An Autoencoder-Based CSI Feedback and Link adaptation in 5G FDD MIMO Systems*

Abdel F. Chabi[1], João Vitor da S. Campos[1], Andson Balieiro[1]

***Abstract*— Massive Multiple-Input Multiple-Output is a key-technology for enabling high data-rate transmissions in Fifth Generation (5G) networks, where base stations (BS) are equipped with a large number of antenna elements to enhance spectral efficiency, coverage, and throughput. In Frequency Division Duplex (FDD) systems, massive MIMO relies on Channel State Information (CSI) feedback from user equipment (UE), with feedback overhead increasing linearly with the number of antennas. The conventional CSI feedback mechanisms standardized by the 3rd Generation Partnership Project (3GPP) are limited by the coarse granularity of the codebook, which can render massive MIMO impractical. In this paper we proposed an autoencoder-based solution to compress CSI at the UE side and reconstruct it at BS.The proposed solution is integrated into the 5G link adaptation mechanism and evaluated not only in terms of CSI compression and reconstruction accuracy, but with respect to its impact on transmission performance. The results demonstrate that the proposed solution accurately reconstructs CSI data, achieving a correlation of 0.99, and outperforms the conventional CSI feedback scheme by approximately 21% in terms of throughput. Error Vector Magnitude (EVM) analysis further indicates enhanced transmission reliability under the proposed method.**

I. Introduction

Massive Multiple-Input Multiple-Output (MIMO) is a key technology for achieving high data-rate transmissions in Fifth Generation (5G) networks, enabling enhanced Mobile Broadband (eMBB) services such as 8K video and 360-degree video streaming, as well as augmented reality (AR) and virtual reality (VR) applications. In Frequency Division Duplex (FDD) systems, massive MIMO relies on Channel State Information (CSI) feedback [1], in which User Equipment (UE) periodically reports wireless channel conditions to the Base Station (BS) to support efficient resource allocation for downlink transmission. However, the amount of CSI feedback increases linearly with the number of antennas, significantly boosting the signaling overhead and computational complexity of massive MIMO systems [2].

To address this issue, deep learning (DL) techniques have emerged as promising solutions. For instance, the authors in [3] propose an autoencoder-based approach for CSI compression. However, the study adopts a very limited scenario, assuming a single receive antenna, and focuses exclusively on the model's capability of reconstructing the channel matrix, without validating its effectiveness in a transmission context. Moreover, the study relies on the COST 2100 channel model, which is an LTE-based channel and therefore does not accurately reflect 5G scenarios. In [4], the authors integrate a Hybrid Learnable Non-Uniform Quantization (HLNUQ) mechanism with a Transformer-based CSI feedback method to reduce the feedback overhead while simultaneously mitigating the errors introduced by the quantization and dequantization processes in FDD Massive MIMO systems. Although the proposal presents promising results and outperforms traditional approaches, its evaluation is limited to Generalized Cosine Similarity (GCS) and does not consider network-level performance metrics in a transmission scenario. Inspired by the bidirectional encoder representations from Transformers (BERT) architecture, the authors in [5] proposes a foundation model (BERT4MIMO) to process high-dimensional Channel State Information (CSI) data in Massive MIMO systems and enhance CSI prediction and reconstruction under varying mobility conditions and channel scenarios. Similarly, [6] addresses the challenge of standardazing AI-based CSI feedback enhancement and demonstrates the capacity of a autoencoder-based models to reconstruct the CSI matrix. Despite achieving strong performance in terms of Mean Squared Error (MSE), both solutions [5] and [6] are not integrated into the link adaptation mechanism, preventing an assessment of their impacts on the user transmission.

