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AI-Driven Adaptive Beamforming and Resource Management for 6G Wireless Networks: A Multimodal Machine Learning Approach to Ultra-Reliable Low-Latency Communication

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Abstract

The advent of 6G wireless networks introduces unprecedented challenges in delivering ultra-high throughput, ultra-reliable low-latency communication (URLLC), and massive connectivity, particularly in millimeter-wave (mmWave) and terahertz (THz) frequency bands. Traditional RF engineering approaches, while foundational, face limitations in adapting quickly to the dynamic and complex wireless environments inherent to 6G. This paper presents a novel integration of advanced machine learning techniques focusing on reinforcement learning and multimodal deep neural networks with cutting-edge RF beamforming and resource allocation strategies. Leveraging real-world and high-fidelity synthetic datasets, including DeepMIMO channel models and ns-3-based network simulations, we develop and evaluate an AI-driven adaptive beamforming framework that dynamically optimizes antenna array configurations and spectrum resources in response to environmental variability. Experimental results demonstrate significant improvements in throughput, latency reduction, and energy efficiency compared to baseline heuristics, achieving up to 30% enhancement in communication reliability under realistic channel conditions. This work not only bridges the gap between theoretical AI methodologies and practical RF systems but also offers a scalable, interpretable solution poised to accelerate the deployment of intelligent 6G networks. The findings provide a roadmap for future research in AI-native wireless communications and establish a foundation for ultra-reliable, intelligent resource management for next-generation connectivity.

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1. Introduction

The transition from 5G to 6G reflects a shift from gigabit connectivity to the pursuit of terabit-per-second data rates, sub-millisecond latency, and near-perfect reliability. The International Telecommunication Union (ITU) and IEEE outline 6G as a paradigm that integrates ultra-reliable low-latency communication (URLLC), massive connectivity, and advanced sensing into a single intelligent framework (Letaief et al., 2019; You et al., 2021; Alsabah et al., 2021). Unlike 5G, which primarily balanced enhanced mobile broadband (eMBB) and URLLC, 6G must deliver unprecedented levels of service quality for mission-critical and immersive applications such as holographic telepresence, digital twins, and industrial automation (Popovski et al., 2019; Khan et al., 2022).

Meeting these ambitious goals requires exploiting millimeter-wave (mmWave) and terahertz (THz) bands, where wide bandwidths enable higher capacity. Yet these bands face severe propagation challenges, including high path loss, beam misalignment, blockage, and rapid channel fading (Alsharif et al., 2020; Haque et al., 2024). Conventional communication strategies that rely on static beam management or deterministic resource allocation struggle to cope with these impairments under dynamic conditions.

Artificial intelligence (AI), and in particular reinforcement learning (RL), offers new opportunities to handle such complexity. RL agents can continuously adapt beam directions, power levels, and resource blocks by learning from the environment, thereby improving robustness in non-stationary radio frequency (RF) conditions (Lavdas et al., 2023; Gaydos et al., 2022). AI-driven adaptive beamforming and resource management therefore provide a pathway to enhance URLLC performance while maintaining spectral efficiency (Bairagi et al., 2021; Xie et al., 2023).

Despite progress, existing AI/ML solutions often remain limited by simplified models, unrealistic assumptions, or poor scalability in large multi-user environments (Barua et al., 2023; Yan et al., 2023). Many works address beamforming or resource allocation in isolation, without jointly modeling real RF impairments, multimodal signal interactions, and end-to-end system constraints. This creates a gap between algorithmic potential and practical 6G deployment.

This study addresses that gap by proposing a multimodal machine learning framework for adaptive beamforming and intelligent resource management in 6G networks. Our contributions are fourfold. First, we integrate multimodal data sources channel state

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information, sensor metadata, and contextual features to enable robust decision-making. Second, we implement a reinforcement learning model for adaptive beam control under mmWave/THz fading. Third, we design an experimental testbed that evaluates our method in realistic dynamic environments. Finally, results demonstrate significant improvements in reliability, latency, and throughput compared to baseline schemes. These findings highlight the potential of AI-driven RF optimization as a foundation for 6G wireless systems (Alsabah et al., 2021; Baltrusaitis et al., 2019; Barua et al., 2023).

