

AI-Driven Geometry-Aware Zero-Pilot Downlink Channel Prediction for Large Frequency Gaps in 5G

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Abstract—In frequency-division duplex (FDD) massive MIMO, the base station must constantly estimate the downlink (DL) channel from limited observations or rely on DL pilots and CSI feedback, both of which become increasingly costly as array sizes and bandwidths grow. Deep learning has recently shown that uplink-to-downlink predictors can be accurate when UL and DL bands are close in frequency, exploiting partial reciprocity between neighboring subbands. However, as the UL-DL gap widens, classical extrapolation and most existing neural predictors quickly deteriorate: small modeling errors in the frequency dependence of path gains and phases are amplified, while the underlying scene geometry remains largely unused. This paper considers an FDD setting with a 700 MHz UL-DL separation where UL and DL share the same propagation paths but exhibit significantly different complex gains. Channels are generated using the Sionna RT ray tracer, which provides per-path attributes, including interaction primitives with scene objects. Building on this, we propose a geometry- and path-type-aware DL predictor (GPA-DL) that constructs a scene graph whose edges carry rich ray-tracing features and explicit face/edge/corner labels, and processes it with a graph attention network to obtain a global geometry embedding. A transformer encodes the UL CFR, and UL tokens attend to the geometry embedding to predict the DL CFR without any DL pilots. We compare GPA-DL against a state-of-the-art CNN-based DL predictor within a 5G transceiver chain, evaluating bit error rate, block error rate, spectral efficiency, inference time, and power consumption. Numerical results on Sionna-based channels show that GPA-DL substantially improves reliability and spectral efficiency while reducing inference latency by more than an order of magnitude and slightly lowering power, pointing towards practical, pilot-free, environment-aware FDD cellular communication.

Index Terms—component, formatting, style, styling, insert

I. INTRODUCTION

Cellular networks such as 5G/6G and next-generation networks use frequency-division duplex (FDD) to support a large number of devices. Characteristics like high data rate, low latency, and high throughput are fundamental characteristics needed in cellular networks to support recent technologies. To achieve this, constant channel estimation is needed. The performance of FDD massive multiple-input multiple-output (MIMO) systems critically depends on accurate downlink (DL) channel state information (CSI) at the base station (BS). Unlike time-division duplex (TDD) systems, where uplink (UL) and DL share the same band and channels are same, preserving the reciprocity that can be directly exploited. Thus TDD can directly reuse either UL or DL channel estimation for other. But both uplink and downlink channel estimation are

done separately in FDD, and they require reference signals or pilot signals explicitly in both directions. DL channel estimation relies on DL pilots and UL feedback, resulting in substantial overhead that scales with the number of antennas and bandwidth [1]. This overhead becomes particularly severe in emerging 5G and 6G scenarios with large antenna arrays and rapidly varying environments [2], [3]. Recent work has shown that deep neural networks can infer DL CSI from UL CSI by learning the underlying mapping between neighboring UL and DL subbands in FDD systems [4], [5]. The key observation is that despite the frequency separation, UL and DL channels share common propagation paths, such as delays and angles of arrival/departure, while path gains exhibit frequency-dependent behavior. By exploiting this partial reciprocity, deep networks can perform DL extrapolation and significantly reduce or even remove [6] DL pilot and feedback overhead. Moreover, owing to reduced correlation, the extrapolation becomes complex when the difference in frequencies of UL and DL is large. However, most existing approaches assume relatively small UL-DL separations (e.g., within a few hundred megahertz), use abstract stochastic channel models, and limit their robustness when the frequency gap is large, or the environment exhibits strong geometric structure.

A. Pilot- and Feedback-Heavy FDD CSI Acquisition

In FDD massive MIMO, obtaining accurate DL CSI at the BS traditionally relies on explicit DL pilots and uplink feedback, and the required overhead grows at least linearly with the number of BS antennas. As antenna arrays scale up in 5G and beyond-5G systems, the number of DL pilot symbols needed for conventional least-squares estimation becomes unaffordable, consuming a significant fraction of time, frequency resources, and transmit energy [7]. Moreover, each user must estimate its DL subchannels and feed them back to the BS, so the feedback payload is proportional to the CSI dimension and thus explodes with large arrays and wideband channels. A large body of work has focused on compressive sensing, optimized pilot design, and CSI feedback compression to mitigate this burden [8], [9], but these schemes still require non-negligible DL training and uplink signalling, and their performance degrades as the number of paths grows.