This work addresses this gap by proposing an autoencoder-based CSI feedback solution for 5G MIMO systems, evaluating not only its CSI compression and reconstruction performance, but also its impact on user transmission when integrated into the link adaptation mechanism. We adopt the 3rd Generation Partnership Project (3GPP) tridimensional (3D) channel model for training and testing the autoencoder-based model and compare the proposed solution, when integrated into the link adaptation mechanism, with the traditional 3GPP Rank Indicator-Precoding Matrix Indicator-Channel Quality Indicator (RI–PMI–CQI) approach. The comparison is conducted in terms of CSI matrix reconstruction accuracy, throughput, and EVM. Our findings revealed a competitive CSI matrix reconstruction by the autoencoder model proposed when compared to the state-of-the-art. Furthermore, the autoencoder compression method increases the throughput by approximately 21% while also enhances the transmission reliability when compared to the 3GPP traditional method. This paper is structured as follows. Section II describes the methodology highlighting the system model, the proposed model architecture as well as the link-level evaluation scenario. Section III analyzes and discusses the results and finally, Section IV concludes this paper and suggests future research directions.

[1] Authors are with Faculty of Computer Science, Federal University of Pernambuco (UFPE), Recife, Brazil {afc9, jvsc2, amb4}@cin.ufpe.br

II. METHODOLOGY

This section describes the methodology, covering dataset description, model architecture, and the evaluation scenario.

A. System Model

We consider a 5G New Radio (NR) downlink MIMO-OFDM system operating in FDD mode. The Base Station (gNB) is equipped with N_{tx} transmit antenna ports and the UE with N_{rx} receive antennas. The channel used is a Clustered Delay Line of type C (CDL-C) defined as Non-Line-of-Sight (NLOS) channel profiles in TR 38.901 [7]. The system operates over a carrier with $\mathbf{K}$ subcarriers, normal cyclic prefix and $\mathbf{L}$ OFDM symbols per slot. For each subcarrier $\mathbf{k} \in \{1, \ldots, \mathbf{K}\}$, the received signal at the UE is given by equation 1

$$\mathbf{y}_k = \mathbf{H}_k \mathbf{W}_k \mathbf{s}_k + \mathbf{n}_k \tag{1}$$

Where $\mathbf{H}_k \in \mathbb{C}^{N_{rx} \times N_{tx}}$ is is the channel matrix at subcarrier $\mathbf{k}$, $\mathbf{W}_k \in \mathbb{C}^{N_{tx} \times \nu}$ is the precoding matrix with ν spatial layers, $\mathbf{s}_k \in \mathbb{C}^{\nu}$ is the transmitted symbol vector and $\mathbf{n}_k$ is additive white Gaussian noise (AWGN). The UE estimates the downlink channel from CSI-RS reference signals periodically transmitted by the gNB. The resulting channel estimate is $\mathbf{H} \in \mathbb{C}^{\mathbf{K} \times \mathbf{L} \times N_{rx} \times N_{tx}}$, containing the frequency response for every subcarrier, OFDM symbol, receive antenna, and transmit antenna port. This estimate constitutes the complete spatial-frequency characterization of the channel as observed by the UE.

B. Dataset Description

The dataset used to train and test our autoencoder-based solution regarding the matrix reconstruction was generated using MATLAB R2024b with 5G and Deep learning Toolbox. A 5G CDL-C channel model was simulated, and channel estimation data were subsequently collected and pre-processed. The MIMO scheme was configured with 8 transmit antennas (Tx) at the gNB and 4 reception antennas (Rx) at UE. The channel estimate matrix is an $\begin{bmatrix} \mathbf{K} & \mathbf{L} & N_{rx} & N_{tx} \end{bmatrix}$ array for each slot. Table I summarizes the carrier and channel configuration as well as the dataset size. The dataset, along with the detailed data generation and preprocessing methodologies and the corresponding script, has been made publicly available on GitHub [8].

TABLE I: 5G System Parameters

Parameter	Value
Dataset size	20,000 samples
MIMO configuration	8×4 (Tx $\times$ Rx)
Maximum Doppler shift	5 Hz
Bandwidth; SCS	10 MHz; 15 kHz
Channel model	CDL-C
Number of subcarriers ($\mathbf{K}$)	624
Number of OFDM symbols per slot ($\mathbf{L}$)	14

C. Proposed Autoencoder Architecture

The proposed autoencoder enhances the CsiNet-inspired baseline architecture provided in [3] by introducing three significant modifications: (i) SNR-conditioned input representation, (ii) a deeper encoder architecture with explicit residual learning blocks, and (iii) multi-scale feature extraction via bottleneck convolutions. The decoder structure, including the RefineNet-style remains unchanged.