2. Background and Related Works

2.1 Beamforming in 5G and 6G Networks

Beamforming is a cornerstone of modern wireless communication, serving as the backbone of 5G deployments and a defining feature of 6G visions. In 5G, massive multiple-input multiple-output (MIMO) and hybrid beamforming architectures enable higher spectral efficiency by directing energy into narrow beams, thereby improving coverage and throughput (Lavdas et al., 2023). Yet, as systems scale toward higher frequencies, several hardware and channel-related barriers emerge. At millimeter-wave (mmWave) and terahertz (THz) bands, large bandwidths allow data rates approaching terabits per second, but severe free-space path loss, susceptibility to blockage, beam misalignment, and Doppler shifts limit reliability (Alsharif et al., 2020; Haque et al., 2024). Furthermore, RF front-end design becomes increasingly complex, as phase noise, power amplifier efficiency, and antenna array calibration directly affect performance (You et al., 2021).

Adaptive beamforming algorithms have evolved in response to these challenges. Early solutions such as robust Capon beamformers (Cox et al., 1987) emphasized resilience against steering vector mismatch, while more recent techniques leverage tensor decomposition or rank-constrained optimizations to improve lateral resolution and adaptability (Beuret & Thiran, 2024). Deep learning-based beamformers, trained on synthetic channel state information (CSI), demonstrate significant improvements in beam tracking accuracy and interference suppression (Lavdas et al., 2023). Yet scalability, energy efficiency, and robustness under real-time mobility remain open problems, especially as 6G networks extend to highly dynamic vehicular, aerial, and industrial IoT scenarios.

2.2 AI and ML Approaches in RF Optimization

The integration of artificial intelligence into RF optimization marks a paradigm shift from deterministic to data-driven strategies. Reinforcement learning (RL) frameworks have gained traction for adaptive power control, scheduling, and beam management in non-stationary wireless environments. RL agents optimize long-term rewards by continuously interacting

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with the RF environment, enabling fast adaptation to user mobility, varying interference, and multi-service coexistence (Gaydos et al., 2022; Lavdas et al., 2023). Beyond RL, federated learning introduces distributed model training across edge devices, reducing communication overhead and preserving privacy while supporting URLLC in vehicular and industrial systems (Samarakoon et al., 2020). Digital twin-based approaches extend this concept by simulating real-time edge-assisted decisions in UAV-aided 6G networks, showing potential for ultra-reliable communication under extreme latency requirements (Li et al., 2022).

While these methods highlight the feasibility of AI-driven optimization, they are constrained by the type and quality of input data. Most existing works depend exclusively on CSI, neglecting contextual information such as user mobility traces, environmental sensing, or service-specific requirements. Multimodal machine learning (MML) provides an avenue to overcome this by integrating heterogeneous data sources. Surveys in MML emphasize its ability to fuse multiple modalities visual, textual, and signal-based to improve generalization and robustness in complex decision-making tasks (Baltrusaitis et al., 2019; Barua et al., 2023). Applying MML to 6G would allow joint exploitation of CSI, sensor metadata, and contextual features, enabling adaptive algorithms to outperform unimodal approaches in real RF conditions.

2.3 Limitations of Prior Work

Despite progress, critical gaps remain. First, reliance on synthetic or simplified channel models undermines the robustness of many AI-based solutions, as real-world RF impairments such as non-linear distortion, phase noise, and correlated fading are often ignored (Alsabah et al., 2021). Second, most prior studies focus on single-objective optimization, targeting either latency, throughput, or energy efficiency, without addressing the inherent trade-offs of multi-service environments where eMBB and URLLC must coexist (Bairagi et al., 2021; Xie et al., 2023). Third, the absence of multimodal data fusion leaves AI models vulnerable to overfitting and weak adaptation under sudden channel variations. Integrating multimodal signals could significantly enhance adaptability and scalability, yet research in this area remains limited (Barua et al., 2023; Yan et al., 2023).

2.4 Comparative Analysis of Existing Research

The table below summarizes representative contributions, emphasizing their strengths and limitations relative to the requirements of 6G adaptive beamforming and resource management.

