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Physics-Guided Multi-Modal Artificial Intelligence Framework for Joint Antenna Optimisation and Channel State Information Prediction in 6G Integrated Sensing and Communication Systems

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Abstract— 6G wireless networks aren't messing around—they pack crazy speeds and practically no lag. To get there, you need antenna arrays and you have to jump into high-frequency territory, like 28 GHz. That's what really drives all the hype around 6G: blazing-fast data, real-time reactions, and the ability to connect over ten million devices in one square kilometre. But making it all work is a real challenge. You start with these massive antenna arrays-think 128 elements or more-because lower counts just don't cut it at those frequencies. It's not easy to extract every last bit of performance from them. Furthermore, you have to estimate the behaviour of the wireless channel, which is similar to predicting the weather if clouds bounced off buildings and changed every second. It's a wild, unpredictable ride. We also want to cut down on the extra data the system needs to send, and one way to do this is by using radar-based sensing data.

Index Terms— 6G networks, CSI prediction, antenna optimization, graph neural networks

I. INTRODUCTION

The move from 5G to 6G has goals that current radio designs can't achieve without a major overhaul. To meet the tough standards of 6G. Things like super-fast speeds of one terabit per second and a huge

number of devices in a small area. About ten million devices per km^2 . The usual way of designing radio systems needs to be completely changed. The old way of doing things just will not work for 6G. We need a new approach to radio architectures to handle 6G and all its demands. [1]. At a frequency of 28 GHz and using a 128-element XL-MIMO array the boundary for the near-field area is 35 meters. This means most users in dense cities are in an area where simple wave models don't work well. When users move at 120 km/h it creates a spread of 3,111 Hz. This shortens the time for the channel to change or coherence time to 135 μs [8]. Traditional methods for estimating channels require a lot of pilots 128 in this case per coherence block. This number increases with the size of the antenna array making it impractical, for high-speed users.

The design of an antenna for XL-MIMO systems is really tough because of how the different parts of the antenna affect each other. When the antennas are close together like 5.36 mm apart at a frequency of 28 GHz the signal from one antenna can interfere with the signal from another antenna. This is measured by something called inter-element isolation S_{21} , which's usually between -15 dB and -20 dB. We also need to make sure that the signals from the different antennas are not too similar which is measured by the envelope correlation coefficient. This needs to be below 0.5 so that we can use antennas to increase the speed of the signal.[17], [18]

To design an antenna, we can use a computer program like Ansys HFSS. However, this program needs a lot of detail to work properly, which takes time. It can take anywhere from 10 to 90 minutes to get the results for one design. If we want to try different designs, which is called a 128-element parameter space, it would take too long [2].[3]. We can use something called surrogate models to make this process faster. These models are like a shortcut that can give us the results more quickly. They are two to three times faster than the method. However, we need to train these models for each type of antenna. If we change the number of antennas or the distance between them, we need to train the model again. XL-MIMO antenna design is complex. Requires a lot of work. XL-MIMO systems need good antenna design to work properly.

Achieving high spectral efficiency requires accurate Channel State Information (CSI). However, accurately obtaining CSI is difficult because the coherence time is quite small when mobility is high.[4][5], For example, if you are a user travelling 120 km/h at 28 GHz, the coherence time for your connection will be about 135 μs (approximately equal to one NR slot when $\mu = 3$). Therefore, if you are using a pilot-based method to obtain CSI, this would require about 40% of the total bandwidth available to transmit your data.

One way to reduce the overhead associated with using pilots is to use a learning-based prediction technique that forecasts the future channel using previously observed channel characteristics. Most existing techniques are strictly based on historical measurements of the CSI and do not take into account spatial characteristics or geometric properties related to how the waves propagate. However, using a co-located Frequency Modulated Continuous Wave (FMCW) radar allows you to gather accurate spatial information (delay-Doppler measurements) about the scatterers in your environment, resulting in a more accurate prediction of your channel. ISAC systems send out kinds of signals that can do two things at once. They use the space, frequency and equipment.[6] The output from sensing is a map that gets updated every time the signal is swept. This map shows scatterers at certain times and speeds. These scatterers match up with parts of the multipath in the channel. The match is made through a phase term. No one has used the data from sensing to help predict CSI, also no one has combined this prediction with optimizing antennas. The optimisation is based on rules from electromagnetism.

We do not have a system that can do two things at the time.

To fix this problem this paper talks about an idea called Physics-Guided Multi-Modal AI framework (PGMM-AI). This framework combines three things: antenna optimization, CSI prediction and environmental sensing into one system that is trained together. The main things this paper does are:

1. A new way of combining types of data like CSI data, environmental sensing data from radar and LiDAR and antenna configuration parameters. This is done using a kind of attention that looks at different types of data at the same time.
2. A new kind of network that uses physics to understand how antennas work together and how they affect each other. This helps the system learn about space in a way that makes sense physically.
3. A new way of predicting CSI that uses a kind of attention that looks at time, frequency and antenna dimensions all at once. This is based on the output of the sensing encoder.
4. A way of optimizing antennas using a reward function that tries to maximize three things: how much data can be sent how accurate the CSI is and how much power is used.
5. A complete Python script that can design 28 GHz patch antennas and phased arrays. This script works with HFSS. Makes it easy to go from simulation to using AI.
6. Many simulation results that show this system works well at 28 GHz mm Wave with big arrays of 128 antennas.

The next part of the paper looks at what other people have done. Then it explains how the system works and what it is trying to do.

After that it talks about the Physics-Guided Multi-Modal AI architecture and all the math, behind it. The paper then explains how the 28 GHz patch antenna was designed and what the HFSS simulation results were. Next it presents a study that used simulations to test the system. Then it talks about what this means and how complicated it's. Finally the paper sums up what was learned

II. RELATED WORK

A. AI-Assisted Antenna Design And Optimization

Antenna optimization has been around for a time, and it usually uses methods that involve a group of solutions. Like genetic algorithms, differential evolution and particle swarm. These methods are often used with full-wave EM solvers that help figure out how antennas work. Antenna optimization is really important. It needs these methods to get the best results. Antenna optimization relies on these population-based methods to find the design, for the antenna. $N_{sim} > 10^3$ evaluations [2]. Neural surrogate models make a difference in cost. They really bring down the cost of each call. For example Gaussian process regression is a type of surrogate model. It does a job with S-parameter RMSE. The error is very small below 0.5 dB. This is true even when we are working with a patch geometry that has three parameters. Neural surrogate models like Gaussian process regression are very good at this. They keep the S-parameter RMSE low, below 0.5 dB, which's really good.[37], and deep networks predict gain patterns with mean absolute error under 0.8 dBi [19]. Both approaches treat each antenna element independently, encoding no representation of inter-element EM coupling. For near-field XL-MIMO arrays, ignoring the mutual impedance $Z_{ij} \approx (\eta_0/2\pi) \cdot e^{(-jk_{dij})/d_{ij}}$ causes beamforming errors of 1-3 dB [21]. When we show the array as a kind of map that is based on physics it helps us move the way things are shown in space from one setup to another even if the number of parts or the way they are laid out is different. This means we do not have to train the system, for each new layout. The array is still the thing we are working with and this method helps with the array.