B. AI-Based DL Channel Estimation

To alleviate feedback overhead, deep learning-based DL channel prediction has emerged as a promising alternative for

FDD massive MIMO. Authors in [1] showed that a neural network can extrapolate DL CSI from UL CSI in adjacent bands with no extra DL pilot or reporting overhead beyond TDD-like uplink training, achieving performance close to systems with perfect CSI on both simulated channels and real massive MIMO measurements. Others further leveraged convolutional and generative models to transfer environment information from UL to DL, again assuming relatively small frequency separations where UL and DL remain strongly correlated [10], [11]. Deep transfer learning-based methods also attempt to reuse trained models across scenarios and carrier frequencies but typically still operate on grid-like CSI tensors and are validated for moderate gaps around a few hundred megahertz [12]. Despite removing explicit DL pilots or feedback, these data-driven UL to DL schemes still have several limitations for next-generation systems. First, most works consider modest UL and DL separations and report significant degradation as the frequency gap increases, since purely data-driven models struggle to learn the highly non-linear frequency dependence of path gains without a stronger structure. Second, they treat the channel as an abstract matrix and seldom exploit explicit geometric information or high-fidelity ray-tracing models; the shared propagation environment is implicit in the CSI, not modelled as a structured object. Third, they do not distinguish between different signal-to-obstacle interaction mechanisms (e.g., diffuse reflection on faces, edge diffraction, and corner scattering), even though these mechanisms can respond very differently to large frequency offsets and strongly affect the UL-DL correlation structure.

C. AI-Based & Ray-Tracing-Modelled Channel Estimation

To improve model accuracy in real-world deployments, ray tracers are used to simulate channels and perform channel estimation. Parallel to DL prediction, there is a rich literature on AI-assisted channel estimation and CSI compression using learned encoders/decoders for CSI feedback [13]. A variety of site-specific ray-tracing tools—such as Wireless InSite, WinProp, and QuaDRiGa [14] have been widely adopted to simulate realistic multipath channels for 5G/6G network planning, coverage analysis, and system-level evaluation. Some ray tracing-based datasets, such as DeepMIMO [15] and newer digital twin platforms [16], integrate realistic 3D geometry, materials, and protocols to create physically grounded testbeds for wireless learning. These environment-aware approaches use complex and computation heavy image analysis. Moreover, signals react differently to various interaction; they reflect from obstacle faces, diffract from edges, and scatter from corners [17], [18]. Existing UL-aided DL prediction methods do not process environment scenes to extract material information and interaction types to obtain DL CFR. Based on our studies, we observed gaps in current research,

- *Dependence on DL pilots and feedback:* Conventional channel estimation and AI-based CSI compression still require dedicated DL pilots and CSI feedback, whose overhead and energy consumption grow with antenna count and bandwidth.

- *Small UL-DL frequency gap:* Existing AI-based UL to DL prediction methods usually target modest offsets (tens to a few hundred megahertz), and their performance degrades as the frequency separation increases, limiting applicability to widely separated FDD bands in the future.
- *Environment geometry processing:* Many works operate directly on grid-like CSI tensors and ignore explicit 3D geometry, scatterer locations, or path interactions when such information is available from ray tracing models.
- *Signal-obstacle interaction:* Prior neural predictors do not distinguish between diffuse reflections on surfaces, edge diffraction, and corner scattering, despite these mechanisms having different frequency dependence and impact on UL-DL correlation.

Based on these issues, we propose DL prediction such that,

- *Zero-pilot DL CFR prediction:* We propose a completely pilot-free DL CFR prediction framework that uses only UL pilots and scene information, eliminating DL pilot transmission overhead.
- *Large UL-DL frequency gap (700 MHz):* We explicitly study an FDD scenario with a 700 MHz separation, where UL and DL share propagation paths but exhibit significantly different gains and phases, pushing DL prediction into a more realistic and challenging regime.
- *Environment geometry processing:* Using Sionna RT, we build a scene graph with BS, UE, and obstacles as nodes and multi-hop paths as edges, where each edge carries rich per-path features (delay, Doppler, angles, gains). A graph attention network ingests this path-type-aware graph, learning attention patterns. Using scene information introduces knowledge about attenuation factors with the degree of attenuation due to each object.
- *Signal-obstacle interaction:* We process the signal paths in the dataset to identify a face, edge, or corner and add an interaction type feature while training.

