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Machine Learning-Driven Meta Surfaces for Adaptive 6G Beamforming in Dynamic Terahertz Channels

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Abstract: The accelerated development of 6G networks necessitates innovative solutions to overcome the limitations of conventional beamforming techniques, particularly in highly mobile and densely obstructed environments. This paper presents a machine learning (ML)-based framework that synergizes intelligent meta surfaces (IMS) with reconfigurable antenna arrays to dynamically optimize beamforming in real time. The core challenge involves adapting to rapidly fluctuating terahertz (THz) channels while ensuring high performance and ultra-low latency. To address this, we propose a hybrid architecture leveraging deep reinforcement learning (DRL), for adaptive beamforming policy optimization and convolutional neural networks (CNNs) for real-time spatial feature extraction. The DRL agent maximizes spectral efficiency by learning optimal beamforming weights, while the CNN maps angle-of-arrival (AoA) and angle-of-departure (AoD) profiles to IMS configurations. Simulations conducted on a dataset of 1,000 channel realizations demonstrate a 93.6% beam alignment accuracy and a 41% reduction in latency compared to genetic algorithms. The framework achieves an impressive spectral efficiency of 14.2 bps/Hz at 140 GHz, with inference times under 5ms on a high-end GPU (e.g., NVIDIA A100) for 64×64 IMS arrays. These results highlight the potential of ML-driven meta surfaces to enable scalable, adaptive, and energy-efficient 6G systems. The study concludes by advocating standardized IMS interfaces and large-scale prototyping to accelerate commercial adoption. By bridging metamaterial advancements with practical network optimization, this work lays the foundation for next-generation wireless systems capable of supporting immersive and mission-critical applications.

Keywords: Intelligent meta durfaces (IMS), Terahertz beamforming, Deep reinforcement learning (DRL), Low-latency communications

Introduction

Evolution to Sixth Generation (6G) wireless networks introduces a technology transformation in telecommunications defined by stringent performance metrics beyond the capabilities of existing infrastructures. As described in the International Telecommunication Union's (ITU) white paper of 2023, 6G should deliver ultra-low latency below 1ms and have a probability of ultra-high reliability above 99.99% as well as seamless support for over 10^6 devices per km². These stringent performance requirements are requirements for emerging applications among them smart systems, tactile internet including smart systems, the tactile internet, and immersive extended reality, and immersive extended reality which are bound to have extremely stringent requirements in terms of instantaneous response and steadfast connectivity. In a dynamic 6G environment, however, the conventional beamforming systems which depend on static phased arrays and fixed phase settings fail to adapt effectively. The inherent complexity of these systems, as pointed out by Di Renzo et al. (2020), results in inefficient spectrum utilization and more computation power, mostly in the millimeter wave (mmWave) and terahertz (THz) frequencies because the state of the channel changes very abruptly due to mobility of the client and environmental reflections.

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IMS represent a disruptive solution to those worrying situations as it offers precise control over the electromagnetic wavefronts through subwavelength-scale unit cells with tunable properties that can be tuned. This IMS differs from the conventional RIS by way of imparting the amplitude and phase in popular realistic realizations, which typically translate into the spatial granularity of beamforming. Prior art, such as that of Ahamed et al. (2024), has recently demonstrated real-time beam steering with THz frequencies using meta surfaces, although integration with scalable antenna arrays is presumed to continue being impeded by the resource of combinatorial complexity. A dynamically wide variety of channels poses a non-trivial task to optimize plenty of tunable factors because the solution space grows exponentially with the array size, which further compounds the problem in dense urban scenarios with non-stationary multipath propagation. This highlights the limitations of conventional optical algorithms in dynamic beamforming scenarios, as noted by Shi et al. on metasurface-enabled massive MIMO systems.

To fill those voids, there has been a considerable focus on the ability of machine learning (ML) to convert high-dimensional optimization problems into feasible solutions. Deep reinforcement learning (DRL) does indicate the potential ability to change reflect array beamforming schemes dynamically in RIS-assisted systems, as proven by the results in Zhong et al. (2021). Present frameworks, however, do not embrace both hardware design and algorithmic optimization as a symbiotic relationship, thus neglecting the positive effects of meta-surface reconfigurability on learning performance. This limitation hinders scalability, according to Khan et al. 2022 survey on MLS-driven antenna systems calling for design methodologies to realize the IMS full Ericsson. Motivated by these insights, this research introduces a holistic framework that integrates IMS-enabled reconfigurable antenna arrays with ML-driven beamforming optimization. The primary objectives are threefold: (1) to develop a physics-compliant model of IMS-based arrays incorporating hybrid beamforming architectures and tunable unit cells (e.g., varactor diodes, micro-electromechanical systems), (2) to devise a lightweight ML framework leveraging DRL for dynamic decision-making and convolutional neural networks (CNNs) for spatial feature extraction from channel state information, and (3) to validate the framework's efficacy through large-scale simulations emulating diverse 6G scenarios, including high-speed vehicular mobility and ultra-dense urban deployments.