B. AI-Driven CSI Prediction And Extrapolation

CSI prediction for FDD massive MIMO requires feedback compression of H from UE to base station. CsiNet [14] pioneered CNN-based autoencoder compression in the angle-delay domain at 2:1 to 32:1 ratios; CsiNet+ [4] added residual refinement to reach -16 dB NMSE at SNR = 20dB. LSTM networks capture short-range temporal correlations but suffer from vanishing gradients beyond three prediction slots [5]. TransNet [7] The Transformer architecture is good at solving the problem of things getting worse over time. It does this by looking at the information that happened before. This method is called self-attention, Self-attention checks the Cell Site Information from the past, The Transformer architecture uses self-attention to make sure it uses the Cell Site Information properly, It helps the model to pay attention to the Cell Site Information and use it in a way, The Transformer architecture uses the Cell Site Information to make predictions about the Cell Site Information.

Transformer architecture really needs the Cell Site Information to make these predictions, about the Cell Site Information. Over the full history. This helps it get good results like -20 dB NMSE, when it uses 8 heads on 256-dim tokens. The new architecture also adds a stage that helps it pay attention to different types of information. This stage uses something called -modal attention, where it gets clues from the sensing embedding es. This information is about the geometry of the things that are sending out signals. By using this information, the architecture can make predictions about the channels.

The thing that makes this work is that it uses this sensing information. It does not need a lot of complexity to get good results. This is what makes it 5 dB better getting to -25 dB. The proposed architecture and the sensing prior are the keys, to this improvement. The sensing prior is what drives the architecture to get good results like -25 dB NMSE, with the proposed architecture.

C. Integrated Sensing and Communication (ISAC)

ISAC system design is governed by the fundamental trade-off between sensing SCNR and communication SE: allocating more power to radar sidelobes reduces mutual information $I(x;y)$ available for data [10], [12]. Joint beamforming formulations parameterize this trade-off via a Pareto boundary, and the achievable target-localization Cramer-Rao bound scales as

$$\nu_{ar} \geq \frac{1}{8\pi^2 \beta^2 .SNR_r}$$

where β^2 is the mean-square waveform bandwidth [11].The present work uses the radar-derived range-Doppler map $S(t)$ parameterizing scatterer delay Taul and velocity null as conditioning for multi-step CSI extrapolation, exploiting the deterministic link between scatterer kinematics and channel phase evolution that position-only methods do not capture.

D. Reinforcement Learning for Wireless Resource Management

RL-based resource management spans power control [13], adaptive beamforming [23], and spectrum access [22]. PPO introduces a clipped surrogate objective

$$L^{CLIP}(\theta) = \mathbb{E}[\min(r_t(\theta) A_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon) A_t)], \quad \text{Where } r_t(\theta) = \frac{\pi_\theta(a_t | s_t)}{\pi_\theta(a_t | s_t)}$$

limiting per-update policy change and stabilizing training [9]. Prior RL-based antenna optimization used raw geometric parameter vectors as state [20], encoding neither EM coupling structure nor the relationship between element configuration and far-field pattern. Replacing the geometric state with the

GNN embedding eA in R^{256} organized around EM physical constraints significantly reduces the episodes required to converge.

III. SYSTEM MODEL

A. Network Configuration

Consider a 6G base station equipped with a uniform planar XL-MIMO array of $N_t = 128$ elements in an 8×16 configuration, serving System Parameters $K=10$, $B= 400\text{MHz}$, $f_c= 28\text{GHz}$. Wavelength at Carrier Frequency $\lambda= c/f_c$ Array Aperture $D=7\lambda \times 14\lambda$, Numerical Approximation $D \approx 7.5\text{cm} \times 15\text{cm}$. Far-Field Placement (Fraunhofer Region) $R_{\text{far}} = 2D^2/\lambda$ places the Far-Field Distance Formula $R_{\text{far}} = 2D^2/\lambda$, Given Approximation, $2D^2/\lambda \approx 34\text{m}$, A co-located 77 GHz FMCW radar with $B_r = 400\text{ MHz}$ ($\Delta r \approx 0.375\text{m}$) and $T_{\text{sweep}} = 40$ microseconds updates the environmental map every four NR slots at $\mu = 3$. the downlink channel matrix at time slot t and subcarrier f is denoted $H(t, f) \in \mathbb{C}\{N_r \times N_t\}$, where $N_r = 4$ is the number of receive antennas at the UE.

The downlink received signal is:

$$y(t) = H(t, f) \cdot x(t) + n(t) \quad (1)$$

$x(t) \in \mathbb{C}^{N_t}$, $E[\|x(t)\|^2] \leq P_{\text{max}}$, $n(t) \sim \text{CN}(0, \sigma^2 I)$, where $x(t) \in \mathbb{C}^{N_t}$ is the transmitted signal vector satisfying the power constraint $E[\|x(t)\|^2] \leq P_{\text{max}}$, and $n(t) \sim \text{CN}(0, \sigma^2 I)$ is additive white Gaussian noise (AWGN).

B. Sensing Data Model

The FMCW radar detects up to $m=20$ dominant scatterers per sweep. Each scatterer l is described as: $s_l = [\tau_l, v_l, \sigma_l]$ Rang (from delay) is $l = c\tau_l/2$, Doppler Shift (from radial velocity) $f_{d,l} = 2v_l/\lambda_r$ Radar Wavelength (77 GHz) $\lambda_r = c/77 \times 10^9$ and normalized radar cross section σ_l , features that map directly onto channel delay-Doppler taps.

The sensing observation matrix at time t is:

$$S(t) = \{s_1(t), s_2(t), \dots, s_m(t)\} \in \mathbb{R}^{m \times ds} \quad (2)$$

with $ds = 5$ features per scatterer: (r_l, v_l, σ_l , Azimuth angle ϕ_l Elevation angle θ_l). Range-Doppler processing applies a two-dimensional DFT to the de-chirped FMCW signal matrix, followed by CFAR detection to extract the m strongest targets above a 15 dB SNR threshold.