The rest of the paper describes the network and highlights the issues in DL and what we aim to solve in section II. Further, we discuss our proposed solution and model architecture in section III. We shortly discuss the simulation setup and implementation details in section IV, followed by an in-depth analysis of performance evaluation in section V. We conclude our paper in section VI with a highlight on future work.

II. PROBLEM STATEMENT

We consider a single-cell FDD massive MIMO system with a base station (BS) equipped with M antennas and a user equipment (UE) with N antennas, operating over an OFDM waveform with K subcarriers. Let f_{UL} and $f_{DL} = f_{UL} + \Delta f$ denote the center frequencies of the uplink (UL) and downlink (DL) bands, respectively, with $\Delta f \approx 700$ MHz in our setup. The complex UL channel frequency response (CFR) between BS antenna m and UE antenna n at subcarrier k is denoted by $\mathbf{H}_{UL}^{(m,n)}[k]$, and corresponding DL CFR $\mathbf{H}_{DL}^{(m,n)}[k]$. Stacking all antenna pairs yields the UL and DL CFR tensors,

$$\mathbf{H}_{UL} \in \mathbb{C}^{M \times N \times K}, \mathbf{H}_{DL} \in \mathbb{C}^{M \times N \times K} \quad (1)$$

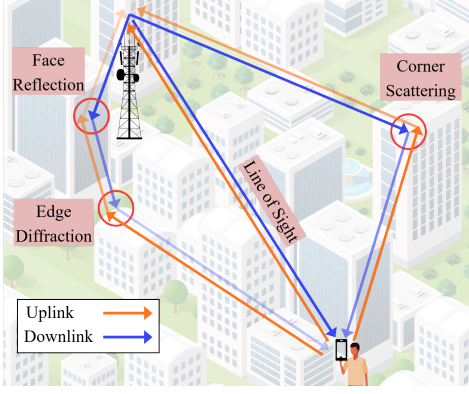


Fig. 1: Uplink and downlink transmission between base station and mobile device with signals facing attenuation and fading after deflections such as diffraction and reflection due to the face, edge, and corners of obstacles.

In FDD systems the physical propagation environment (scatterers, paths) is shared between UL and DL (as shown in Fig. 1), but the complex path gains generally differ due to frequency-dependent material responses and array responses, leading to only partial reciprocity between $\mathbf{H}_{UL}$ and $\mathbf{H}_{DL}$. We assume that standard UL pilots are transmitted, so that the BS has access to (an estimate of) $\mathbf{H}_{UL}$, while no DL pilots nor DL CSI feedback are used for acquiring $\mathbf{H}_{DL}$. Moreover, we also assume that the angles of arrival and departure are the same at all array elements due to small antenna size. The goal is to infer $\mathbf{H}_{DL}$ directly from UL and scene information, thereby removing DL pilot and feedback overhead. We specifically deal with in-band communication with shared paths of uplink and downlink, which may make limited delay resolution inefficient for multipath resolution, but our scope is to extrapolate paths with maximum gain, so that the received signal is easily and correctly demodulated.

A. Ray-Tracing-Based Shared Paths Channel Representation

To model the propagation environment, we use a site-specific ray-tracing engine (Sionna RT) that simulates radio propagation in a 3D scene $\mathcal{S}$, composed of BS, UE, and a set of obstacles with frequency-dependent material properties. For a given BS-UE pair, Sionna RT provides a set of propagation paths $\mathcal{P} = \{p_1, p_2, \dots, p_P\}$ that are common to UL and DL, each path being characterized by frequency-independent geometric parameters and frequency-dependent complex gains.