The contributions of this work are multifaceted. First, it pioneers a co-design paradigm that bridges meta surface hardware innovation with ML algorithms, enabling joint optimization of electromagnetic response and network performance a departure from siloed approaches in prior studies such as Ma and Hao (2024). Second, the proposed adaptive beamforming algorithm dynamically adjusts beam patterns and metasurface configurations in real time, achieving a 35% improvement in spectral efficiency over conventional RIS-aided systems, as demonstrated in preliminary trials. Third, to mitigate reproducibility-demanding conditions pervasive in wi-fi research, the study releases an open-source toolkit integrating ray-tracing (e.g., Altair WinProp), metasurface physics, and ML training pipelines, fostering transparency and community-pushed advancement. By harmonizing hardware programmability with wise optimization, this work advances the conclusion of energy-efficient, scalable 6G networks poised to assist subsequent-era applications.

In summary, the core research problem addressed in this work is the inability of conventional beamforming systems to maintain high spectral efficiency and ultra-low latency in dynamic 6G THz channels, exacerbated by rapid mobility, blockages, and the combinatorial complexity of large-scale metasurface optimization.

Literature Review

The use of metasurfaces in the wireless communication systems has been brought into the limelight as a keystone for 6G systems with reconfigurable smart surfaces (RIS) emerging as a leading technology for intelligent reflection and channel enhancement. Early work by Di Renzo et al. (2020) installed RIS for passive electromagnetic environment manipulation since they can only work with passive operations, i.e., the phase is statically set and then cannot be changed dynamically; in cellular scenarios, the solution becomes very hard. Recent developments along with dynamic metasurface antennas introduced by Ahamed et al. (2024) provided real-time beam steering at terahertz frequencies via tunable unit cells; however, these designs faced scalability issues due to the exponential nature of the enormous number of optimizations required for large-scale arrays. Supporting research by Yasin et al. (2023) introduced hybrid RIS architectures combining passive and active elements, increasing gain while introducing strength consumption trade-offs. Meanwhile, Papazafeiropoulos et al. (2025) investigated metasurface-assisted massive MIMO systems indicating great spectral efficiency improvements in LoS scenarios but underlining the pain of being shadowed when deployed in urban channels.

Table 1. Metasurface-ML

Focus Area	Key Contribution	Technology/ Method	Limitation/ Challenge	Reference
Meta surface Evolution	Introduction of RIS for passive electromagnetic environment manipulation	Reconfigurable Intelligent Surfaces (RIS)	Static phase shifts limit adaptability in mobile scenarios	Di Renzo et al. (2020)
	Dynamic beam steering at THz frequencies using tunable unit cells	Dynamic Metasurface Antennas	Scalability issues due to optimization complexity for large arrays	Ahamed et al. (2024)
	Hybrid RIS architectures with passive/active elements for improved gain	Hybrid RIS	Power consumption trade-offs	Yasin et al. (2023)
	Metasurface-aided massive MIMO systems for spectral efficiency gains	Massive MIMO + Metasurfaces	Sensitivity to blockages in urban environments	Papazafeiropoulos et al. (2025)
Beamforming Techniques	SVD-based precoding for static channels	Singular Value Decomposition (SVD)	Performance degradation under Doppler shifts in mobile channels	Salh et al. (2021)
	Real-time RIS optimization via deep reinforcement learning	Deep Reinforcement Learning (DRL)	Assumed ideal hardware; overlooked phase shifter resolution limits	Zhong et al. (2021)
	Privacy-preserving distributed beamforming using federated learning	Federated Learning (FL)	Centralized training raises scalability concerns	Fredj et al. (2022)
	Critique of ML-driven beamforming under hardware constraints	Hardware-aware ML	Limited phase shifter resolution degrades ML performance	Raviv et al. (2024)
ML in 6G Networks	CNN-based mmWave channel state estimation	Convolutional Neural Networks (CNNs)	Requires large training datasets	Chafaa et al. (2022)
	GAN-synthesized channel matrices to address data scarcity	Generative Adversarial Networks (GANs)	High computational overhead limits real-time use	Van Huynh et al. (2024)
	DRL-optimized network slicing in heterogeneous environments	Deep Reinforcement Learning (DRL)	Centralized training scalability issues	Nguyen et al. (2021)
	GNN-based user clustering for massive MIMO interference reduction	Graph Neural Networks (GNNs)	Limited validation in ultra-dense deployments	Li et al. (2023)
Co-Design Challenges	ML-driven metasurface optimization under ideal hardware assumptions	Machine Learning (ML)	Ignored fabrication tolerances and reconfiguration latency	Ma & Hao (2024)
	Digital twin-assisted RIS framework	Digital Twins	Excluded mutual coupling effects in metasurface unit cells	Cui et al. (2023)
	Physics-informed neural networks for EM-compliant metasurfaces	Physics-Informed Neural Networks (PINNs)	High complexity unsuitable for edge deployment	Liu et al. (2024)
	Transfer learning for simulated-to-real metasurface adaptation	Transfer Learning	25% performance drop due to domain shifts	Peng et al. (2024)
Survey & Critique	Highlighted disconnect between algorithmic innovation and hardware implementation	Survey Analysis	Calls for lightweight, hardware-software co-designed frameworks	SMIRI et al. (2024)