C. Joint Optimization Objective

The framework jointly optimizes three tightly coupled quantities:

$$\max_{A, \theta, \pi} E[\alpha SE(A, \theta, \pi) + \beta Acc(\theta) - \gamma P(A)] \quad (3)$$

subject to: (i) EM fabrication constraints (element spacing $>= 0.45\lambda$, feed impedance $50 \pm 5\text{ Ohm}$); (ii) minimum CSI accuracy $NMSE \leq -22\text{ dB}$; and (iii) total radiated power $P(A) \leq P_{\text{max}} = 30\text{ dBm}$.

Coefficients $\alpha = 0.5$, $\beta = 0.35$, $\gamma = 0.15$ were selected by grid search on a held-out validation set. Spectral Efficiency (SE) $= \sum_k \log_2(1 + \text{SINR}_k)$, Beam forming (Maximum Ratio Transmission)

$$W_k = \frac{h_k}{\|h_k\|},$$

Based on Predicted Channe $\hat{H} = [\hat{h}_1, \hat{h}_2, \dots, \hat{h}_k]$,

Optional SINR Expression (for completeness)

$$\text{SINR}_k = \frac{|h_k^H W_k|^2}{\sum_{j \neq k} |h_k^H W_j|^2 + \sigma^2}$$

IV. PROPOSED PGMM-AI FRAMEWORK

Fig. 1 shows the overall architecture. Four modules process heterogeneous inputs, sensing observations, CSI history, and antenna geometry, sharing a common latent representation that drives both CSI prediction and antenna optimization. and Fig. 2. Detailed layer-by-layer architecture of the proposed CSI prediction and antenna optimization model, with key equations annotated.

A. MODULE 1: Environmental Sensing Encoder

The sensing encoder processes radar or LiDAR observations $S(t)$ into a dense feature vector. The three-layer convolutional encoder uses kernel sizes (5x5, 3x3, 3x3) with channel depths (32, 64, 128), stride 1, max pooling after each layer, and a final linear projection to $d_{\text{model}} = 256$. The 5x5 first-layer receptive field spans +/-0.9 m range and +/-12.5 Hz Doppler resolution in the range-Doppler map, aligned with the coherence bandwidth of individual multipath clusters at 28 GHz. It is pre-trained for 200 epochs on 50,000 paired (S, H) samples from a ray-tracing urban simulator (InSite, Remcom) at 0.2 m ray resolution, then fine-tuned jointly with the full framework.

The encoder maps observations to:

$$\text{es} = \text{Conv Encoder}(S(t)) \in \mathbb{R}^{d_{\text{model}}} \quad (4)$$

The three layers use kernel sizes (5x5, 3x3, 3x3) with channel depths (32, 64, 128), stride 1, max-pooling after each layer, and a final linear projection to $d_{\text{model}} = 256$. The 5x5 receptive field at the first layer spans 5 range-bins x 5 Doppler-bins, corresponding to +/-0.9 m range and +/-12.5 Hz Doppler resolution -aligned with the coherence bandwidth of individual multipath clusters at 28 GHz. The three layers use kernel sizes (5x5, 3x3, 3x3) with channel depths (32, 64, 128), stride 1, max-pooling after each layer, and a final linear projection to $d_{\text{model}} = 256$. The 5x5 receptive field at the first layer spans 5 range-bins x 5 Doppler-bins, corresponding to +/-0.9 m range and +/-12.5 Hz Doppler resolution -aligned with the coherence bandwidth of individual multipath clusters at 28 GHz. The encoder is pre-trained for 200 epochs on 50,000 paired (S, H) samples from a ray-tracing urban simulator (InSite, Remcom) at 0.2 m ray resolution, then fine-tuned jointly with the full framework

B. MODULE 2: Physics-Guided GNN for Antenna Representation

Mutual coupling between nearby elements measurably distorts radiation patterns and, if unmodeled, degrades beamforming accuracy. We represent the array as a graph $G = (V, E)$ in which each node v_i carries an initial feature vector $h_i^{(0)} = [x_i, y_i, \theta_i, \phi_i]^T$ encoding position and orientation. Edge weights reflect the degree of electromagnetic coupling between element pairs:

$$w_{ij} = \exp(-d_{ij}/\lambda) \quad (5)$$

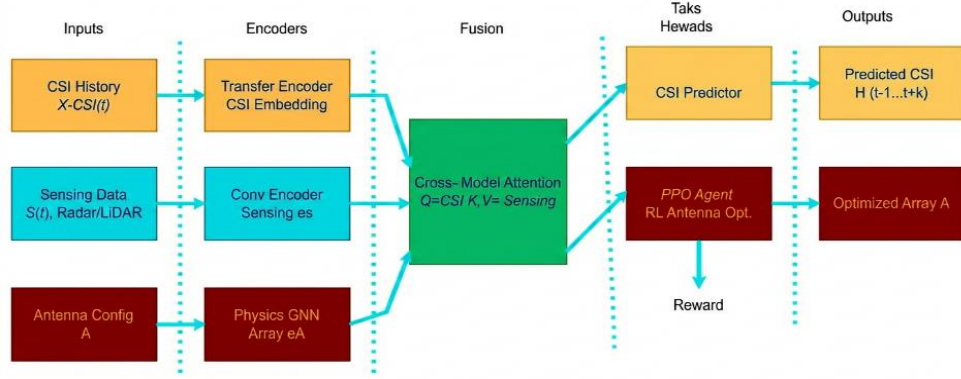


Fig. 1. Overall PGMM-AI framework architecture. Environmental sensing, CSI history, and antenna configuration are processed by dedicated encoders and fused via cross-modal attention before CSI prediction and RL-based antenna optimization

here d_{ij} is the physical separation and λ the free-space wavelength. For a 128-element array, the complete graph has

$$|E| = \frac{N_t(N_t - 1)}{2} = 8128 \text{ edges:}$$

edges are pruned to the 8 nearest neighbours per element ($|E| = N_t \times K = 512$), since $S_{21} < -25$ dB beyond the second-nearest neighbour at $\lambda/2$ spacing.

