect to feeding back all the elements of the CFR matrix for each transmitter and receiver antenna pair and over each subchannel.

4 Performance Evaluation of Multi-path-based Feedback

In this first evaluation, we assess the effectiveness of our proposed multi-path parameter-based feedback approach. We propose a CNN-based approach to extract the parameters of the multi-path components. In this first implementation, we consider the joint contribution of the phase parameters (propagation delay, AoA, AoD, Doppler effect), i.e., we estimate two parameters for each multi-path component, being the amplitude and the phase information.

4.1 Multi-path Parameter Estimation

Once the CFR $\hat{\mathbf{H}}[k]$ is estimated at the receiver device based on pilot signals irradiated by the transmitter, we use a learning-based approach to extract the multi-path components to be used as feedback information. We design a CNN-based approach that learns to extract the sparse multi-path structure implicit in the frequency-domain measurements, effectively performing an implicit domain transformation and parameter extraction in a single step.

The CNN directly outputs the multi-path component parameters for each path $p \in \{0, \ldots, P-1\}$ being the path amplitude $\hat{\alpha}_p$ (corresponding to $|A_p|$ in the full model) and composite phase $\hat{\phi}_p$. The CNN architecture and training process are detailed in Section 4.3. This parametric representation is particularly efficient for indoor environments, where the number of significant multi-path components remains small (typically $P < 30$).

The amplitude and phase parameters for each path $p \in \{0, \ldots, P-1\}$ are then quantized for feedback as follows

$$\tilde{\alpha}_p = Q_{b_\alpha}\left(\hat{\alpha}_p\right), \tag{3}$$

$$\tilde{\phi}_p = Q_{b_\phi}\left(\hat{\phi}_p\right), \tag{4}$$

where $Q_b(\cdot)$ denotes a b-bit quantizer, with b_α and b_ϕ representing the bit allocations for amplitude and phase, respectively. The amplitude quantization employs logarithmic scaling to better capture the dynamic range of path gains, while phase is uniformly quantized over $[-\pi, \pi)$.

This approach achieves significant compression while maintaining channel reconstruction fidelity sufficient for effective precoding.

4.2 Channel Reconstruction and Precoding at the Transmitter

Upon receiving the quantized multi-path parameters, the transmitter reconstructs the frequency-domain channel estimate. Since the CNN outputs amplitude and phase parameters without explicit delays, the reconstruction uses a composite phase model:

$$\tilde{H}_{\ell,r}[k] = \sum_{p=0}^{P-1} \tilde{\alpha}_p e^{j\tilde{\phi}_p} e^{-j2\pi k \Delta f \tau_p^{\text{ref}}}, \tag{5}$$

where τ_p^{ref} represents reference delays that can be predetermined based on the channel's delay spread characteristics or learned during training. The composite phase $\tilde{\phi}_p$ implicitly captures the effects of array responses and path-specific phase shifts that were present in the full model of Equation 2.

Given the reconstructed channel $\tilde{\mathbf{H}}[k]$, the transmitter designs the precoding matrix $\mathbf{W}[k] \in \mathbb{C}^{N_t \times N_s}$ to map $N_s \leq \min(N_t, N_r)$ data streams to the transmit antennas. The precoded signal is:

$$\mathbf{x}[k] = \mathbf{W}[k]\mathbf{s}[k], \tag{6}$$

where $\mathbf{s}[k] \in \mathbb{C}^{N_s \times 1}$ represents the data symbols with unit power:

$$\mathbb{E}[\mathbf{s}[k]\mathbf{s}^H[k]] = \mathbf{I}_{N_s}. \tag{7}$$

4.3 Simulation Results

To evaluate our proposed multi-path parameter-based feedback approach under realistic propagation conditions, we leveraged Sionna's ray tracing [6] capabilities to generate a comprehensive dataset of wireless channel instances. Sionna's ray tracer simulates electromagnetic wave propagation through complex 3D environments by computing exact ray paths including direct, reflected, diffracted, and scattered components based on geometric optics and the uniform theory of diffraction. For our study, we configured indoor scenarios with varying materials, simulating a 1×8 MIMO system operating at 80 MHz bandwidth divided into 256 subcarriers. As output, the ray tracer provides the channel response decomposed into the multi-path parameters for each propagation path. For each channel realization, we associated the CFR estimated using pilot transmission with the ground truth multi-path parameters—amplitudes $\{\alpha_l\}$ and phases $\{\phi_l\}$—directly from the ray tracing output, providing physically accurate labels for supervised learning.