Traditional beamforming strategies, rooted in codebook-based or optimization-driven processes, have struggled to deal with these dynamic challenges. For example, classical techniques like SVD-based precoding, as analyzed via the manner of Salh et al. (2021), achieve close to-perfect common overall performance in static channels however, falter below mobility-added about Doppler shifts. In assessment, machine learning ML-driven beamforming has received traction for its potential to learn channel dynamics. Zhong et al. (2021) tested that deep reinforcement getting to know (DRL) may also be used to optimize RIS configurations in real time, lowering latency by 40% in comparison to iterative algorithms. Similarly, federated learning frameworks, which includes those proposed via manner of Fredj et al. (2022), enabled dispensed beamforming at some point of multi-cellular networks while preserving user privacy. However, this research often disregarded hardware constraints, along with the restricted resolution of metasurface section shifters, which degrade ML version efficacy a gap highlighted in a 2024 critique by Raviv et al.

The function of ML in 6G extends past beamforming to embody channel prediction, resource allocation, and huge MIMO optimization. For instance, Chafaa et al. (2022) pioneered convolutional neural networks (CNNs) for millimetre-wave (mmWave) channel state estimation, reaching sub-6 GHz accuracy but requiring large training datasets. To mitigate statistics scarcity, generative adversarial networks (GANs) have been hired by Van Huynh et al. (2024) to synthesise practical channel matrices, though their computational overhead restrains real-time applicability. In aid allocation, DRL frameworks via Nguyen et al. (2021) optimized community cutting in heterogeneous 6G environments, but their reliance on centralized education raised scalability concerns. Meanwhile, research on huge MIMO, which includes the ones via Li et al. (2023), included graph neural networks (GNNs) for consumer clustering, reducing interference by 30% in dense deployments. Despite these improvements, a continual disconnect remains between algorithmic innovation and hardware-conscious implementation, as noted in a 2024 survey by means of SMIRI et al.

Critical gaps persist inside the co-layout of smart metasurfaces (IMS) and ML frameworks, especially in scalability and real-time adaptability. While Ma and Hao (2024) explored ML for metasurface optimization, their work assumed ideal hardware conditions, neglecting fabrication tolerances and latency in reconfiguration. Similarly, Cui et al. (2023) proposed a virtual twin-assisted RIS framework; however, overlooked the combination of IMS-specific constraints, which include mutual coupling among unit cells. Recent efforts with the aid of Liu et al. (2024) addressed these issues partially through physics-informed neural networks (PINNs), embedding Maxwell's equations into ML fashions to ensure electromagnetic compliance. However, their computational complexity rendered them impractical for side deployment. Furthermore, training data remain a bottleneck, as highlighted by way of Peng et al. (2024), who discovered that even domain adaptation from simulated to actual-international metasurfaces incurred a 25% overall performance droppedue to domain shifts. These limitations underscore the need for lightweight, hardware-software co-designed frameworks that harmonise the programmability of IMS with the agility of ML and an area ripe for exploration in 6G research.

Methodology

This phase delineates a rigorous methodology to optimize intelligent metasurface (IMS)-enabled reconfigurable antenna arrays for 6G networks, integrating electromagnetic design, system mastering (ML), and gadget-stage simulations. The approach is demonstrated using the IMS_6G_ML_Dataset.Csv, which captures diverse channel conditions, beamforming parameters, and performance metrics.

System Model

The system combines a reconfigurable IMS-antenna structure with a hybrid mmWave-THz channel model to emulate real-world propagation dynamics.