In real deployments, the channel quality estimate $\hat{\mathbf{H}}$ is strongly dependent on operating SNR conditions. Under low-SNR conditions, noise corruption significantly degrades the channel estimate. Consequently, a non-SNR-aware encoder may waste codeword encoding noise artifacts rather than the meaningful channel structures. To address this limitation, our proposed encoder is conditioned on the instantaneous SNR via constructing constant-valued spatial map, which is incorporated as a third input channel. The input tensor used in CsiNet is $X_{\text{base}} \in \mathbb{R}^{T \times N_{tx} \times 2}$, where T is the number of delay taps and 2 represents the real and imaginary components. The proposed architecture augments the input tensor with a third channel carrying normalized SNR information, which leads to an input representation $X \in \mathbb{R}^{T \times N_{tx} \times 3}$.

The encoder used in CsiNet consists of a single 3×3 convolutional layer with only 2 filters, followed by batch normalization (BN), Leaky ReLU activation ($\alpha = 0.3$), a flatten layer, and a fully connected (FC) layer that projects to the latent codeword. This shallow architecture limits the model's capacity to capture the spatial correlation structure inherent in MIMO channel matrices. The proposed encoder pipeline is organized into four stages, as shown in Fig. 1.

*1) **Initial Convolution**:* A 3×3 convolutional layer with 16 filters processes the input channel, followed by batch-normalization (BN) layer and Leaky ReLU layer. This block processes three input channels, allowing the learned filters to jointly learn spatial representations from the channel estimate and the corresponding SNR contex.

*2) **Residual Block 1**:* A residual learning block with two consecutive 3×3 convolutional layers with 16 filters each, followed by BN layers, with a skip connection that bypasses both layers.

*3) **Channel Expansion and Residual Block 2**:* A transition layer expands the feature dimensionality from 16 to 32 channels via a 3×3 convolution with BN and Leaky ReLU. This is followed by a second residual block employing a bottleneck design: a 1×1 convolution first reduces the channel count from 32 to 16 (cross-channel mixing without spatial aggregation), followed by a 3×3 convolution that restores 32 channels.

*4) **Latent Projection**:* The previous stage output is flattened and projected to the compression size dimensional codeword via a fully connected layer followed by another BN layer. The BN layer normalizes the codeword distribution, providing implicit regularization without the range constraint imposed by the sigmoid activation used in CsiNet. Table II summarizes the main differences between CsiNet and the proposed architecture.

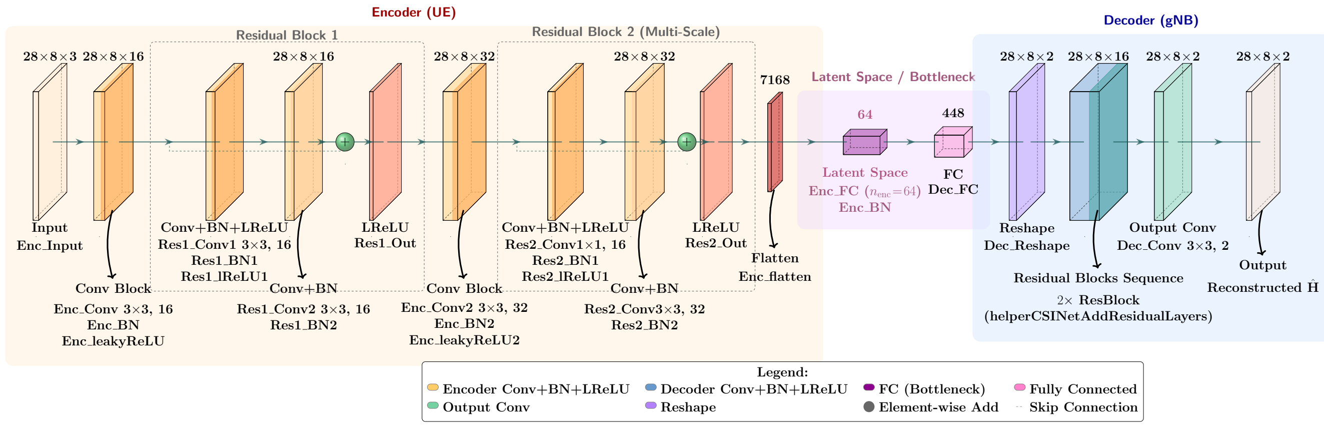

Fig. 1: Proposed autoencoder architecture for CSI Reconstruction.