To estimate amplitude and phase of each multi-path component, we developed a deep CNN-based architecture that directly estimates multi-path parameters from CFR measurements. The network employs a three-stage encoder architecture with progressive feature extraction through convolutional blocks, batch normalization, and dropout regularization, followed by global average pooling and dual prediction heads for amplitude and phase estimation. The model is trained with Mean Square Error (MSE) loss between the

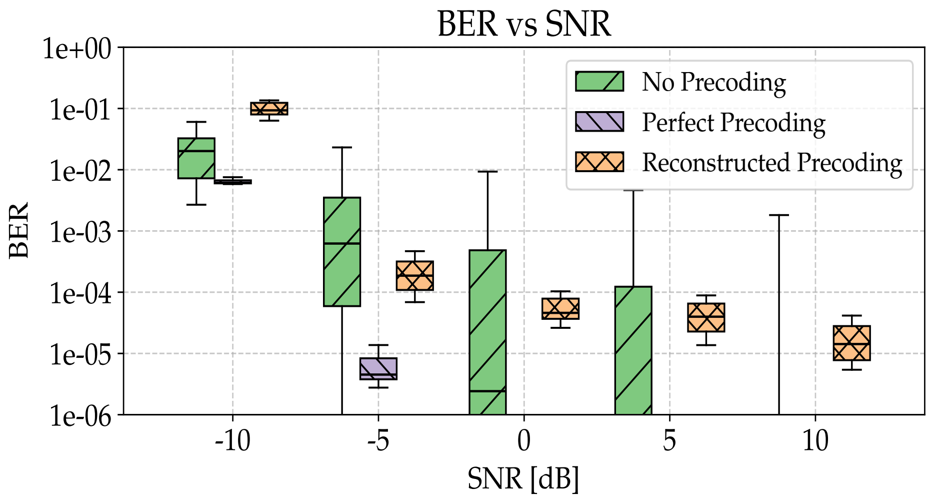


Figure 2. BER comparison between CFR-based feedback and multi-path parameter-based in simulation.

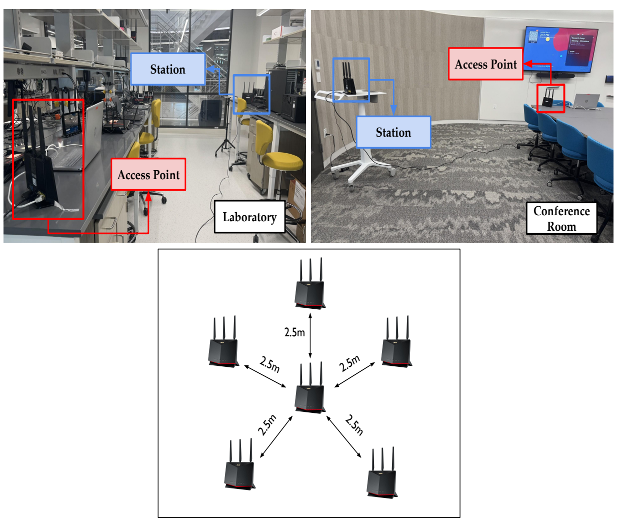
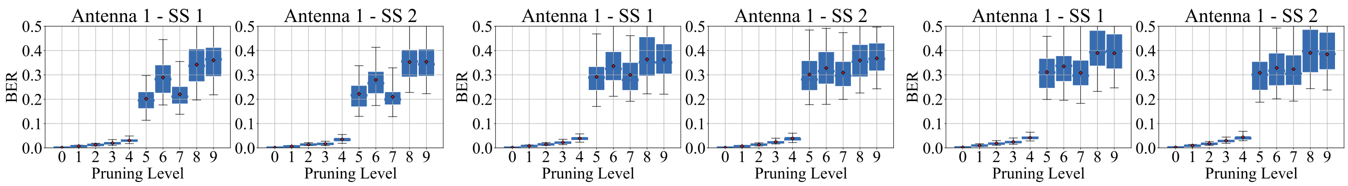