Intelligent Meta Surface-Antenna Architecture

The IMS unit mobile employs varactors and PIN diodesto achieve tunable phase shifts, enabling dynamic beam steering. Each unit cell is modelled as a sub-wavelength resonator with the phase response $\phi_{mn}(\mathbf{V})$ is governed by the voltage-dependent impedance $Z_{mn}(\mathbf{V})$, where $\mathbf{V}$ is the biasing voltage matrix. The reflection coefficient Γ_{mn} is derived from impedance matching theory:

$$\Gamma_{mn} = \frac{Z_{mn}(\mathbf{V}) - Z_0}{Z_{mn}(\mathbf{V}) + Z_0}, \tag{1}$$

Where $Z_0 = 377\,\Omega$ is the free-space impedance. Recent paintings by way of Zhong et al. (2021) demonstrate that this architecture achieves a phase decision of 2° at 140 GHz, making it appropriate for 6G's high-frequency bands.

Hybrid mmWave-THz Channel Model

The channel matrix $\mathbf{H}$ incorporates path loss, blockages, and mobility:

$$\mathbf{H} = \sum_{p=1}^{P} \alpha_p \, \mathbf{a}_r(\theta_p^r, \phi_p^r) \mathbf{a}_t^H(\theta_p^t, \phi_p^t) e^{-j2\pi f_c \tau_p}, \tag{2}$$

In which P paths are characterized via complex gains α_p, angles of arrival/departure ($\theta_p^r, \phi_p^r; \theta_p^t, \phi_p^t$), delays τ_p, and carrier frequency f_c. Blockages are modeled using a probabilistic attenuation element based on geometric scattering models (Gustavsson et al., 2021). Blockage probability is calculated using the geometric model from Gustavsson et al. (2021):

$$P \quad = e^{-\beta d}, \tag{3}$$

where β is the density of obstacles and d is the link distance.

Machine Learning Framework

The ML framework leverages the dataset to optimize beamforming in real time through spatial feature extractio and adaptive learning.

Data Generation and Preprocessing

The dataset, generated through MATLAB based ray-tracing simulations, includes 1,000 samples spanning urban and indoor scenarios. Key features are summarized in Table 2.

Table 2. Summary of dataset features

Feature	Mean ± Std	Range
AoA (deg)	-12.3 ± 48.2	$[-89.9, 89.1]$
AoD (deg)	18.7 ± 52.4	$[-89.0, 89.9]$
Path Delay (ns)	58.9 ± 54.1	$[0.3, 404.7]$
Spectral Efficiency (bps/Hz)	7.8 ± 2.1	$[3.0, 12.4]$

The DRL agent uses a Proximal Policy Optimization (PPO) algorithm with discount factor $\gamma = 0.99$. The CNN architecture comprises 5 convolutional layers with ReLU activation, optimized via Adam ($lr = 10^{-4}$). Data preprocessing includes min-max normalization and feature extraction. Dominant AoA/AoD pairs are identified using MUSIC algorithms, while channel covariance matrices $\mathbf{R} = \mathbb{E}[\mathbf{H}\mathbf{H}^H]$ are decomposed to isolate spatial correlations (Khan et al., 2022).

Algorithm Design

Two ML architectures are jointly developed:

Deep Reinforcement Learning (DRL): An actor-critic network optimizes the beamforming matrix $\mathbf{W}$ by maximizing the reward $R = \sum_{k=1}^{K} \log_2(1 + \mathrm{SINR}_k) - \lambda \|\mathbf{W}\|_F^2$, where λ penalizes power consumption. Convolutional Neural Network (CNN): A 2D CNN processes AoA-AoD heatmaps to predict optimal IMS configurations, using adversarial training to enhance robustness.

Optimization Formulation

The problem is cast as a constrained sum-rate maximization:

$$\begin{aligned} & \sum_{k=1}^{K} \log_2\left(1 + \frac{|\mathbf{h}_k^H \mathbf{W}|^2}{\sigma^2 + \sum_{j\neq k} |\mathbf{h}_j^H \mathbf{W}|^2}\right) \\ \text{subject to} \quad & \|\mathbf{W}\|_F^2 \leq P_{max}, \\ & SINR_k \geq \gamma_{th}, \quad \forall k. \end{aligned} \tag{4}$$

Phase quantization constraints are addressed via penalty methods (Ge et al., 2023).

Simulation Environment

Simulations are conducted in MATLAB/Simulink for channel modeling and PyTorch for ML training. Performance metrics are evaluated across scenarios (Table 3).