TABLE II: Comparison Between CsiNet and the Proposed Architecture

Attribute	CsiNet	Proposed
Input channels	2 (Re, Im)	3 (Re, Im, SNR map)
SNR conditioning	None	SNR map
Conv. layers (encoder)	1	7
Filters (initial conv.)	2	16
Residual blocks (encoder)	0	2 (skip connections)
Bottleneck 1×1 conv.	Absent	Present (32→16→32)
Multi-scale extraction	No	Yes (1×1 + 3×3)
Encoder depth (total layers)	4	16
Decoder architecture	RefineNet + Conv	Unchanged

D. Link-Level Simulation

To analyze the impact of our solution on user transmission, a system-level link adaptation simulation that implements the complete 5G NR PDSCH transmit-receive chain has been developed using MATLAB. In this chain, the channel information is reported by the UE to the gNB through a capacity-limited uplink feedback channel. The simulation follows a slot-based structure where, at each slot, the gNB transmits a PDSCH transport block using the most recent CSI feedback, and the UE attempts to decode it. The accumulated throughput over the number of radio frames is measured at several SNR operating points. The simulation operates as a closed-loop system, interacting dynamically across slots: channel estimation, CSI feedback, link adaptation, precoded transmission, equalization, and decoding. Two CSI feedback modes, namely the autoencoder-based approach and the RI-PMI-CQI method, are considered for comparative analysis.

1) ***Autoencoder-based Feedback****:* In Autoencoder-based Feedback, the UE compresses $\mathbf{H}$ through the trained autoencoder encoder into a compact codeword $\mathbf{z}$ which is transmitted to the gNB. The gNB decoder reconstructs an estimate of the channel, denoted $\hat{\mathbf{H}}_k$, from the received codeword and computes its Singular Value Decomposition (SVD) as $\hat{\mathbf{H}}_k = \hat{U}_k\,\hat{\Sigma}_k\,\hat{V}_k^H$. Where $\hat{U}_k \in \mathbb{C}^{N_{rx}\times N_{rx}}$ contains the left singular vectors, $\hat{\Sigma}_k = \mathrm{diag}(\hat{\sigma}_1,\ldots,\hat{\sigma}_{N_{rx}})$, $\hat{\sigma}_1 \geq \hat{\sigma}_2 \geq \cdots \geq \hat{\sigma}_{N_{rx}} \geq 0$ contains the singular values, and $\hat{V}_k \in \mathbb{C}^{N_{tx}\times N_{tx}}$ expresses the right singular vectors. The precoder is formed from the first ν columns of $\hat{V}_k$, with each direction weighted by a Wiener shrinkage coefficient given by $w_i = \frac{\hat{\sigma}_i^2}{\hat{\sigma}_i^2+\alpha}$, where α is an adaptive regularization parameter, which depends on the locally estimated noise variance. The number of layers ν, the modulation and coding scheme (MCS) are selected at the gNB based on the reconstructed channel.

2) ***RI-PMI-CQI Based Feedback****:* In RI-PMI-CQI based Feedback, the UE processes $\mathbf{H}$ locally and reports the Rank indicator (RI), the precoding matrix indicator (PMI) and channel quality indicator (CQI) selected from the type I single panel codebook defined in TS 38.214 [9]. The SVD of the estimated channel is performed by the UE and expressed as $\mathbf{H}_k = U_k\,\Sigma_k\,V_k^H$, the resulting decomposition is used to compute the feedback indices. The rank indicator is selected by equation 2, where $\nu \in \{1,\ldots,N_{rx}\}$ is the candidate number of spatial layers, σ_i is the $i-th$ singular value of $\mathbf{H}_k$ and N_0 is the noise power spectral density.

$$\mathrm{RI} = \arg\max_{\nu} \sum_{i=1}^{\nu} \log_2\left(1+\frac{\sigma_i^2}{N_0}\right) \tag{2}$$