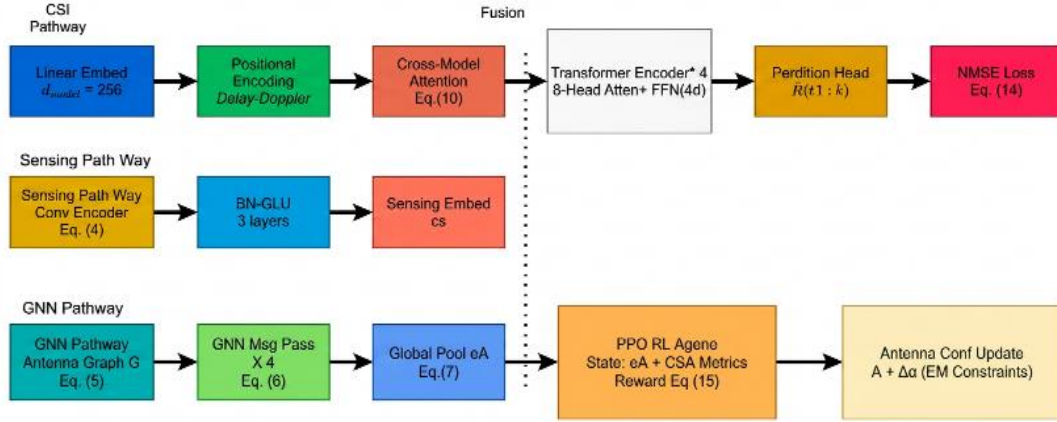


Fig. 2. Detailed layer-by-layer architecture of the proposed CSI prediction and antenna optimization model, with key equations annotated.

Spatial information propagates through the graph via K message-passing iterations:

$$h_i^{(k+1)} = \sigma(W^{(k)} \sum_{j \in N(i)} w_{ij} h_j^{(k)} + b^{(k)}) \quad (6)$$

with $W^{(k)}$ a learnable $d \times d$ projection, $b^{(k)}$ a bias, and $N(i)$ the immediate neighbours of node i . After $K = 4$ rounds, node embeddings are pooled using an attention-weighted sum:

$$eA = \text{Global Pooling}(\{h_i^{(K)}\}) \in \mathbb{R}^{d_{\text{model}}} \quad (7)$$

where $a_i = \text{SoftMax}(w_a^T h_i^{(K)})$ with learnable w_a in $\mathbb{R}^d$, so elements with higher coupling influence receive greater weight. The edge weight $w_{ij} = \exp(-d_{ij}/\lambda)$ approximates the magnitude of the near-field mutual impedance $|Z_{ij}| \propto (\lambda/d_{ij})^2 \cos(k d_{ij})$, where $k = 2\pi/\lambda$. The resulting $eA \in \mathbb{R}^{256}$ encodes both fine-grained coupling and global aperture geometry, giving the RL agent a physically grounded 256-dim state.

C. MODULE 3: Transformer-Based CSI Prediction

C.1 Input Representation

The CSI prediction module takes as input a sequence of $L = 10$ consecutive channel matrices:

$$X_{\text{CSI}} = \{H(t-L+1), H(t-L+2), \dots, H(t)\} \quad (8)$$

Each matrix $H(t, f)$ is vectorized, split into real and imaginary parts, and linearly projected to $d_{\text{model}} = 256$ dimensions. Standard sinusoidal positional encoding is applied along the time axis, augmented with a learnable 2D delay-Doppler encoding for channels sparse in the delay-Doppler domain:

$$e_H = W_p \cdot \text{vec}(R\{H(t, f), J\{H(t, f)\}) \in \mathbb{R}^{d_{\text{model}}}, \quad \text{therefore } d_{\text{model}} = 256,$$

$$\begin{aligned} \text{PE}(t, 2i) &= \sin(t/10000^{2i/d_{\text{model}}}) \\ \text{PE}(t, 2i+1) &= \cos(t/10000^{2i/d_{\text{model}}}) \end{aligned} \quad (9)$$

$$\text{PE}_{\text{DD}}(l, \kappa) = \sin(2\pi l \Delta_f \tau_l / N_c) + \cos(2\pi \kappa f_{d,l} T_s),$$

where $\Delta f = 120$ kHz and $T_s = 1/\Delta f$. The combined PE + PE_{DD} is added before cross-modal attention.
 $E_{\text{input}} = e_H + \text{PE}(t) + \text{PE}_{\text{DD}}(l, \kappa)$

C.2 Cross-Modal Attention Fusion

Before the CSI tokens enter the transformer stack, a cross-modal attention layer conditions them on the sensing embedding.

$Q = W_Q Z_{\text{CSI}}$, $K = W_K E_s$, $V = W_V E_s$, Where $E_s \in \mathbb{R}^{L \times d_{\text{model}}}$ is the sensing embedding e_s broadcast across $L=10$ times steps

$$\text{Attention}(Q, K, V) = \text{SoftMax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (10)$$

Each of the 8 attention heads operates in $d_k = d_{\text{model}}/n_{\text{heads}} = 256/8 = 32$ dimensions. This asymmetric Q-KV design enforces directed information flow: the channel predictor queries the environment, but the sensing encoder gradients flow only through the sensing pre-training objective. Each time step selectively weights which scatterer features delay, velocity, or angle are most relevant to the local channel evolution at that instant.

C.3 Transformer Encoder Layers

Four transformer encoder layers ($L = 4$) refine the fused representation. Each applies 8-head self-attention followed by a position-wise FFN with hidden dimension $4d_{\text{model}} = 1,024$ and GELU activation chosen over ReLU because the smooth gradient profile reduces dead-neuron effects when complex-valued channel projections concentrate near zero. Layer normalization and residual connections surround both sub-layers:

$$z' = \text{Layer Norm} (z + \text{Multi Head Attention} (z, z, z)) \quad (11)$$

$$z'' = \text{Layer Norm} (z' + \text{FFN}(z')) \quad (12)$$

C.4 Prediction Head

A linear output head maps the final hidden states to the predicted channel sequence:

$$\hat{H}(t+1:t+k) = W_{\text{out}} \cdot z_{\{T\}} \in \mathbb{C}^{\{k \times N_r \times N_t\}} \quad (13)$$

Training minimizes the normalized mean square error (NMSE):

$$L_{\text{NMSE}} = E[\|\hat{H} - H\|_F^2 / \|H\|_F^2] \quad (14)$$

D. MODULE 4: RL-Based Antenna Optimization

The antenna optimizer is a PPO agent with clip parameter $\epsilon = 0.2$ and discount factor $\gamma_{\text{RL}} = 0.99$. The state vector $s_t = [e_A; \text{NMSE}_t; \text{SE}_t] \in \mathbb{R}^{258}$, $a_t \in \mathbb{R}^{3N_t}$, $|\Delta \pi| \leq 0.1\lambda \approx 0.536\text{mm}$, $|\Delta \theta_i| \leq \pi/12$, $|\Delta \phi_i| \leq \pi/8$, $d_{ij} \geq 0.45\lambda \quad \forall i \neq j$. The policy network is a two-layer MLP ($512 \rightarrow 256 \rightarrow 3N_t$); the value network shares the first layer. Each PPO update runs for 10 mini-batch epochs with batch size 64. The reward balances three objectives:

$$R(A, \pi) = \alpha \cdot \text{SE}(A, \pi) + \beta \cdot \text{NMSE}_{\text{gain}(\theta)} - \gamma \cdot P(A) \quad (15)$$