For path p , let τ_p denote delay, $\phi_{p,AoA}, \phi_{p,AoD}$ the azimuth/elevation angles of arrival and departure, and $g_p(f)$ the complex path gain at frequency f . Under a standard ray-tracing model, the UL and DL CFR's are [3],

$$\mathbf{H}_{UL} = \sum_{p=1}^P g_p(f_{UL}) \delta(t - \tau_p), \quad (2)$$

$$\mathbf{H}_{DL} = \sum_{p=1}^P g_p(f_{DL}) \delta(t - \tau_p) \quad (3)$$

Thus UL and DL share the same set of paths $\{\tau_p, \phi_{p,(AoA/AoD)}\}$, but differ in the complex gains $g_p(f_{UL})$ and $g_p(f_{DL})$ [19]. Crucially, we also consider per-interaction primitives describing how each ray interacts with obstacles, including specular reflection on faces, diffraction around edges, and scattering or diffraction at corners. We encode each path p with a discrete interaction type, $t_p \in \{\text{face}, \text{edge}, \text{corner}\}$, plus its 3D interaction points and normals extracted from the ray-tracing output. These labels capture dominant physical mechanisms that exhibit distinct frequency dependence and hence influence how strongly UL and DL CFRs correlate for each path.

B. Geometry-Aware Zero-Pilot DL CFR Prediction Problem

Let $\mathcal{G}$ denote a structured representation of the scene geometry and paths for a given BS-UE pair, such as a scene graph whose nodes correspond to BS, UE, and obstacles, and whose edges correspond to multi-hop propagation segments annotated with per-path features (delay, Doppler, angles, gains) and interaction type t_p . In deployment, we assume that:

- The BS has access to UL CFR $\mathbf{H}_{UL}$ estimated from UL pilot signals.
- The 3D scene geometry $\mathcal{S}$ and associated graph representation $\mathcal{G}$ are available (e.g., from a digital twin or precomputed ray-traced model). We assume that the scene is static, the BS is located in a predefined location, and the UE takes multiple locations.
- No DL pilots or DL CSI feedback are used for the current channel realization.

The learning objective is to find a predictor f_θ , parameterized by θ such that, $\hat{\mathbf{H}} = f_\theta(\mathbf{H}, \mathcal{G})$ and $\hat{\mathbf{H}}_{DL}$ closely approximates the true DL CFR $\mathbf{H}_{DL}$. Given a training dataset $\mathcal{D} = \{(\mathbf{H}_{UL}^i, \mathcal{G}, \mathbf{H}_{DL}^i)\}_{i=1}^N$ generated by Sionna RT for multiple BS-UE positions in the same scene, we formulate the problem as minimizing an expected loss,

$$\min_{\theta} \mathbb{E}_{(\mathbf{H}_{UL}, \mathcal{G}, \mathbf{H}_{DL})} [\mathcal{L}(\mathbf{H}_{DL}, f_\theta(\mathbf{H}_{UL}, \mathcal{G}))], \quad (4)$$

where $\mathcal{L}(\cdot)$ is a suitable complex-valued distortion measure, e.g., a combination of element-wise l_1/l_2 loss and normalized MSE over antennas and subcarriers. The environment geometry obtained from scene information is taken from the operator-fed scenes and not the images taken over time. Thus, geometry processing and path extraction is a one-time effort rather than repeated image processing overhead.

III. PROPOSED SOLUTION

We propose a geometry- and path-type-aware DL predictor (GPA-DL) neural architecture that predicts the downlink CFR $\mathbf{H}_{DL}$ from the uplink CFR $\mathbf{H}_{UL}$ and a ray-tracing-based scene description $\mathcal{G}$, without any DL pilots or DL CSI feedback. The model explicitly exploits that UL and DL share propagation paths in an FDD system, while their complex gains differ due to the large frequency separation. An important point to highlight is that the ground truth of DL signals using pilots is used for training, but inference uses only UL information. This makes sure that when this pretrained model is deployed