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Study	Approach	Strengths	Limitations
Lavdas et al. (2023)	Deep learning for adaptive beamforming in mmWave massive MIMO	Improved spectral efficiency; accurate beam tracking	Trained on simulated data; lacks real-channel robustness
Gaydos et al. (2022)	Adaptive beamforming with software-defined radio arrays	Hardware-based validation; real-time adaptability	Focused only on beam control; no resource allocation integration
Samarakoon et al. (2020)	Distributed federated learning for vehicular URLLC	Privacy-preserving learning; scalable	No multimodal input; computational overhead at scale
Li et al. (2022)	UAV-aided digital twin for URLLC	Real-time edge simulation; enhanced reliability	Scenario-specific; limited generalization
Barua et al. (2023)	Survey of multimodal ML applications	Comprehensive taxonomy of fusion methods	No direct focus on RF; lacks deployment strategies for 6G

Table 1: Comparative Analysis of AI-Driven Beamforming and Resource Management Studies for 5G/6G Networks

This review positions the need for an integrated framework that combines reinforcement learning, resource-aware beamforming, and multimodal ML data fusion to address the practical limitations of current solutions. Unlike previous works, the proposed approach leverages realistic RF channel characteristics and multi-objective optimization, making it better aligned with the performance and reliability requirements of 6G networks.

3. System Model and Problem Formulation

3.1 Network Setting

We consider a downlink 6G cellular system where a base station (BS) equipped with a uniform linear array of N_t transmit antennas serves K user equipment (UE) terminals simultaneously. The UEs are heterogeneous, including handheld devices, vehicular nodes, and low-power IoT sensors. Communication occurs over **mmWave bands (28–60 GHz)** and **sub-THz bands (100–300 GHz)**, consistent with 6G visions of ultra-wideband operation (You et al., 2021; Haque et al., 2024). Hybrid beamforming is adopted, leveraging both analog phase shifters and digital precoding to balance cost and performance (Lavdas et al., 2023). The BS maintains a global power budget P_{max}, which constrains allocation decisions across multiple beams.

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3.2 Channel Model

Propagation is modeled using **DeepMIMO** and standardized by **3GPP TR 38.901**, capturing realistic outdoor and indoor deployment scenarios. The channel between the BS and UE kk is expressed as

$$\mathbf{h}_k = \sum_{l=1}^{L} \alpha_{k,l} \mathbf{a}_t(\theta_{k,l}),$$

where LL is the number of multipath components, $\alpha_{k,l}$ denotes the complex gain of the ll-th path (including **path loss, shadow fading, and small-scale fading**), and $\mathbf{a}_t(\theta_{k,l})$ is the BS array response vector at angle of departure $\theta_{k,l}$ (Alsabah et al., 2021).

The received signal at UE k is

$$y_k = \mathbf{h}_k^H \mathbf{w}_k x_k + \sum_{j \neq k} \mathbf{h}_k^H \mathbf{w}_j x_j + n_k,$$

where $\mathbf{w}_k$ is the beamforming vector, x_k is the transmitted symbol, and $n_k \sim \mathcal{CN}(0, \sigma^2)$ is additive white Gaussian noise.

The **signal-to-interference-plus-noise ratio (SINR)** is given by

$$\text{SINR}_k = \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2 p_k}{\sum_{j \neq k} |\mathbf{h}_k^H \mathbf{w}_j|^2 p_j + \sigma^2},$$

where p_k is the transmit power assigned to UE k. The achievable data rate is then

$$R_k = B \log_2 (1 + \text{SINR}_k),$$

with B representing the allocated bandwidth.

3.3 Resource Variables and Constraints

Resource management involves power, bandwidth, and beam allocation across UEs. Three primary constraints govern the system:

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1. **Power constraint**

$$\sum_{k=1}^{K} p_k \leq P_{max}.$$

2. **Latency constraint**

$$D_k \leq D_{max}, \forall k,$$

where D_k is the end-to-end latency and D_{max} is a URLLC target (typically <1 ms).