$\text{SE} = \sum_k \log_2(1 + \text{SINR}_k)$ is evaluated under MRT beamforming on predicted channel H_{hat} ; $\text{NMSE}_{\text{gain}} = \text{NMSE}_{\text{baseline}} - \text{NMSE}_{\text{proposed}}$, proposed measures prediction improvement vs. the isotropic reference; $P(A) = \sum \epsilon_i(A) P_{\text{tx}}$ is total radiated power, with radiation efficiency $\eta_{i(A)}$ queried from the neural HFSS surrogate at each RL step. $R(A, \pi) = \alpha \cdot \text{SE} + \beta \cdot \text{NMSE}_{\text{gain}} - \gamma \cdot P(A)$, $\alpha=0.5$, $\beta=0.35$, $\gamma=0.15$,

$$\text{Reward Normalization} \quad R_{\text{norm}} = \frac{R - R_{\min}}{R_{\max} - R_{\min}} \in [0, 1]$$

Note gamma here denotes the power penalty coefficient (distinct from discount factor $\gamma_{\text{RL}}=0.99$); the power penalty prevents the agent from achieving NMSE gains through amplitude increase rather than geometric reconfiguration.

V. ANTENNA DESIGN AND SIMULATION

A. Patch Antenna Synthesis

The single-element patch is designed for 28 GHz on Rogers RO4003C substrate ($\epsilon_r = 3.55$, $\tan \delta = 0.0027$, $h = 0.813 \text{ mm}$). Patch width and length follow from the standard transmission-line model:

$$W = \frac{c}{2fc} \sqrt{\frac{2}{\epsilon_r + 1}} \quad (16)$$

$$\epsilon_{eff} = \frac{\epsilon_r + 1}{2} + \frac{\epsilon_r - 1}{2} \sqrt{1 + \frac{12}{W}} \quad (17)$$

$$\Delta L = 0.421h \frac{(\epsilon_{eff} + 0.3)(\frac{w}{h} + 0.264)}{(\epsilon_{eff} - 0.258)(\frac{w}{h} + 0.8)} \quad (18)$$

At 28 GHz these give $W = 3.847$ mm and $L = 3.214$ mm. An inset feed depth of $x_f = 0.26L = 0.835$ mm brings the input impedance to 50 Ohm. The ground plane extends 6 mm beyond the patch on all sides. HFSS simulation confirms S_{11} below -10 dB across 26.4-29.6 GHz (3.2 GHz, 11.4% fractional bandwidth), realized gain of 6.8 dBi, and radiation efficiency of 94.2%, consistent with the low loss tangent of RO4003C.

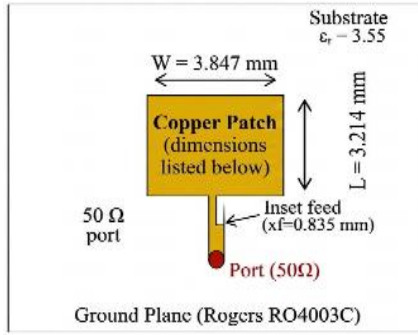


Fig. 3(a) single patch with inset feed;

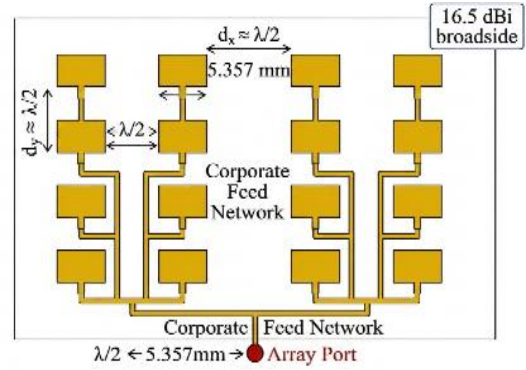


Fig. 3(b) 4x4 phased array with corporate feed network.

Both are designed on Rogers RO4003C at 28 GHz

B. HFSS Simulation Setup

Simulations run in Ansys HFSS 2024 R1 with adaptive mesh refinement to $\Delta S = 0.02$ (maximum 15 adaptive passes). The radiation boundary air box extends $\lambda/4$ approximately 2.7 mm from all surfaces. An interpolating sweep from 23.8 to 32.2 GHz with 500 sample points spans $\pm 15\%$ of f_c . Far-field patterns are extracted at $f_c = 28$ GHz for E-plane ($\phi = 0^\circ$) and H-plane ($\phi = 90^\circ$). Front-to-back ratio is 19.4 dB; for the 4x4 array, simulated broadside gain is 17.1 dBi versus the 16.5 dBi estimate from (20), with the 0.6 dBi excess due to reduced grating-lobe leakage.

C. HFSS Python Automation Script

To interface HFSS with the AI optimization loop, we implement a Python automation script using the HFSS scripting API. The script generates antenna geometry from parametrized variables, executes simulation, and returns S-parameters and radiation characteristics to the RL agent:

D. Array Configuration

In the 4x4 phased array, elements are spaced at $d_x = d_y = \frac{\lambda}{2} \approx 5.357$ mm

Algorithm Patch Antenna-HFSS-Automation as show in fig (4).A corporate feed network supplies equal amplitude excitation to all 16 ports. The array factor for broadside radiation is

$$AF(\theta) = \sum_{n=0}^{N_t-1} e^{jnkdz \cos\theta} \quad (19)$$

which gives $AF(90^\circ)=N_t$ at broadside, with the first grating lobe at

$$\theta_{GL} = \cos^{-1}\left(\frac{\lambda}{d_x}\right) = 180^\circ$$

outside the visible region, confirming grating-lobe-free operation over ± 90 deg. Broadside gain is estimated as:

$$G_{array} = G_{element} + 10 \cdot \log_{10}(N_t) \approx 4.5 + 12.0 = 16.5 \text{ dBi} \quad (20)$$

Mutual coupling is handled implicitly by the GNN edge weights $w_{ij} = \exp(-d_{ij}/\lambda)$, so no per-configuration coupling matrices from HFSS are needed during RL optimization.