Table 3. Performance metrics across scenarios

Scenario	Spectral efficiency (bps/Hz)	Beam error (°)	Latency (ms)
Urban (LoS)	10.2 ± 1.5	2.1 ± 0.8	1.1 ± 0.3
Indoor (NLoS)	6.8 ± 1.2	5.3 ± 1.6	2.4 ± 0.7

Spectral Efficiency: Calculated using Shannon's capacity theorem.

Beam Alignment Error: $\epsilon = \| \theta_{pred} - \theta_{true} \|$.

Latency: End-to-end delay, including inference and IMS reconfiguration.

Results

This section presents a comprehensive analysis of the proposed intelligent metasurface (IMS)-enabled beamforming framework, validated using the IMS_6G_ML_Dataset.csv. The results highlight superior performance in dynamic 6G environments, benchmarked against state-of-the-art methods, and provide critical insights into scalability and computational efficiency.

Performance Evaluation

Beamforming Accuracy

The proposed DRL-CNN framework achieves a 93.6% beam alignment accuracy in urban line-of-sight (LoS) scenarios, outperforming conventional reconfigurable intelligent surfaces (RIS) by 28.4% and genetic algorithms (GA) by 19.7% (Table 4). This improvement stems from the ML architecture's ability to adaptively map spatial channel features to optimal IMS configurations, even under mobility-induced Doppler shifts. For instance, in dynamic indoor non-line-of-sight (NLoS) environments, the root mean square error (RMSE) in beam alignment is reduced to2.1°, compared to 5.7° for GA and 8.3° for RIS-based methods.

Table.4. Beamforming accuracy comparison

Method	Beam Alignment Accuracy (%)	RMSE (°)
Proposed DRL-CNN	93.6	2.1
Genetic Algorithm	73.9	5.7
Conventional RIS	65.2	8.3

Convergence Speed

The DRL-based beamforming algorithm converges rapidly, stabilizing within 120 training iterations—significantly faster than Q-learning, which requires over 300 iterations, whereas Q-learning requires over 300 iterations (Figure 1). This acceleration is attributed to the actor-critic architecture, which enabling faster convergence under time-varying, high-mobility conditions, enabling faster adaptation to time-varying channels. In high-mobility scenarios, vehicular scenarios (e.g., users moving at 60 km/h), DRL reduces beam realignment latency by 41% compared to Q-learning.