The precoding matrix indicator is determined by quantizing the dominant right singular vectors against the codebook and is given by equation 3, where $V_k(:,1:\nu) \in \mathbb{C}^{N_{tx}\times\nu}$ denotes the first ν columns of the right singular matrix (V_k) from SVD, $W_{\mathrm{cb}}(j)$ is the $j-th$ precoding matrix in the Type I Single Panel codebook.

$$\mathrm{PMI} = \arg\min_{j} \left\| V_k(:,1:\nu) - W_{\mathrm{cb}}(j) \right\|_F \tag{3}$$

The CQI reports the highest MCS sustainable under the estimated per-layer Signal-to-Interference-plus-Noise Ratio (SINR).

III. Results and Discussion

This section presents the results. First, the channel matrix reconstruction of the proposed method is evaluated by comparing the reconstruction error against state-of-the-art approaches. Subsequently the performance of the proposed method is analyzed relative to the conventional RI-PMI-CQI method in a link adaptation scenario using throughput and Error Vector Magnitude (EVM) as evaluation metrics.

A. Channel estimation matrix reconstruction

The trained autoencoder is evaluated across a full operational SNR range by performing a discrete sweep over SNR values ranging from $-5dB$ to $40dB$ in 5 dB steps. For each test SNR value, the clean normalized test set is corrupted with AWGN at the corresponding noise power ($10^{-\frac{\mathrm{SNR}}{10}}$), and the SNR-conditioned third input channel is assigned the normalized SNR value $\frac{\mathrm{SNR}}{\mathrm{SNR_{max}}}$. The network then produces a reconstruction $\hat{\mathbf{H}}$, which is denormalized to the original scale for metric computation. Normalized Mean Squared Error (NMSE) and Cosine Similarity (ρ) or correlation defined in Eq. 4 are computed for the reconstruction performance evaluation, where $\mathbf{H}$ and $\hat{\mathbf{H}}$ are the original and the recovered channel, $\mathbf{h}_k$ is the channel estimate vetor of the kth subcarrier, $\hat{\mathbf{h}}_k$ the reconstructed channel estimate vector of the kth subcarrier, $\hat{\mathbf{h}}_k^H$ is the conjugate transpose of $\hat{\mathbf{h}}_k$, and $\mathbf{K}$ is the number of subcarriers.

$$\rho = \mathbb{E}\left\{\frac{1}{K}\sum_{k=1}^{K}\frac{\left|\hat{\mathbf{h}}_k^H\mathbf{h}_k\right|}{\left\|\hat{\mathbf{h}}_k\right\|_2\left\|\mathbf{h}_k\right\|_2}\right\}; \mathrm{NMSE} = \mathbb{E}\left\{\frac{\left\|\mathbf{H}-\hat{\mathbf{H}}\right\|_2^2}{\left\|\mathbf{H}\right\|_2^2}\right\} \tag{4}$$

The original CsiNet work in [3], evaluates reconstruction quality by reporting a single aggregate NMSE value, which implicitly assumes that compression quality is the dominant bottleneck and that noise effects are secondary. This assumption holds in idealized scenarios but breaks down in practical deployments since in a real 5G NR system the channel estimate fed to the encoder already carries estimation errors that depend on the received SNR. A model that reaches excellent NMSE at 20 dB may degrade severely at 5 dB, and a single-point metric conceals this behavior entirely. To ensure a fair comparison, we adopt the compression ratio notation used in CsiNet works, where a single compression ratio of $\gamma = \frac{1}{7}$ is employed. The results reveal high-fidelity reconstruction under noiseless condition (when SNR $\geq 10dB$) with the $NMSE \leq -18.67$ and $\rho \geq 0.993$. Under noise condition (SNR < 10), the reconstruction performance degrades slightly. The worst reconstruction scenario is experienced with SNR $= -5$ when $NMSE = -8.89$ and $\rho = 0.933$. Table III and figure 2 summarize $NMSE$ and ρ values for each SNR.