Figure 3. Experimental setup across two distinct environments with fixed and variable STA positioning for multi-path feedback pruning evaluation.

predicted multi-path parameters and their ground truth values obtained from ray tracing simulations. This learning-based approach enables robust path parameter extraction even from incomplete pilot patterns, where only a subset of subcarriers contain pilot symbols, demonstrating the feasibility of accurate CIR estimation in practical OFDM systems with limited pilot overhead. Figure 2 presents the performance comparison between CFR and multi-path parameter-based feedback approaches across varying signal-to-noise ratio (SNR) conditions. The bit error rate (BER) performance (left) demonstrates that multi-path parameter-based feedback achieves comparable to CFR across SNR values, with both methods converging to approximately 10^{-5} BER at 30 dB SNR. Notably, the feedback overhead comparison (right) reveals the significant efficiency advantage of the MPC approach. This dramatic decrease in feedback overhead is achieved by exploiting the sparse nature of wireless channels in the delay domain. The hatched bar patterns indicate consistent overhead increase by increasing the MIMO dimensionality when using the CFR-based feedback, while our multi-path-based approach adapts to the channel's inherent sparsity. These results validate that multi-path parameter-based parametric feedback not only maintains communication reliability but does so with substantially reduced signaling overhead, making it particularly attractive for bandwidth-constrained feedback channels in practical MIMO-OFDM systems.

5 Performance Evaluation of Multi-path Parameter Pruning

As a second preliminary evaluation, we investigate which MPC are required for maintaining acceptable system-level performance through removal of weak propagation components. By recognizing that weak multi-path components often contribute more noise than useful signal information, we show that it is possible to achieve acceptable MIMO system performance with fewer multi-path components. This selective approach represents a paradigm shift from comprehensive channel tracking to intelligent weak multi-path recognition and removal. We designed a MIMO precoding emulator based on real channel measurements from commercial Wi-Fi devices for evaluating the impact of weak multi-path identification and removal on system-level performance in IEEE 802.11ax networks. Our emulator replicates the complete physical layer processing chain while enabling controlled evaluation of different multi-path selection strategies under realistic propagation conditions. We systematically analyse



(a) Conference Room - 40 MHz **(b)** Conference Room - 80 MHz **(c)** Conference Room - 160 MHz

Figure 4. BER performance comparison across different bandwidth configurations in conference room environment with multi-path pruning at SNR = 20 dB for both spatial streams.