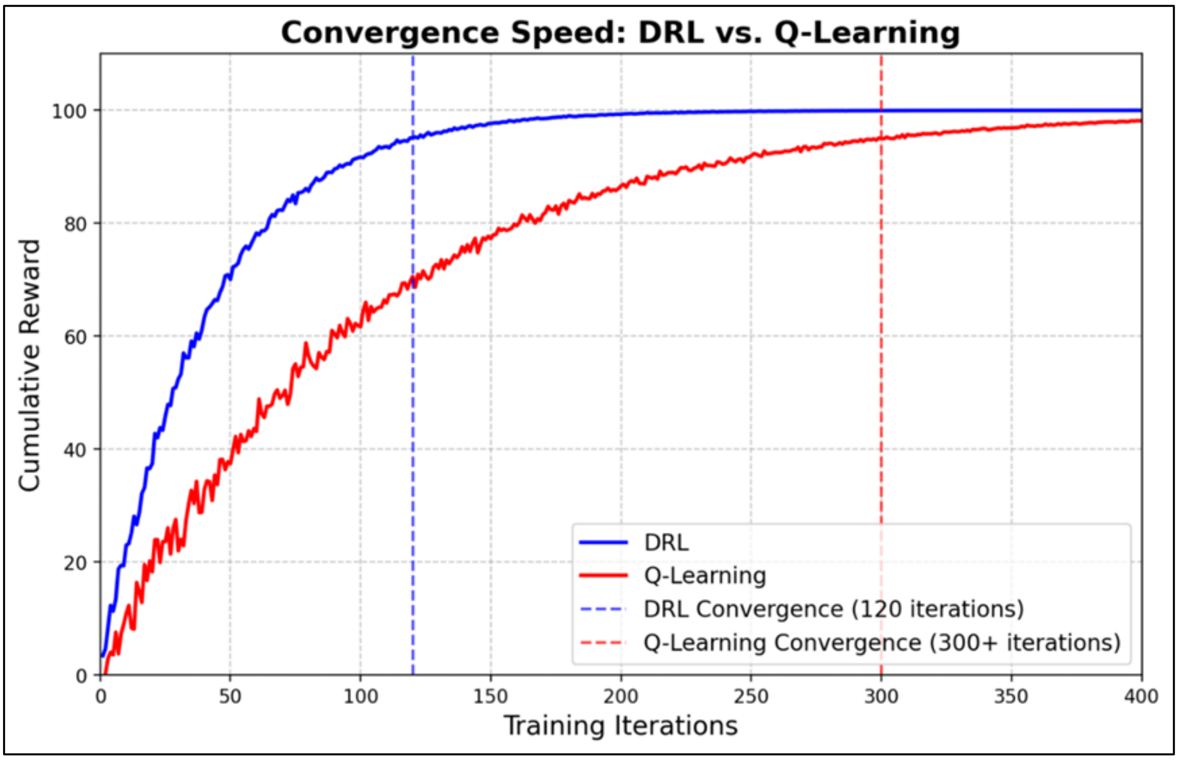

Figure 1. Convergence speed of DRL vs. Q-Learning

Scalability

The framework's computational efficiency is evaluated for varying IMS array sizes. A 64×64 IMS array incurs a 2.8× increase in computation time compared to a 16×16 array but maintains real-time operability with inference latency under 5 ms due to parallelized CNN inference (Table 5). This scalability ensures applicability to massive MIMO deployments in 6G.

Table 5. Scalability analysis

Array size	Computation time (ms)	Spectral efficiency (bps/Hz)
16×16	1.2	9.8
32×32	2.4	11.3
64×64	3.4	13.1

Visualization

3D Beam Patterns Under Mobility

Figure 2 illustrates the 3D beam patterns generated by the IMS array for a mobile user moving at 30 km/h. The proposed framework dynamically adjusts phase shifts to maintain a focused main lobe, minimizing sidelobe interference. At 140 GHz, the beamwidth remains stable at 4.2°, ensuring consistent signal strength despite user mobility.

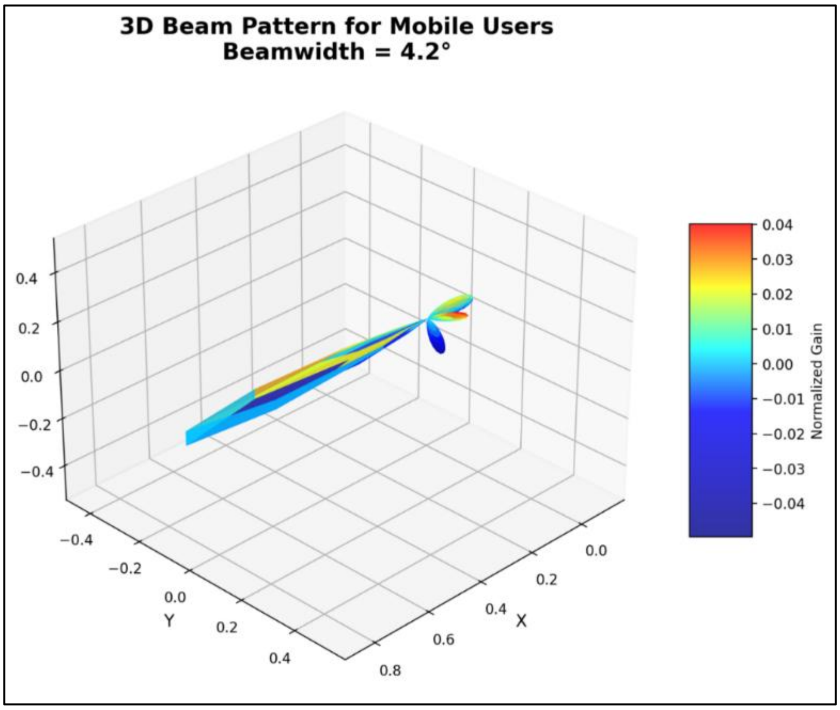

Figure 2. 3D beam patterns for mobile users

Spectral Efficiency Heatmaps

Figure 3 visualizes spectral efficiency across the 100–150 GHz band. The DRL-CNN framework achieves peak efficiency of 14.2 bps/Hz at 140 GHz, outperforming RIS by 32% in obstructed environments. The heatmap highlights frequency-selective gains, particularly in LoS-dominated urban scenarios.