The proposed method is compared with state-of-the-art approaches in terms of reconstruction performance, extending the comparative analyses presented in [10] and [11]. For a fair comparison we consider the SNR point with the higher NMSE, which represents the reconstruction error that would be measured if the system were evaluated on a noiseless CSI (same method adopted by CsiNet [3]). Furthermore, the comparison is performed at a compression ratio of $\gamma = \frac{1}{8}$, as it most closely matches the ratio employed in this work. The comparison results are presented in Table IV. Despite

TABLE III: Reconstruction result as a function of SNR

SNR (dB)	Mean ρ	Mean NMSE (dB)
-5	0.93295	-8.89
0	0.97115	-12.73
5	0.98656	-16.01
10	0.99288	-18.67
15	0.99507	-20.20
20	0.99585	-20.93
25	0.99612	-21.22
30	0.99621	-21.32
35	0.99622	-21.32
40	0.99619	-21.28

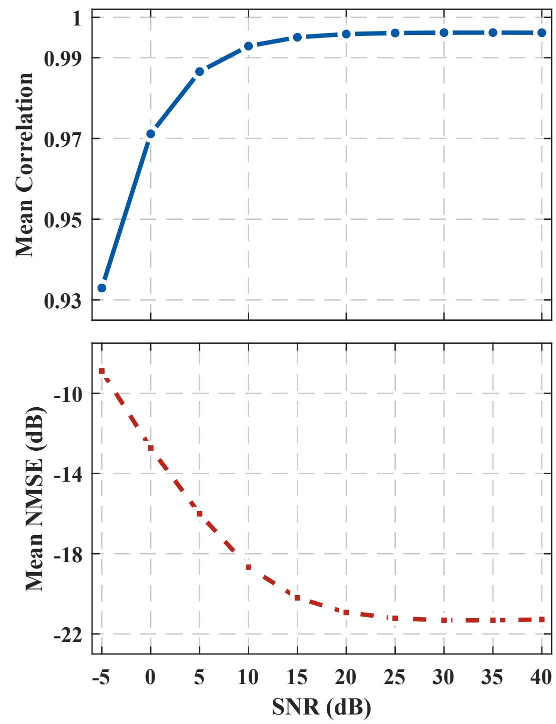

Fig. 2: Proposed Method NMSE and Correlation per SNR

operating under a more challenging 3GPP CDL-C channel model, characterized by a Doppler shift of $5Hz$ and a multipath delay spread of $300ns$, in contrast to the COST2100 indoor picocellular scenario employed in the CsiNet family of works, the proposed system achieves competitive performance ($\mathbf{NMSE = -21.32}$) at a comparable compression ratio. Moreover, it provides a robustness characterization across the full SNR operating range, an evaluation dimension that is largely overlooked by the existing literature.

B. Throughput Performance Analysis

Although accurate reconstruction of the channel estimation matrix reflects strong model performance, it does not necessarily guarantee effective performance in link adaptation scenarios. Fig. 3 presents the downlink throughput as a function of SNR for both the proposed autoencoder-based and the conventional RI-PMI-CQI CSI feedback scheme. The results reveal two distinct operating regimes, low-SNR

TABLE IV: NMSE at compression ratio $\gamma = \frac{1}{8} \approx \frac{1}{7}$

Method	NMSE (dB)
CsiNet	-12.70
CRNet	-15.04
CLNet	-15.60
CsiNet+	-18.29
Proposed	**-21.32**
CSI-StripeFormer	-22.29
TransNet	-22.91

and moderate-to-high SNR, both regimes separated by a crossover point at approximately $\mathrm{SNR} = 12dB$.