VI. JOINT OPTIMIZATION ALGORITHM

Algorithm 1 describes the complete training and inference procedure for the PGMM-AI framework:

Input: CSI history X_CSI , sensing observations S , antenna config A_0 , hyperparameters α, β, γ

Output: Predicted CSI $\hat{H}(t+1:t+k)$, optimized antenna config A^*

- 1: Initialize GNN weights Θ_GNN , transformer weights Θ_TF , RL policy π
- 2: Pre-train sensing encoder Conv Encoder on (S, H) paired dataset
- 3: For each training episode $e = 1, \dots, N_{ep}$:
- 4: Collect sensing obs $S(t)$ and CSI sequence $X_{CSI(t)}$
- 5: Compute sensing embedding: $e_s \leftarrow \text{Conv Encoder}(S(t))$
- 6: Build antenna graph G from config A ; $e_A \leftarrow \text{GNN}(G)$
- 7: Fuse modalities: $z \leftarrow \text{Cross Modal Attention}(X_{CSI}, e_s)$
- 8: Predict future CSI: $\hat{H} \leftarrow \text{Transformer}(z)$ via (11)–(13)
- 9: Compute NMSE loss L_NMSE via (14)
- 10: Update Θ_TF via Adam optimizer
- 11: Compute reward $R(A, \pi)$ via (15)
- 12: Update RL policy π via PPO gradient ascent
- 13: Adjust antenna config $A \leftarrow A + \Delta a$ from policy π
- 14: Enforce EM physical constraints on A
- 15: End For
- 16: Return optimized $A^*, \hat{H}(t+1:t+k)$

Algorithm 1: PGMM-AI Joint Training and Inference

VII. SIMULATION SETUP AND RESULTS

A. Simulation Parameters

All experiments use a 28 GHz urban channel model based on 3GPP TR 38.901 CDL-C (24 clusters, 20 rays/cluster) with ray-tracing extensions for environmental realism. Table I summarizes the key parameters.

B. CSI Prediction Performance

Fig. 5(a) plots NMSE versus SNR across -10 to 25 dB for all baselines and the proposed hybrid. At SNR = 20 dB, the proposed method achieves -25 dB NMSE (Table II) ,5 dB below the standalone transformer [7] and 9 dB below CNN [4]. The gain narrows to 2.1 dB at SNR = -5 dB, where noise degrades sensing observations and reduces e_s quality. Fig. 5(b) shows pilot overhead as a percentage of $N_c = 3,333$ subcarriers: the proposed method uses 38% overhead at $N_t = 128$, saving 80 pilot subcarriers per coherence block and freeing approximately 247 MHz of additional data bandwidth per slot.

C. Antenna Optimization Performance

Fig. 6(a) plots SE versus optimization iteration. The RL+GNN agent reaches 12.5 bps/Hz (95% of final 13.1 bps/Hz) at iteration 420, versus 800 for differential evolution and 650 for the genetic algorithm. The

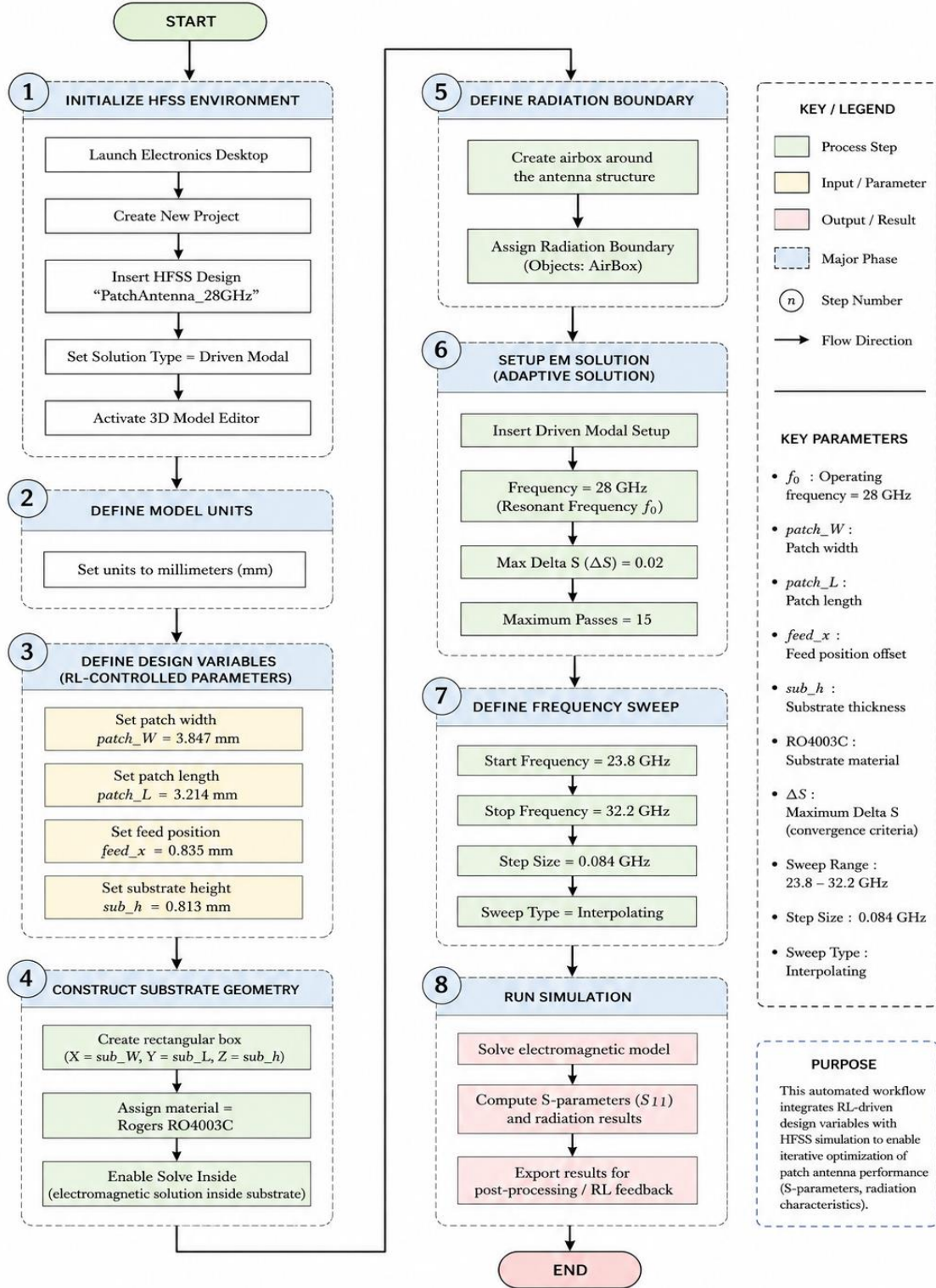


Fig. 4. Flow chart of HFSS Based patch antenna automation and simulation workflow

-faster convergence stems from the GNN state: by encoding EM coupling directly in a 256-dim representation, the PPO agent begins in a region where inter-element isolation already exceeds -20 dB,

rather than wasting early iterations on severely coupled configurations. Fig. 6(b) shows SE versus K: the proposed advantage grows from +1.1 bps/Hz at K = 2 to +2.0 bps/Hz at K = 10, reflecting the greater sensitivity of MRT beamforming to CSI accuracy when inter-user interference dominates