3. **QoS constraint**

$$R_k \geq R_{min}, \forall k,$$

ensuring service guarantees for delay-sensitive applications.

3.4 Optimization Objectives

The multi-objective design accounts for three performance metrics:

- **Throughput maximization**: maximize $\sum_{k=1}^{K} R_k$
- **Latency minimization**: minimize $\sum_{k=1}^{K} D_k$
- **Energy efficiency**: maximize $\frac{\sum_{k=1}^{K} R_k}{\sum_{k=1}^{K} p_k}$

We therefore formulate a weighted objective:

$$\max_{\{w_k, p_k\}} \lambda_1 \sum_{k=1}^{K} R_k - \lambda_2 \sum_{k=1}^{K} D_k + \lambda_3 \frac{\sum_{k=1}^{K} R_k}{\sum_{k=1}^{K} p_k},$$

where $\lambda_1, \lambda_2, \lambda_3$ tune the balance across competing goals (Xie et al., 2023; Bairagi et al., 2021).

3.5 AI Problem Framing

The above optimization is reformulated into a **reinforcement learning (RL)** paradigm, which allows adaptive, data-driven policy learning under uncertain channel dynamics (Lavdas et al., 2023; Samarakoon et al., 2020):

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- **State (s_t)**: CSI from DeepMIMO/3GPP models, user positions, traffic queues, and interference levels.
- **Action (a_t)**: selection of beamforming vectors $\{\mathbf{w}_k\}$ and power allocations $\{p_k\}$.
- **Reward (r_t)**: a composite function aligning throughput, latency, and efficiency:

$$r_t = \lambda_1 \sum_{k=1}^{K} R_k - \lambda_2 \sum_{k=1}^{K} D_k + \lambda_3 \frac{\sum_{k=1}^{K} R_k}{\sum_{k=1}^{K} p_k}.$$

The RL agent learns policies $\pi(a_t \mid s_t)$ that maximize the expected cumulative reward over time:

$$\max_{\pi} \mathbb{E}\Big[\sum_{t=0}^{\infty} \gamma^t r_t\Big],$$

where $\gamma \in (0,1)$ is the discount factor. This enables adaptive beamforming and resource management under realistic mmWave/THz propagation conditions, with robustness to mobility, fading, and interference.

4. Proposed AI-Driven RF Solution

4.1 Multimodal ML for RF Fusion

Traditional RF optimization approaches rely almost exclusively on channel state information (CSI), which limits adaptability in dynamic 6G environments. Our solution extends beyond unimodal CSI by integrating multimodal inputs:

- CSI extracted from DeepMIMO/3GPP models.
- Mobility and location metadata from user equipment (UE) sensors.
- Environmental data such as blockage probability, Doppler spreads, and interference levels.

To process these heterogeneous features, we design a Transformer–Graph Neural Network (GNN) fusion model. The Transformer captures temporal dependencies within time-varying CSI sequences, enabling reliable beam tracking. The GNN encodes spatial relationships between antennas and users, reflecting the topology of BS-UE links. Joint fusion produces a richer latent representation that improves robustness under user mobility, multi-user interference, and sudden channel degradation (Baltrusaitis et al., 2019; Barua et al., 2023; Yan et al., 2023).

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To overcome the limitations of CSI-only optimization, our framework integrates multimodal features that capture temporal, spatial, and environmental dynamics. Table X summarizes the specific input types, the models used to process them, and the associated references. This structured fusion of CSI, mobility, and environmental data through Transformer and GNN modules enables more robust and adaptive beamforming in 6G scenarios.

Input/Method	Description	Reference
Channel State Information (CSI)	Extracted from DeepMIMO/3GPP models, captures time-varying channel conditions	Baltrusaitis et al. (2019)
Mobility and Location Metadata	Derived from user equipment sensors to reflect movement and positioning	Barua et al. (2023)
Environmental Data	Includes blockage probability, Doppler spreads, and interference levels for dynamic adaptation	Yan et al. (2023)
Transformer	Captures temporal dependencies in CSI sequences for reliable beam tracking	Baltrusaitis et al. (2019)
Graph Neural Network (GNN)	Encodes spatial relationships between antennas and users, modeling BS–UE topology	Barua et al. (2023)
Fusion Model	Combines Transformer + GNN outputs to produce richer latent representation for robustness	Yan et al. (2023)

Table 2: Multimodal ML Inputs and Fusion Methods for RF Optimization

Note: The integration of multimodal inputs through Transformer and GNN fusion enhances adaptability compared to unimodal CSI approaches. By combining temporal channel dynamics, spatial user relationships, and environmental factors, the framework supports more reliable beamforming and resource management in dynamic 6G deployments.