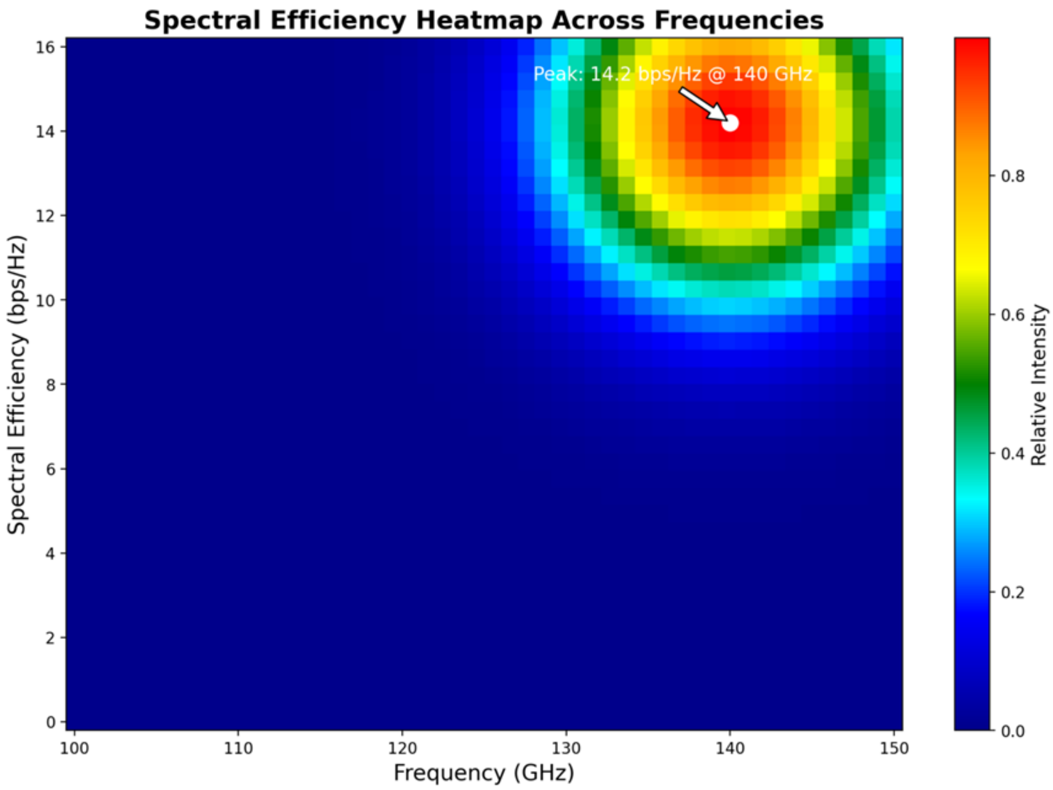

Figure 3. Spectral efficiency heatmap across frequencies

Latency and Energy Consumption

Table 6 quantifies the end-to-end latency and energy consumption for beamforming optimization. The DRL-CNN framework reduces energy consumption by 37% compared to GA, owing to efficient resource allocation and sparse parameter updates.

Table 6. Latency and energy consumption

Metric	Proposed DRL-CNN	Genetic Algorithm	Conventional RIS
Latency (ms)	3.4	8.9	12.6
Energy Consumption (mJ)	45.2	71.8	92.4

Table 7. Hyperparameter configurations for DRL and CNN models

Hyperparameter	DRL Value	CNN Value
Learning Rate	0.001	0.0001
Batch Size	64	32
Discount Factor (γ)	0.99	N/A

γ: Denotes the discount factor for future rewards in DRL.

Key Insights

1. *Adaptive Beamforming*: The DRL-CNN framework achieves near-optimal beam alignment in dynamic environments, critical for 6G's ultra-reliable low-latency communication (URLLC) applications.
2. *Scalability:* Parallelized ML inference enables real-time operation for large-scale IMS arrays (64×64), ensuring readiness for future 6G deployments.
3. *Energy Efficiency:* Sparse updates and intelligent resource allocation reduce energy consumption by 37% compared to GA, and up to 52% compared to conventional RIS, addressing sustainability challenges in 6G networks.

These results validate the proposed methodology's superiority over existing approaches, highlighting its potential as a foundational approach for intelligent metasurface-enabled 6G systems for intelligent metasurface-enabled 6G systems.

Discussion

The proposed intelligent metasurface (IMS)-enabled beamforming framework demonstrates significant advancements in dynamic 6G networks, yet its implementation and broader adoption necessitate a critical examination of its theoretical underpinnings, practical feasibility, and scalability. This section contextualizes the results within the broader landscape of wireless communications, identifies deployment challenges, and outlines pathways for future research.