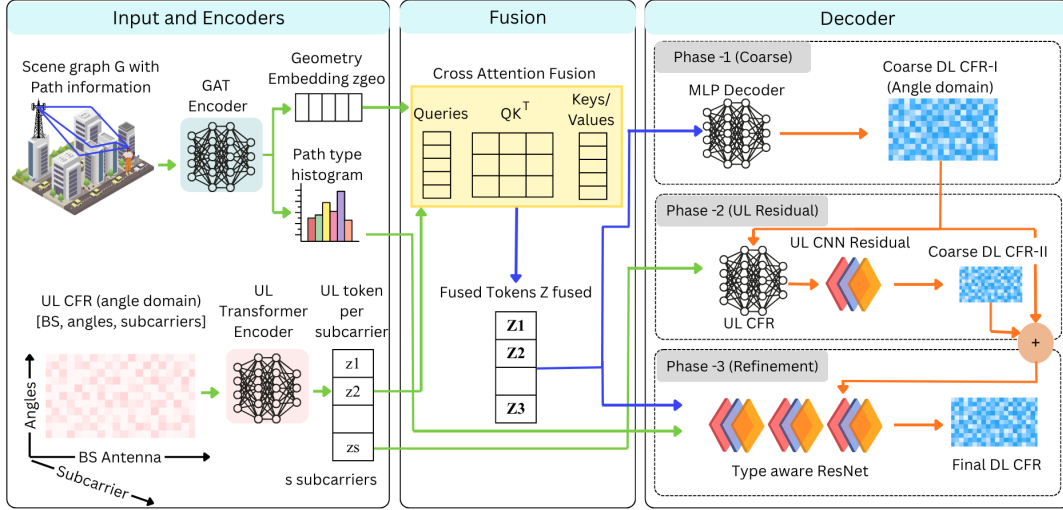


Fig. 2: Proposed geometry- and path-type-aware UL to DL downlink CFR prediction architecture

in a real environment, the DL pilot signals are not used and the predicted DL channel is purely based on zero-DL-pilot signals. The overall pipeline, as shown in Fig.2 has 3 components,

A. Path-type-aware geometry encoder

Using Sionna RT, we build a scene graph with nodes for BS, UE, and obstacles, and edges corresponding to multi-hop propagation segments enriched with per-path attributes (delay, Doppler, angles, gain) and a discrete interaction type label (face, edge, corner). A graph attention network with edge features encodes this graph into a global geometry embedding z_{geo} , and we also compute a global histogram of path types that summarizes the fraction of face/edge/corner paths.

B. UL CFR encoder and UL-geometry fusion

The UL CFR is transformed into the angular domain along the BS antenna dimension and treated as a sequence of per-subcarrier tokens, processed by a transformer encoder. A cross-attention block then lets these UL tokens attend to the geometry embedding z_{geo} , producing fused per-subcarrier features that jointly reflect UL observations and scene structure.

C. Three-phase DL CFR decoder

A shared MLP first maps the fused features to a coarse DL CFR estimate. A lightweight 1D CNN adds a UL-driven residual that captures local frequency-domain morphology between UL and DL. Finally, a 2D ResNet refines the DL CFR, with its feature maps modulated by the global face/edge/corner histogram via Feature-wise Linear Modulation (FiLM), so that face-dominated, edge-dominated, and corner-dominated links are corrected differently under a large UL-DL frequency gap.

IV. IMPLEMENTATION

DL prediction using geometry and path-aware DL (GPA-DL) CFR predictor is implemented using a ray tracing-based Sionna-generated dataset using parameters in Table I. This

TABLE I: Simulation parameters

Parameter	Value
Scene / environment	Sionna-RT Munich 3D urban
BS antennas	1×4 planar array (TR 38.901 pattern)
UE antennas	1
UL carrier frequency f_{UL}	28 GHz
DL carrier frequency f_{DL}	28.7 GHz (≈ 700 MHz gap)
FFT size / subcarriers	128
Subcarrier spacing	30 kHz
OFDM symbols per slot	12
Number of UE positions	10000
PUSCH PRBs	16
Target Eb/N0 for SE/BLER	10 dB

dataset is used for training our DL prediction model. Training uses PyTorch with AdamW and gradient clipping on a single GPU. We use 90% of the dataset for training and the remaining for testing and validation. For preprocessing, global UL and DL mean and std are estimated from a subset of samples and used for CFR normalization. Each batch contains UL CFR in the angle domain, DL CFR targets, UL delays, node/edge tensors for the scene graph, and global features; variable-size path sets are padded only along the path dimension. A complex MSE on normalized DL CFR + NMSE on denormalized CFR + a spectral-shape loss that enforces correlation across subcarriers. AdamW with a tuned learning rate and weight decay, and gradient norm clipping are used for optimization. After training, predicted and true DL CFRs on the validation set are saved as .npz files, converted to time-domain CIRs, and wrapped into objects in TensorFlow. These are plugged into Sionna's PUSCH chain to run BER, BLER, and spectral-efficiency simulations with: ground truth DL from ray-tracing, LMMSE DL from pilots; our predicted DL from GPA-DL with no DL pilots, and a CNN-based state-of-the-art model (SOTA-CNN) from [10].