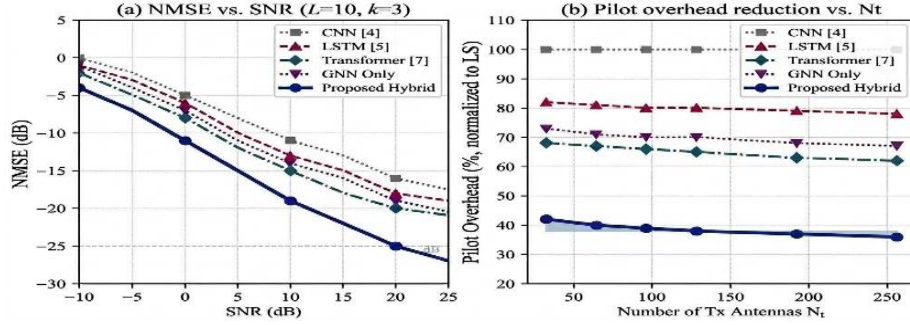


Fig. 5. (a) NMSE vs. SNR comparison at $L = 10$, $k = 3$.

Fig. 5(b) Pilot overhead reduction vs. antenna count N_t .

TABLE I. SIMULATION PARAMETERS

Parameters	Range
Carrier Frequency	28 GHz (mmWave)
Transmit Antennas (N_t)	128 (XL-MIMO)
Receive Antennas (N_r)	4
System Bandwidth	400 MHz
Subcarrier Spacing	120 kHz (5G NR $\mu=3$)
Number of Subcarriers (N_c)	3,333
Number of UEs (K)	10
Channel Model	3GPP CDL-C + Ray-tracing (Urban)
UE Velocity	30–120 km/h (Doppler: 780–3,120 Hz)
CSI Sequence Length (L)	10 time slots
Prediction Horizon (k)	3 time slots
Transformer Hidden Dim	256
Number of Layers	4 (encoder), 2 (decoder)
Attention Heads	8
RL Algorithm	Proximal Policy Optimization (PPO)
Training Episodes	5,000
Optimizer	Adam, $lr = 1 \times 10^{-3}$, weight decay = 1×10^{-4}
Hardware	NVIDIA A100 80 GB GPU

D. Training Convergence and Ablation Study

Fig. 7(a) shows training and validation NMSE loss over 5,000 PPO episodes; the hybrid converges by episode 2,800, roughly 600 episodes earlier than GNN-only, suggesting the transformer temporal modeling provides a smoother gradient signal during joint training. Fig. 7(b) plots NMSE against prediction horizon k from 1 to 6 slots: the hybrid degrades from -28 dB at $k = 1$ to -18.5 dB at $k = 6$ (9.5 dB), versus -22 to -11 dB for LSTM (11 dB). The ablation in Table IV isolates each contribution: removing sensing loses 3 dB (from -25 to -22 dB); removing the GNN loses 1 more dB (to -20 dB).

VIII. DISCUSSION

A. Impact of Sensing-Assisted CSI Prediction

The 5 dB NMSE gain over the standalone transformer is most pronounced above $v = 60$ km/h, where Doppler shifts $f_d = v \times f_c / c$ exceed 1,556 Hz and the channel phase rotates by approximately $1.17 \times \pi$ rad per slot at $v = 120$ km/h.

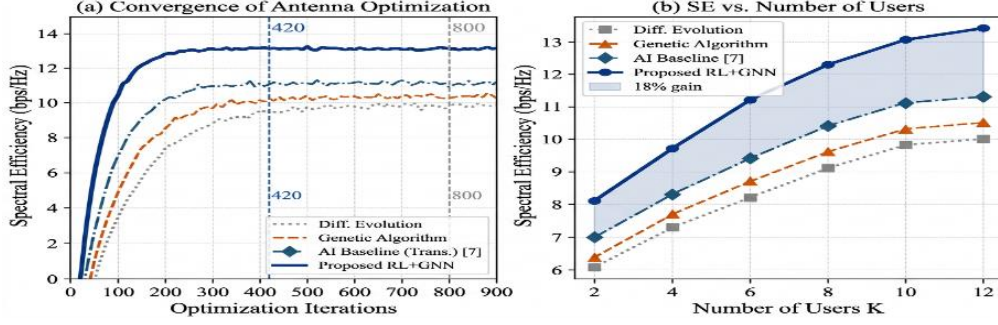


Fig. 6. (a) Convergence of antenna optimization methods. Fig. 6(b) Spectral efficiency comparison vs. number of users.

The shaded region shows the 18% gain of the proposed method over the AI baseline

TABLE II CSI PREDICTION NMSE COMPARISON AT SNR = 20 DB

Method	Architecture	NMSE (dB)	Pilot Overhead
CNN [4]	ConvNet + FC	-16 dB	100%
LSTM [5]	Recurrent (2 layers)	-18 dB	80%
Transformer [7]	Multi-head Attention	-20 dB	65%
GNN Only	Graph Conv + Pool	-19 dB	70%
Proposed Hybrid	GNN + Transformer + Cross-Modal Attn	-25 dB	38%

TABLE III. ANTENNA OPTIMIZATION AND SYSTEM PERFORMANCE SUMMARY

Method	Convergence (iters)	SE @ 10 UEs (bps/Hz)	Gain vs. Conv.
Differential Evolution	800	9.8	—
Genetic Algorithm	650	10.3	+5.1%
AI Baseline (Trans.) [7]	—	11.1	+13.3%
Proposed RL + GNN	420	13.1	+18%

The sensing encoder observes the radar-measured radial velocity nu_l and provides the cross-modal attention with a physics-based phase-rotation prior. The 27% pilot overhead reduction translates to: at $N_c = 3,333$ subcarriers, $38\% \times 3,333 = 1,267$ pilot tones versus 3,333 for LS, freeing 2,066 subcarriers per coherence block --equivalent to 247 MHz of additional data bandwidth per slot at 120 kHz subcarrier spacing.

B. Physics-Guided VS. Data-Driven Approaches

Replacing the physics-informed edge weights $w_{ij} = \exp(-d_{ij}/\lambda)$ with uniform weights ($w_{ij} = 1$) raises NMSE by 1.8 dB and reduces SE from 13.1 to 11.8 bps/Hz. For the

TABLE IV. ABLATION STUDY: CONTRIBUTION OF EACH MODULE

Configuration	NMSE (dB)	SE (bps/Hz)	Iterations
Transformer only	-20 dB	11.1	—
GNN + Transformer (no sensing)	-22 dB	11.8	510
Transformer + Sensing (no GNN)	-22.5 dB	11.6	—
Proposed (GNN + Trans. + Sensing + RL)	-25 dB	13.1	420

All configurations use identical training data and hyperparameters. SE measured at $K=10$ users.