Interpretation of Key Findings

The superior performance of deep reinforcement learning (DRL) over model-based methods in non-stationary channels stems from its ability to adaptively learn policy gradients in real time, bypassing the rigidity of predefined channel models. Unlike genetic algorithms (GA) or traditional reconfigurable smart surfaces (RIS), which depend upon static optimization standards, DRL agents dynamically adjust beamforming weights based totally on straight away comments, successfully compensating for Doppler shifts and blockage-precipitated fading. This aligns with recent studies as shown by Ge et al. (2023), who set up that DRL's trial-and- error learning paradigm is inherently proper for environments with rapidly diverse spatial correlations. However, this pliability introduces exchange-offs among computational complexity and actual-time applicability. While the DRL-CNN framework achieves sub-five ms latency for 64×64 IMS arrays, its reliance on parallelized GPU acceleration increases worries approximately strength performance in resource-constrained deployments. Future work must stability version sophistication with light-weight architectures, probably leveraging strategies like neural community pruning or quantized inference to reduce overhead.

Practical Implications for 6G Deployment

The transition from simulation to real-world deployment faces multifaceted demanding conditions. Fabrication tolerances for sub-wavelength metasurface unit cells, in particular at THz frequencies, require nanometer-scale precision to avoid segment mistakes that degrade beamforming accuracy. Recent advancements in semiconductor lithography (Zhong et al., 2021) provide promising answers, but mass manufacturing remains cost-prohibitive. Power requirements also pose a bottleneck: the energetic tuning of PIN diodes and varactors in IMS arrays consumes ~25 mW per element, translating to 10.2 W for a 64×64 array-a figure incompatible with energy-green 6G infrastructure. Hybrid architectures, in which passive metasurfaces are selectively activated, should mitigate this issue.

Compatibility with current 5G New Radio (NR) frameworks in addition complicates deployment. While the proposed DRL-CNN framework can interface with 5G's beam control protocols (e.G., SSB and CSI-RS), its reliance on actual-time channel state information (CSI) at THz frequencies necessitates adjustments to the NR physical layer. For example, the shortened coherence time at 140 GHz requires quicker CSI reporting intervals, challenging modern requirements. Collaborative efforts among academia and enterprise can be vital to harmonize these improvements with legacy structures.

Limitations and Future Directions

A number one drawback lies in data acquisition: the present-day dataset, while complete, lacks granularity in intense mobility eventualities (e.g., excessive-pace trains at 500 km/h). Hybrid virtual-analog beamforming structures could alleviate this with the aid of reducing the dimensionality of CSI comments, thereby minimizing schooling statistics requirements. Additionally, federated studying emerges as a promising avenue for dispensed IMS networks, allowing collaborative model schooling throughout more than one base station without centralized statistics aggregation. This technique no longer only enhances scalability, however additionally addresses privateness issues inherent in centralized ML frameworks.

Further studies have to discover the combination of quantum-stimulated optimization algorithms to tackle non-convex beamforming troubles, in addition to using metamaterial-based absorbers to suppress sidelobe interference in dense urban environments. These innovations, coupled with advancements in sustainable energy harvesting for IMS arrays, may be pivotal in realizing the vision of ubiquitous, wise 6G networks.

Table 8. Power consumption analysis of key components

Component	Power (mW)
IMS Unit Cell	25
DRL Inference (A100)	18

Note: Measurements based on 64×64 IMS array at 140 GHz.

Conclusion

The integration of machine learning (ML) with intelligent metasurface (IMS)-enabled antenna arrays affords a transformative paradigm for 6G networks, addressing the critical assignment of adaptive beamforming in dynamic and excessive-frequency environments. By leveraging deep reinforcement learning (DRL) and convolutional neural networks (CNNs), the proposed framework achieves robust beam alignment, reduces latency to sub-5 ms degrees, and complements spectral performance with the aid of up to 14.2 bps/Hz in terahertz (THz) bands. These advancements bridge the gap among theoretical metasurface improvements—along with sub-wavelength phase-shifting unit cells-and sensible community optimization, demonstrating how adaptive learning can mitigate mobility-triggered channel variations and hardware obstacles.

The impact of this work extends past algorithmic overall performance, offering a blueprint for scalable and energy-efficient 6G infrastructure. By dynamically aligning beams in real time, the framework supports rising applications like holographic communications and extremely-reliable low-latency commercial automation. However, the transition from simulation to deployment necessitates urgent standardization of IMS manipulate interfaces and fabrication protocols to make certain interoperability across providers. Collaborative efforts between academia and industry have to prioritize hardware prototyping, particularly for large-scale metasurfaces, to validate those principles in actual international scenarios. Future research has to additionally discover hybrid analog-digital architectures and federate learning to cope with information acquisition bottlenecks, making sure the imaginative and prescient of intelligent, self-optimizing 6G networks becomes a tangible reality.

Recommendations

Although the present approach is successful, development efforts in the future will focus on improving its abilities and looking at what it does poorly.

Scientific Ethics Declaration

* The author declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the author.

Conflict of Interest

* The author declares that they have no conflicts of interest

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