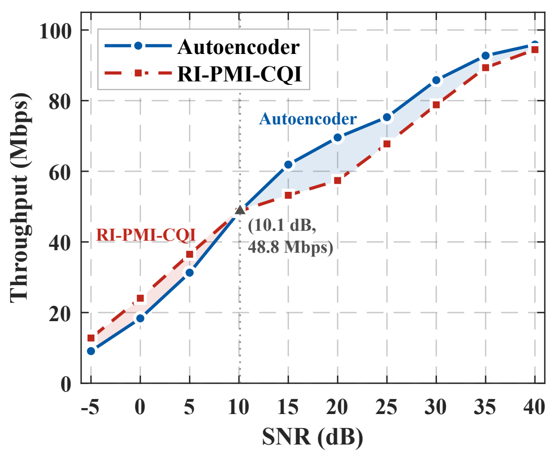

Fig. 3: Throughput Comparison per SNR

In the low-SNR regime $\mathrm{SNR} < 12dB$, RI-PMI-CQI scheme outperforms the autoencoder. The peak advantage is observed at $\mathrm{SNR} = 5dB$, when the conventional feedback achieves $12.80Mbps$ against $9.09Mbps$ for the autoencoder, representing a gap of approximately 29%.In moderate-to-high SNR regime $\mathrm{SNR} \geq 12dB$, the autoencoder c. At 15 dB, the proposed method achieves a gain of 16.3% 61.89 against 53.21 Mbps, and this advantage is sustained across the next SNR points, reaching 1.5% at 40 dB, where both schemes approach the transport block size limit. The maximum gain of 21.2% occurs at 20 dB. Table V summarizes the throughput values achieved by the Autoencoder-Based and RI-PMI-CQI CSI Feedback schemes and their respective gains. The results are consistent with the fundamental characteristics of MIMO systems. In low-SNR regime ($\mathrm{SNR} < 10\mathrm{dB}$), system performance is primarily noise-limited, with limited effective multiplexing, thereby reducing the impact of advanced feedback schemes. RI-PMI-CQI scheme is inherently more robust in this regime, as it relies on codebook-based quantization of a small number of structured parameters, which are less sensitive to estimation noise than a raw compressed channel representation. The proposed autoencoder is particularly well-suited for deployment in moderate-to-high SNR conditions, which correspond to the majority of scheduled transmissions in interference-limited 5G NR networks. The throughput gain in this regime

TABLE V: Throughput achieved by the Autoencoder-based and RI-PMI-CQI CSI feedback schemes under different SNR values.

SNR (dB)	Proposed (Mbps)	RI-PMI-CQI (Mbps)	Gain (%)
-5	9.09	12.80	-28.984
0	18.36	24.07	-23.722
5	31.30	36.51	-14.270
10	48.45	48.65	-0.411
15	61.89	53.21	**16.313**
20	69.57	57.39	**21.223**
25	75.32	67.75	**11.173**
30	85.80	78.82	**8.856**
35	92.74	89.34	**3.806**
40	95.86	94.44	**1.504**

is explained by the ability of the autoencoder to learn a compact, data-driven representation of the full channel matrix, bypassing the quantization granularity and codebook mismatch inherent to fixed RI-PMI-CQI reporting.

C. Error Vector Magnitude

In addition to the throughput metric, the EVM is evaluated during the simulations. EVM plays a fundamental role in the design of reliable 5G systems, as it quantifies the impact of various impairments on the received signal. Lower EVM values indicate higher signal fidelity and improved transmission quality. Fig. 4 illustrates EVM performance as a function of SNR for RI-PMI-CQI and the proposed autoencoder-based CSI feedback for one layer during the simulation. The curves represent the mean EVM and the shaded regions indicate the variability range between the 5th (P5) and 95th (P95) percentiles, which contain the central 90% of the measured EVM values. At low SNR points ($\mathrm{SNR} < 5dB$), the mean EVM is slightly lower under autoencoder-based scheme (29.92% against 34.73 at $5dB$). Within the range of 5 to 30 dB, EVM mean values showed minimal variation between both method. The peak variation occurs after 30 dB when RI-PMI-CQI yields higher EVM values compared to the autoencoder. The maximum EVM value measured at 35dB under RI-PMI-CQI is 23.50% against 3.44% for the autoencoder, this suggests that the Type I codebook intermittently selects suboptimal precoders in certain transmission intervals, potentially when attempting higher-rank configurations with insufficient angular resolution. In contrast, the autoencoder does not exhibit this limitation, as its precoder is derived from the full channel information via SVD. The overall variability, as indicated by the P5–P95 range, is lower for the autoencoder than for the RI-PMI-CQI scheme, suggesting more stable and reliable performance of the proposed autoencoder-based method. Table VI summarizes the statistical comparison of EVM values for the two employed CSI feedback methods.