V. RESULTS

We evaluate our proposed geometry and path-aware DL (GPA-DL) model and SOTA-CNN [10] baseline in a link-level

simulation based on Sionna RT ray-traced FDD channels with a 700 MHz UL-DL separation, using the same modulation, coding, OFDM numerology, and receiver processing for all methods. The SOTA-CNN has an implementation available online, which helped us to compare with our results. The True DL curve corresponds to perfect DL CSI, where the receiver is given the ground-truth ray-traced downlink CFR. The true DL refers to the perfectly ideal downlink channel that every channel estimator seeks to recover. It does not correspond to any specific model; rather, it is the actual downlink channel present in the environment that estimators attempt to predict to obtain a 100% accurate representation of the DL channel. GPA-DL and SOTA-CNN both operate in a zero-DL-pilot regime: only UL pilots are used to estimate, which is then fed to the respective predictor to obtain a DL CFR estimate that drives NMSE equalization and LDPC decoding. For each Energy per bit to Noise power spectral density ratio (E_b/N_0), we simulate many independent Sionna RT channel realizations and noise seeds and report average bit error rate (BER), block error rate (BLER), and spectral efficiency (SE), as well as average inference time and power consumption for 10 transmissions measured on the same hardware platform.

A. Reliability: BER and BLER Performance

We show the BER as a function of E_b/N_0 for True DL, GPA-DL, and SOTA-CNN in Fig. 3a. Across the entire SNR range GPA-DL significantly outperforms the CNN baseline: the GPA-DL curve has a much steeper slope and remains consistently closer to the True-DL curve, while SOTA-CNN exhibits a noticeably slower decay and high residual BER even at high E_b/N_0 . At moderate SNRs (e.g., around 8-12 dB), GPA-DL roughly halves the BER compared to SOTA-CNN, demonstrating that injecting geometry and path-type information translates into more reliable symbol decisions in the large-gap FDD regime. The BLER curves in Fig. 3b provide an even sharper picture. With perfect DL CSI, the system reaches very low BLER at moderate SNR; in contrast, SOTA-CNN remains essentially stuck near $BLER \approx 1$ across the tested E_b/N_0 range, indicating that its DL CFR predictions are too inaccurate to allow successful LDPC decoding under a 700 MHz separation. GPA-DL behaves markedly better: it still requires a higher E_b/N_0 than True DL to reach low BLER, but it shows a clear waterfall region and eventually achieves BLER well below 0.1 at the highest SNR point. This confirms that GPA-DL moves the system from an essentially “always failing” regime under SOTA-CNN to a practically usable reliability regime without any DL pilots. Higher BLER and BER are due to the urban environment with many obstacles.

B. Throughput: Spectral Efficiency

Spectral efficiency (bits/symbol) versus E_b/N_0 for the three cases is shown in Fig. 3c. As expected, True DL achieves the highest SE across all SNRs, serving as an upper bound. GPA-DL tracks this upper bound much more closely than SOTA-CNN: the SE gap between GPA-DL and True DL is moderate and tends to shrink with increasing E_b/N_0 , while

SOTA-CNN suffers from a substantial throughput loss at all SNRs. For mid-range SNRs, GPA-DL yields roughly 1-2 bits/symbol higher SE than SOTA-CNN, and at the highest SNR point, GPA-DL approaches the True-DL curve, whereas SOTA-CNN still lags significantly behind. These results indicate that more accurate DL CFR prediction from GPA-DL directly translates into higher spectral efficiency, enabling the system to harvest a larger fraction of the capacity that would be achievable with perfect DL CSI.