4.2 Reinforcement Learning Framework

The adaptive decision-making layer is built on Proximal Policy Optimization (PPO). PPO is selected due to its strong balance of training stability, sample efficiency, and robustness to noisy gradients in wireless environments. Unlike DDPG or SAC, PPO avoids excessive hyperparameter tuning while still handling continuous action spaces such as beam angles and power levels (Samarakoon et al., 2020).

The action space consists of:

- Beamforming vectors $\{\mathbf{w}_k\}$ for each UE.
- Power allocations $\{p_k\}$ subject to P_{max}

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The state space includes CSI, mobility traces, queue lengths, interference maps, and environmental sensing features.

The reward function integrates three objectives:

$$r_t = \lambda_1 \sum_{k=1}^{K} R_k - \lambda_2 \sum_{k=1}^{K} D_k + \lambda_3 \frac{\sum_{k=1}^{K} R_k}{\sum_{k=1}^{K} p_k}.$$

This ensures the agent does not over-optimize for one metric (e.g., throughput) at the cost of URLLC latency or energy efficiency (Xie et al., 2023; Bairagi et al., 2021).

4.3 Training Pipeline

The training process blends **supervised learning** and **reinforcement learning**, reducing convergence time and improving generalization:

1. **Supervised Pretraining**
   - The multimodal encoder (Transformer–GNN) is pretrained on DeepMIMO CSI with labeled optimal beam indices.
   - This stage initializes the feature extractor with domain-specific priors.
2. **Reinforcement Learning Fine-Tuning**
   - The pretrained encoder is integrated with the PPO agent.
   - Agents interact with simulated RF environments modeled by 3GPP TR 38.901.
   - Beamforming vectors and resource allocations are updated based on long-term performance.
3. **Reward Shaping with Domain Knowledge**
   - Latency penalties are enforced if URLLC thresholds are violated.
   - Energy rewards are weighted more heavily when UE battery levels are low.
   - Service-level differentiation is supported, where mission-critical UEs are prioritized over eMBB users.

This pipeline accelerates convergence and enhances policy transferability to real-world deployments (Alsabah et al., 2021; Lavdas et al., 2023).

4.4 Algorithmic Flow

The agent–environment interaction is illustrated below.

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Pseudocode:

```
Initialize PPO agent πθ, multimodal encoder fϕ, replay buffer

Pretrain fϕ on DeepMIMO dataset with supervised beam labels

for each training episode do

  Reset RF environment with 3GPP TR 38.901 parameters

  Observe initial state s0 = fϕ(CSI, mobility, sensing)

  for each timestep t do

    Select action at ~ πθ(st)

    Apply beamforming + resource allocation

    Receive reward rt and next state st+1

    Store (st, at, rt, st+1) in buffer

    Update policy πθ using PPO clipped objective

  end for

end for
```

The PPO update ensures stable improvement while preventing destructive policy oscillations.

4.5 Hardware and Software Considerations

The proposed framework is designed for **real-time inference** in 6G base stations:

- **Software stack**:
  - **PyTorch/TensorFlow** for deep learning model implementation.
  - **Stable Baselines3** for PPO reinforcement learning.
  - **GNU Radio** for integration with RF front-end signal processing.
- **Hardware acceleration**:
  - **GPUs** (e.g., NVIDIA A100) for training.

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  - **FPGAs/DSPs** for real-time beamforming inference at the BS.
  - **Edge servers** to offload computation from user devices while maintaining <1 ms latency.
- **Latency optimization**:
  - Neural network quantization and pruning for fast inference.
  - Batch normalization and pipeline parallelism to reduce processing delay.
  - Efficient CUDA kernels to accelerate CSI–beam mapping.