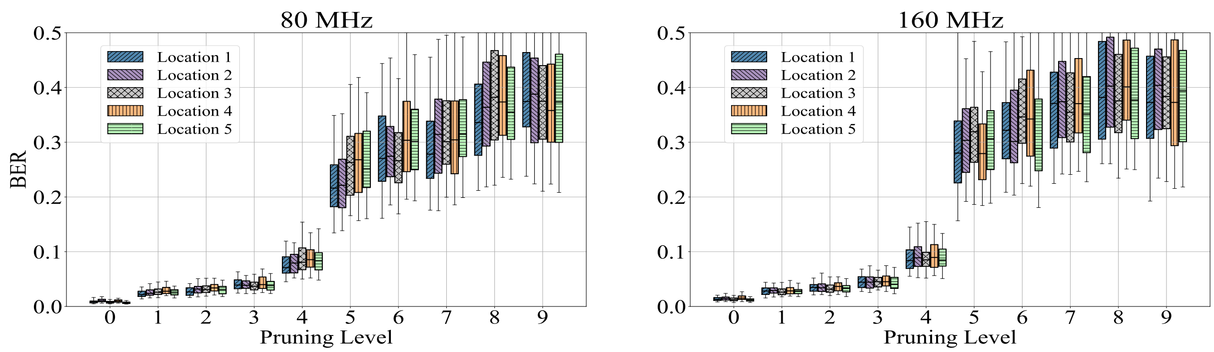


Figure 5. BER versus multi-path pruning level across different bandwidth configurations in the laboratory with changing the location of STA.

the trade-off between multi-path component selection and BER degradation by identifying and removing progressively weaker multi-path components. For an unbiased evaluation, we develop a fair comparison methodology that tests all pruning levels on identical channel realizations and quantifies BER performance . This approach enables us to recognize the minimum number of multi-path components in order to have an acceptable system-level performance.

5.1 Experimental Setup

The experimental evaluation framework involves comprehensive CFR measurements across multiple bandwidth configurations and indoor propagation environments to validate the multi-path pruning approach for IEEE 802.11ax MIMO systems. As depicted in Figure 3, the experimental testbed utilized commercial IEEE 802.11ax equipment operating in MIMO mode to capture authentic channel characteristics. Specifically, ASUS RT-AX86U routers served as both the AP and STA, and physical separation maintained at approximately 2.5 m. The wireless network operated on channel 64, with measurements conducted across 40 MHz, 80 MHz, and 160 MHz bandwidth configurations to evaluate the impact of frequency diversity on multi-path pruning performance.

CFR data collection was systematically conducted in two representative indoor environments that provide contrasting multi-path propagation characteristics. The first environment was a conference room with typical office furniture and the second environment was a research laboratory containing various equipment.

To capture spatial diversity effects and angular-dependent multi-path variations, measurements were conducted under two distinct mobility scenarios: (i) where the STA is fixed in one location, and (ii) where the STA was systematically repositioned after each data collection session at different equally-spaced locations along a distance of 2.5 meters from the AP.

5.2 Experimental Results

Figure 4 and Figure 5 demonstrate that multi-path pruning can safely eliminate up to 50% of the weakest multi-path components (pruning levels 0–4) without significantly degrade communication performance, i.e., maintaining BER values below 0.1 across diverse indoor environments. Beyond the critical threshold at pruning level 5, system performance deteriorates dramatically with BER increasing to 0.4–0.5, which indicates that essential propagation information required for effective precoding is being removed. The results reveal remarkable bandwidth-invariant behavior across 40, 80, and 160 MHz configurations, that suggests pruning effectiveness is governed by spatial-temporal propagation characteristics rather than spectral occupancy.

6 Conclusions

In this report, we propose a new approach for channel feedback in MIMO networks which overhead is independent on the number of antennas in the system and the operational bandwidth. Our approach, based on multi-path parameter decomposition, allows drastically reducing the feedback overhead thus enabling large scale MIMO deployments. The proposed method achieved approximately more than 90% reduction in feedback overhead by exploiting the sparse multi-path structure of wireless channels, while maintaining BER performance comparable to standard CFR-based feedback across all SNR ranges. We show that the integration of a deep CNN for multi-path parameter estimation enables robust extraction of amplitude and phase information from the CFR, which validates the practical feasibility of the approach. In addition, we show that weak multi-path components can be pruned without significally impacting communication performance. Overall, this work establishes multi-path parameter-based feedback as a promising technique for large-scale MIMO networks and is particularly relevant for emerging 5G and beyond systems where efficient CFR acquisition remains a fundamental challenge.

References

[1] Ahmed Alkhateeb and Robert W Heath. 2016. Frequency selective hybrid precoding for limited feedback millimeter wave systems. *IEEE Transactions on Communications* 64, 5 (2016), 1801–1818.