D. Uplink Feedback Overhead

The uplink feedback overhead differs substantially between the two schemes. The conventional RI-PMI-CQI report, configured with Type I Single-Panel codebook (8 CSI-

TABLE VI: EVM Statistics Comparison Between Autoencoder-Based and RI-PMI-CQI Feedback Schemes

	Autoencoder (%)					**RI-PMI-CQI (%)**				
SNR (dB)	**Mean**	**Median**	**P5**	**P95**	**Max**	**Mean**	**Median**	**P5**	**P95**	**Max**
-5	29.92	28.78	24.08	38.08	38.84	34.73	34.63	33.82	35.91	36.46
0	18.61	18.17	14.73	23.09	23.53	20.69	20.68	19.98	21.44	21.99
5	11.44	11.20	8.81	14.49	14.96	11.87	11.83	11.45	12.34	12.61
10	8.15	7.58	5.48	12.43	13.69	7.11	6.78	6.58	8.90	8.99
15	5.72	5.26	3.43	8.45	9.20	4.16	3.87	3.73	5.19	5.32
20	3.39	3.04	1.96	5.08	5.70	2.60	2.21	2.11	3.63	3.76
25	1.96	1.77	1.11	2.94	3.10	2.10	2.02	1.68	3.02	3.20
30	1.28	1.40	0.65	2.00	2.27	1.39	1.22	1.02	1.97	2.31
35	1.32	1.05	0.60	2.65	3.44	6.53	0.95	0.64	**22.81**	**23.50**
40	0.86	0.77	0.34	1.62	2.48	3.90	0.54	0.36	**14.14**	**14.67**

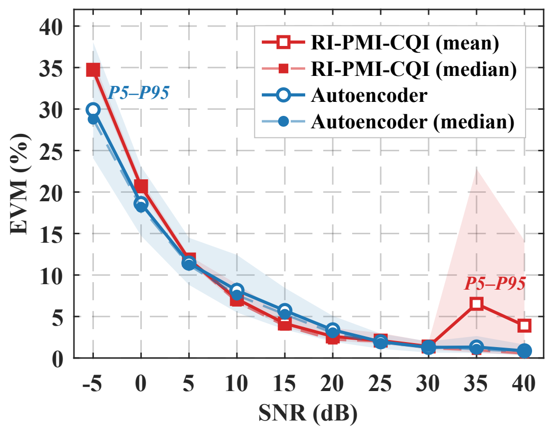

Fig. 4: EVM distribution as a function of SNR

RS ports, CodebookMode 1), subband PMI with subband size 4, and wideband CQI, requires approximately 41 bits per report (3 for RI, 8 for wideband PMI i_1, 26 for subband PMI i_2 across 13 subbands, and 4 for CQI). The Autoencoder-based CSI feedback transmits the compressed codeword of size 64 with 4-bit uniform quantization, totaling 256 bits per report. The overhead increased by a factor of 6.2, however, this result in a full channel representation enabling SVD-based precoding unconstrained by codebook granularity, yielding superior throughput and lower EVM value during the transmission.

IV. Conclusion

This paper proposes an autoencoder-based solution to address the CSI Feedback challenge in 5G MIMO systems, with potential extension to massive MIMO scenarios. We achieved an accurate CSI reconstruction at comparable compression ratio under a more challenging channel model when compared to the existing CsiNet family of works. Furthermore, the proposed method considered noise impact during the reconstruction providing a characterization that reflects practical systems. Throughput and EVM evaluation with the proposed solution in a link-level scenario demonstrates that autoencoder-based CSI feedback outperforms the conventional RI-PMI-CQI method in moderate to high SNR range, which corresponds to the majority of scheduled transmissions in 5G MIMO systems. This suggest a more efficient and reliable transmission under the autoencoder-based feedback in spite of the uplink overhead increase by a factor of 6.2. The gain of autoencoder-based feedback in 5G systems is expected to be more expressive in massive MIMO context, when the high number of antennas make the use of the conventional method unfeasible, for future work, we suggest analyzing the solution under a higher number of antennas, which could reflects the complexity and dynamism of massive MIMO.

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