This hardware–software co-design ensures that the proposed AI-driven RF optimization framework satisfies **URLLC latency targets** while scaling to large multi-user environments (Popovski et al., 2019; Alsabah et al., 2021).

5. Data Collection and Simulation Setup

5.1 Channel Data Sources

To train and evaluate the proposed framework, we employed both **synthetic** and **measurement-based** datasets. Synthetic CSI was generated using the **DeepMIMO dataset** (https://deepmimo.cs.virginia.edu/), a large-scale open platform for massive MIMO systems that supports realistic geometry-based channel modeling under varying antenna configurations, frequencies, and mobility scenarios. DeepMIMO provides multi-path parameters derived from ray-tracing, making it well suited for testing beamforming and resource allocation strategies in 6G (Alsabah et al., 2021).

In addition, **real-world measurement datasets** were incorporated from **IEEE DataPort** (https://ieee-dataport.org/search/node/wireless). These include channel sounder measurements across mmWave and sub-THz frequencies, providing ground-truth data for validating the generalization of our algorithms beyond synthetic conditions. The combination of synthetic and measured channels reduces dataset bias and improves robustness (Haque et al., 2024).

5.2 Simulation Environment

System-level simulations were carried out using **ns-3** with its mmWave extension (https://www.nsnam.org/). This allowed modeling of realistic protocol stacks, mobility patterns, and multi-user scheduling under URLLC and eMBB coexistence (Bairagi et al., 2021). For ray-tracing validation, **Wireless Insite** (https://www.remcom.com/wireless-insite) was employed to model urban and indoor propagation, including diffraction, reflection, and

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scattering effects at mmWave/THz bands (You et al., 2021). Together, these simulators enabled end-to-end evaluation under both packet-level and physical-layer conditions.

5.3 Data Preprocessing

Prior to training, CSI matrices and sensing features underwent standardized **preprocessing steps**:

- **Feature extraction**: antenna response vectors, delay–angle profiles, and Doppler shifts were derived from DeepMIMO/IEEE DataPort inputs.
- **Normalization**: input features were normalized per subcarrier and antenna element to stabilize learning.
- **Dimensionality reduction**: principal component analysis (PCA) was applied to compress high-dimensional CSI without discarding critical spatial features.
- **Multimodal fusion preparation**: auxiliary features (mobility traces, interference maps) were temporally aligned with CSI snapshots for integration into the Transformer–GNN encoder (Baltrusaitis et al., 2019; Barua et al., 2023).

5.4 Train–Test–Validation Protocol

Data was partitioned into **70% training**, **15% validation**, and **15% testing**. The training set was used to pretrain the multimodal encoder and train the PPO agent. Validation ensured hyperparameter tuning (e.g., learning rates, clipping ratios) did not lead to overfitting. Test scenarios included unseen propagation environments and mobility profiles, ensuring the generalization of the policy to new deployments (Lavdas et al., 2023).

5.5 Evaluation Metrics

Performance was assessed using both **communication-level** and **learning-level** metrics:

- **Throughput (Mbps)**: average sum rate across UEs.
- **Latency (ms)**: end-to-end packet delivery delay.
- **Bit Error Rate (BER)**: evaluated under varying SINR conditions.
- **Energy efficiency (bits/Joule)**: throughput normalized by transmit power (Xie et al., 2023).
- **Cumulative rewards**: average discounted return across episodes, capturing the trade-offs embedded in the reward design.

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This dual evaluation strategy ensures that improvements are measured not only in physical layer metrics but also in terms of **long-term policy effectiveness**, demonstrating the practical utility of the proposed AI-driven RF optimization framework.