[2] Niloofar Bahadori, Yoshitomo Matsubara, Marco Levorato, and Francesco Restuccia. 2023. SplitBeam: Effective and Efficient Beamforming in Wi-Fi Networks Through Split Computing. In *Proceedings of IEEE International Conference on Distributed Computing Systems (ICDCS)*. IEEE, 864–874.

[3] Oscar Bejarano, Eugenio Magistretti, Omer Gurewitz, and Edward W Knightly. 2014. MUTE: Sounding Inhibition for MU-MIMO WLANs. In *Proceedings of IEEE International Conference on Sensing, Communication, and Networking (SECON)*. IEEE, 135–143.

[4] Matthew S Gast. 2013. *802.11ac: A Survival Guide: Wi-Fi at Gigabit and Beyond.* " O'Reilly Media, Inc.".

[5] Khandaker Foysal Haque, Francesca Meneghello, KM Rumman, and Francesco Restuccia. 2024. m3MIMO: An 8× 8 mmWave Multi-User MIMO Testbed for Wireless Research. In *Proceedings of the 30th Annual International Conference on Mobile Computing and Networking*. 1922–1929.

[6] Jakob Hoydis, Sebastian Cammerer, Fayçal Ait Aoudia, Merlin Nimier-David, Lorenzo Maggi, Guillermo Marcus, Avinash Vem, and Alexander Keller. 2022. *Sionna.* https://nvlabs.github.io/sionna/.

[7] Hyungyu Ju, Seokhyun Jeong, Seungnyun Kim, Byungju Lee, and Byonghyo Shim. 2024. Transformer-assisted parametric CSI feedback for mmwave massive MIMO systems. *IEEE Transactions on Wireless Communications* (2024).

[8] Xiaofu Ma, Qinghai Gao, Ji Wang, Vuk Marojevic, and Jeffrey H Reed. 2017. Dynamic Sounding for Multi-user MIMO in Wireless LANs. *IEEE Transactions on Consumer Electronics* 63, 2 (2017), 135–144.

[9] Ehud Reshef and Carlos Cordeiro. 2022. Future Directions for Wi-Fi 8 and Beyond. *IEEE Communications Magazine* 60, 10 (2022), 50–55. doi:10.1109/MCOM.003.2200037

[10] Pedram Kheirkhah Sangdeh, Hossein Pirayesh, Aryan Mobiny, and Huacheng Zeng. 2020. LB-SciFi: Online Learning-Based Channel Feedback for MU-MIMO in Wireless LANs. In *2020 IEEE 28th International Conference on Network Protocols (ICNP)*. IEEE, 1–11.

[11] Pedram Kheirkhah Sangdeh and Huacheng Zeng. 2021. DeepMux: Deep-learning-based Channel Sounding and Resource Allocation for IEEE 802.11 ax. *IEEE Journal on Selected Areas in Communications* 39, 8 (2021), 2333–2346.

[12] Shi Su, Wai-Tian Tan, Xiaoqing Zhu, Rob Liston, Herb Wildfeuer, and Behnaam Aazhang. 2021. Motion-Aware Optimizations for Downlink MU-MIMO in 802.11 ax Networks. *IEEE Transactions on Network and Service Management* 18, 4 (2021), 4088–4102.

[13] Chao-Kai Wen, Wan-Ting Shih, and Shi Jin. 2018. Deep learning for massive MIMO CSI feedback. *IEEE Wireless Communications Letters* 7, 5 (2018), 748–751.

[14] Binggui Zhou, Xi Yang, Jintao Wang, Shaodan Ma, Feifei Gao, and Guanghua Yang. 2024. A Low-Overhead Incorporation-Extrapolation based Few-Shot CSI Feedback Framework for Massive MIMO Systems. *IEEE Transactions on Wireless Communications* (2024).

[15] Ziyi Zuo, Yi Zhong, Yapu Li, Jun Zhang, and Xiaohu Ge. 2024. AIML-Enhanced Adaptive Quantization for Channel Sounding Feedback in Wireless Communications. In *2024 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE, 1–6.