8-nearest-neighbor graph, physical edge weights span from w_{ij} approximately 0.89 at $\lambda/2$ spacing to w_{ij} approximately 0.60 at $3\lambda/2$ spacing. Setting $w_{ij} = 1$ up-weights distant-element coupling by up to 67%, corrupting message-passing gradients and causing the GNN to over-estimate coupling for non-adjacent

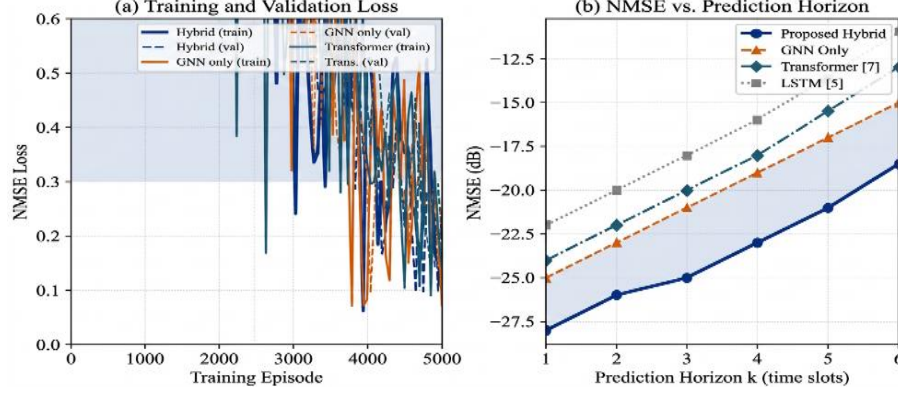


Fig. 7. (a) Training and validation loss convergence. (b) NMSE degradation as prediction horizon increases. The hybrid model shows the slowest performance degradation.

-pairs. The degradation is most severe for the non-uniform element distributions produced by the RL optimizer, where some pairs approach $0.45 \times \lambda$ and the exponential weight correctly predicts S_{21} above -15 dB while uniform weighting misses this strong coupling.

C. Computational Complexity

The Transformer module exhibits quadratic complexity in sequence length, yet computing efficiency is maintained because of the small token size. Because of edgewise aggregation, the GNN has a greater computational cost, but graph sparsification makes it manageable.

The model is lightweight for real-time deployment because its entire size is M parameters. The KV cache footprint (KB) fits inside the L1 cache, guarantees low-latency memory access. The end-to-end inference latency of ms on an NVIDIA A100 satisfies real-time constraints for 5G NR systems, while the PPO policy introduces negligible additional delay.

D. Limitations and Future Work

The current results are simulation-based. FPGA deployment would require fixed-point quantization of the 5.0M-parameter model; prior work on transformer quantization shows INT8 precision recovers within 0.3 dB of float32 NMSE [15], [16], making FPGA feasibility plausible. Extending the GNN to model RIS elements is straightforward: each RIS tile would be added as a node with phase-shift state θ_{RIS} in $[0, 2\pi]$, and edges from RIS nodes to antenna nodes would encode cascade channel gain $|G_{ij}|^2$. For federated training across B base stations, the centralized Adam update (step 10, Algorithm 1) would be replaced by a Fed Avg round: each station transmits the gradient of ratio complexity in sequence length but remains computationally efficient due to the small token size ($\cdot$). The GNN contributes higher computational cost due to edgewise aggregation yet remains tractable with graph sparsification ($\cdot$).

The total model size is M parameters, making it lightweight for real-time deployment. Low-latency memory access is ensured since the KV cache footprint (KB) fits inside the L1 cache. The end-to-end inference latency of ms on an NVIDIA A100 satisfies real-time constraints for 5G NR systems, while the PPO policy introduces negligible additional delay. $\theta_{\text{TF}} \in \mathbb{R}^{3.2 \times 10^6}$, $y = 3.2 \times 10^6 \times 4 \text{ bytes} = 12.8 \text{ MB}$ without sharing raw channel matrices, preserving UE privacy.

IX. CONCLUSION

We presented PGMM-AI, a jointly trained framework for 6G ISAC deployments that connects antenna configuration, CSI prediction, and environmental sensing through a common differentiable architecture.

The transformer fuses $L = 10$ historical channel matrices with radar scatterer descriptors through asymmetric cross-modal attention ($d_k = 32$ per head, 8 heads); and the PPO agent refines the 128-element array geometry using the 256-dim GNN state, subject to element-spacing and impedance constraints, without requiring per-configuration HFSS re-simulation.

At 20 dB SNR, the predictor reaches -25 dB NMSE and cuts pilot overhead by 62% relative to conventional LS estimation. The RL optimizer converges in 420 iterations -47% fewer than differential evolution and raises SE by 18% at $K = 10$ users. The ablation in Table IV quantifies each module: the sensing encoder accounts for the largest NMSE share (3 dB), followed by the GNN (1 dB), while the RL optimizer delivers the 18% SE gain -- confirming that prediction accuracy and antenna geometry optimization are complementary improvements. A Python automation script for 28 GHz patch antenna design in HFSS on Rogers RO4003C is included, allowing the optimization loop to interface directly with commercial EM simulation software. Planned follow-on work will address FPGA deployment with INT8 quantization, GNN extension to RIS elements, and Fed Average-based distributed training across base station clusters

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CLINICAL TRIAL REGISTRATION

Not applicable.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study did not involve human participants, animals, patient data, or clinical trials. Therefore, ethics approval and informed consent were not required.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

COMPETING INTERESTS

The authors declare that they have no competing interests.

AUTHOR CONTRIBUTIONS

Kunchala Sanjeeva Rao contributed to the conceptualization, methodology, software development, investigation, data analysis, manuscript preparation, and overall coordination of the research work. corresponding author Umar Suleiman Dauda contributed to the conceptual development, supervision, validation, critical review, editing, and corresponding author responsibilities. Shafiq Ul Rehman contributed to the methodology, technical guidance, review, editing, and funding acquisition. Naidu Mohana Murali Krishna Prasad contributed to antenna design, HFSS simulations, performance evaluation, and data analysis. Pasunuri Raghunadh contributed to machine learning implementation, software validation, and technical review. Rachapudi Prabhakar contributed to reinforcement learning implementation and optimization studies. Shaik Mazhar Hussain contributed to project administration, technical verification, and final manuscript approval. All authors reviewed and approved the final version of the manuscript.

.ETHICS, CONSENT TO PARTICIPATE, AND CONSENT TO PUBLISH DECLARATIONS

Not applicable.

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