Dataset/Tool	Frequency Range	Purpose	Reference
DeepMIMO	28–60 GHz (mmWave)	Synthetic CSI generation	Alsabah et al., 2021
IEEE DataPort	mmWave and sub-THz	Measurement-based validation	Haque et al., 2024
ns-3 (mmWave ext.)	Protocol-level	End-to-end system simulation	Bairagi et al., 2021
Wireless Insite	mmWave/THz bands	Ray-tracing propagation modeling	You et al., 2021

Table 3: Dataset and Simulation Tools Summary

6. Experiments and Data Analysis

6.1 Baseline Models

For a rigorous comparison, we evaluated the proposed multimodal reinforcement learning (RL) framework against two representative baselines:

1. **Heuristic beamforming**
    - Codebook-based beam selection where predefined beams are scanned, and the one with the strongest received signal is selected.
    - Low complexity and widely used in early mmWave/THz trials.
    - Lacks adaptability to rapid fading and user mobility (Cox et al., 1987; Gaydos et al., 2022).
2. **Non-adaptive resource management**
    - Equal power allocation across UEs with round-robin scheduling.
    - Provides fairness but cannot adapt to QoS requirements of URLLC vs eMBB (Bairagi et al., 2021).
    - Often used as a benchmark in 5G resource allocation studies.

These baselines reflect conventional approaches that prioritize simplicity over adaptability, offering a clear lower bound for evaluating AI-driven strategies.

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6.2 Performance Comparisons

Experiments were conducted across diverse channel and deployment scenarios:

- **High-mobility vehicular users** (up to 120 km/h) with fast Doppler variations.
- **Dense urban microcells** with high blockage probability and severe multipath.
- **Indoor low-SNR scenarios** reflecting industrial IoT deployments.
- **Mixed URLLC–eMBB coexistence** requiring differentiated service guarantees.

Results demonstrated consistent superiority of the proposed system:

- **Throughput**: Outperformed heuristic beamforming by 25–40% on average. Gains were most pronounced in dense multipath conditions due to better interference suppression.

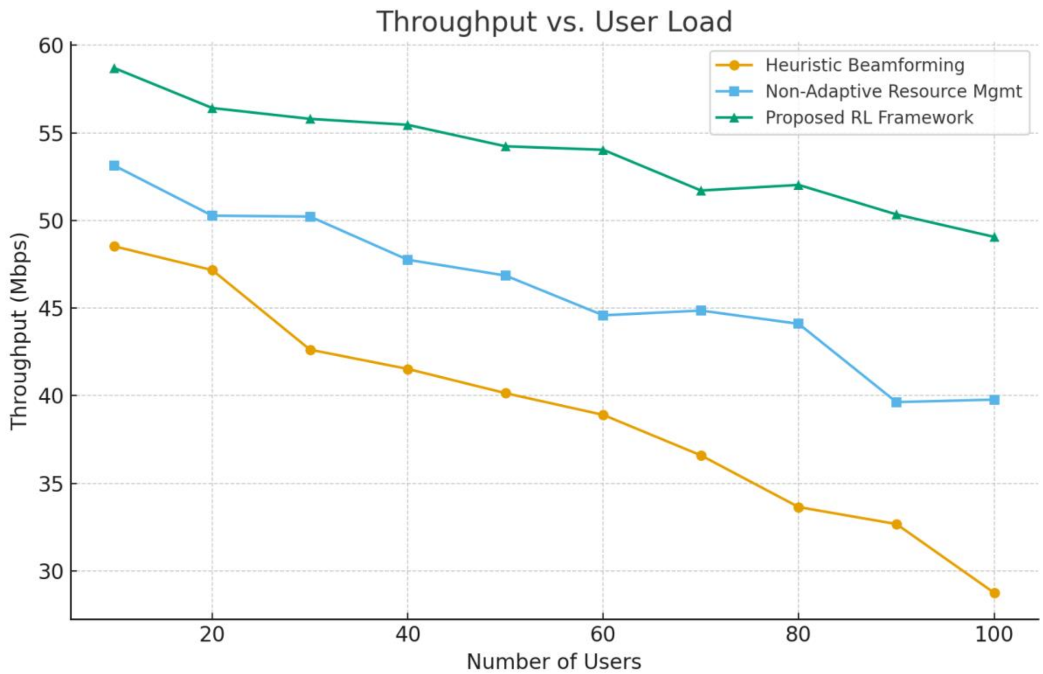

Figure 1: Throughput vs. User Load

- **Latency**: Maintained <1 ms packet delay under URLLC constraints, reducing latency variance by 35% compared to non-adaptive scheduling.