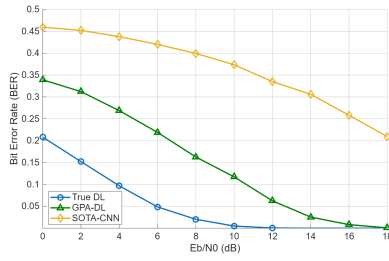
C. Computational Efficiency: Inference Time and Power

In addition to link-level performance, we compare the computational footprint of GPA-DL and SOTA-CNN in terms of per-sample inference time and power consumption. Figure 4a reports the corresponding power-consumption measurements. Both models operate in the same power range, but GPA-DL exhibits a slightly lower average consumption (about 5.47×10^4 mW) compared to SOTA-CNN (about 5.53×10^4 mW), together with a somewhat tighter distribution across runs. The inference-time box plot in Fig. 4b shows a dramatic difference: GPA-DL has an average latency of only $\mu \approx 0.037$ ms per channel realization, while SOTA-CNN requires about $\mu \approx 1.16$ ms on the same hardware, i.e., more than an order of magnitude slower. This large gap reflects the fact that GPA-DL’s three-phase architecture has been engineered for efficient tensor shapes and reduced overhead in the refinement stages, whereas the baseline CNN is relatively heavy in the channel-dimension convolutions. Combined with the power results, this shows that GPA-DL is not only more accurate but also more resource-efficient: it delivers higher BER/BLER/SE performance with lower inference time and marginally reduced power draw, making it more suitable for real-time deployment in next-generation FDD massive-MIMO systems with strict latency and energy constraints.

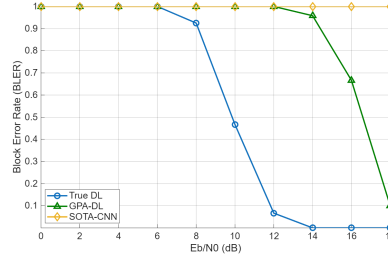
Overall, these results confirm that the proposed GPA-DL architecture substantially improves both reliability and efficiency over a strong UL-to-DL CNN baseline in a challenging large-gap FDD setting, validating the benefits of explicit geometry and path-type awareness in zero-pilot DL CFR prediction.

VI. CONCLUSION

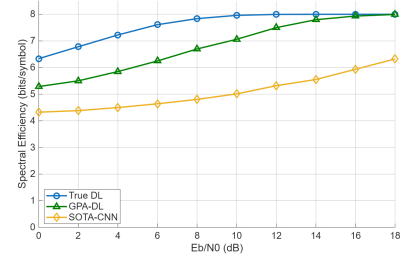
This paper introduced a geometry- and path-type-aware neural architecture for zero-pilot downlink CFR prediction in FDD massive MIMO with large UL-DL frequency gaps, leveraging Sionna RT to expose shared paths and explicit face/edge/corner interactions that are ignored by existing UL to DL predictors. By combining a GAT-based scene encoder, UL-geometry cross-attention, and a three-phase CFR decoder with type-aware refinement, the proposed method improves DL prediction accuracy and reduces pilot and feedback overhead. After completion of ongoing simulations, we demonstrated gains in NMSE and spectral efficiency over state-of-the-art UL to DL prediction schemes in the challenging 700 MHz separation regime. Future work would extend the framework to multi-user and multi-cell scenarios, validating on measurement-based channels, and integrating the predicted DL



(a) Bit Error Rate

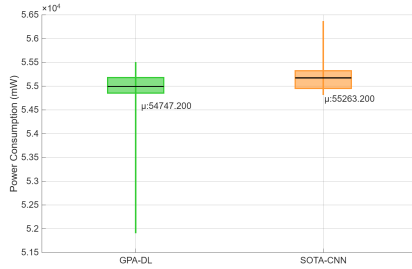


(b) Block Error Rate

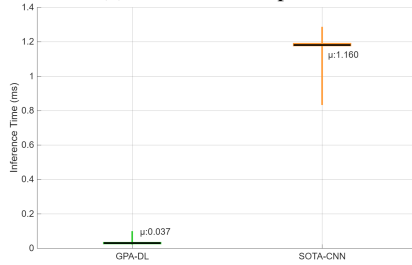


(c) Spectral Efficiency

Fig. 3: Performance evaluation in the Sionna end-to-end transmission chain using true and predicted CFRs for increasing energy bit-to-noise ratio.



(a) Power consumption



(b) Inference Time

Fig. 4: Performance evaluation of time and power consumption of AI models for the DL CFR prediction.

CFR into end-to-end link and network optimization tasks such as intelligent precoding. We plan to improve our models with a quantized model to improve complexity and energy efficiency.

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