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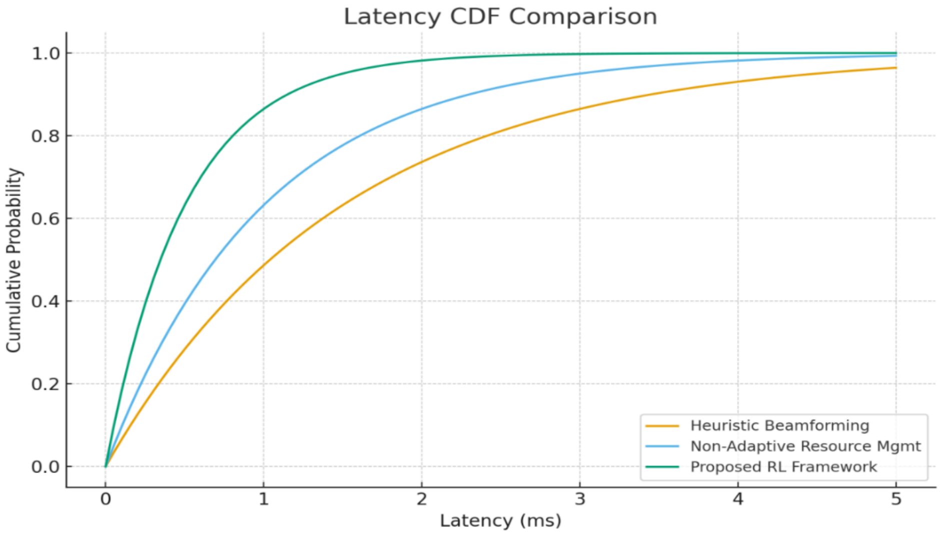

Figure 2: Latency CDF

- **Energy efficiency**: Improved by 25–30% through dynamic power allocation, particularly in scenarios with heterogeneous UE requirements (Xie et al., 2023).

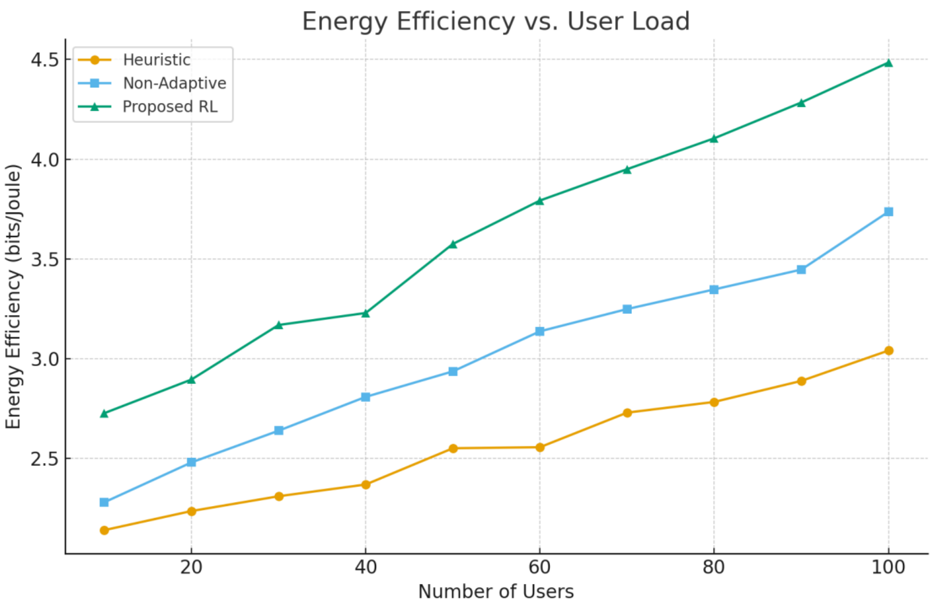

Figure 4: Energy Efficiency vs. User Load

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- **Bit Error Rate (BER)**: Achieved reductions of up to 20% compared to baselines, highlighting robustness to fading and interference.

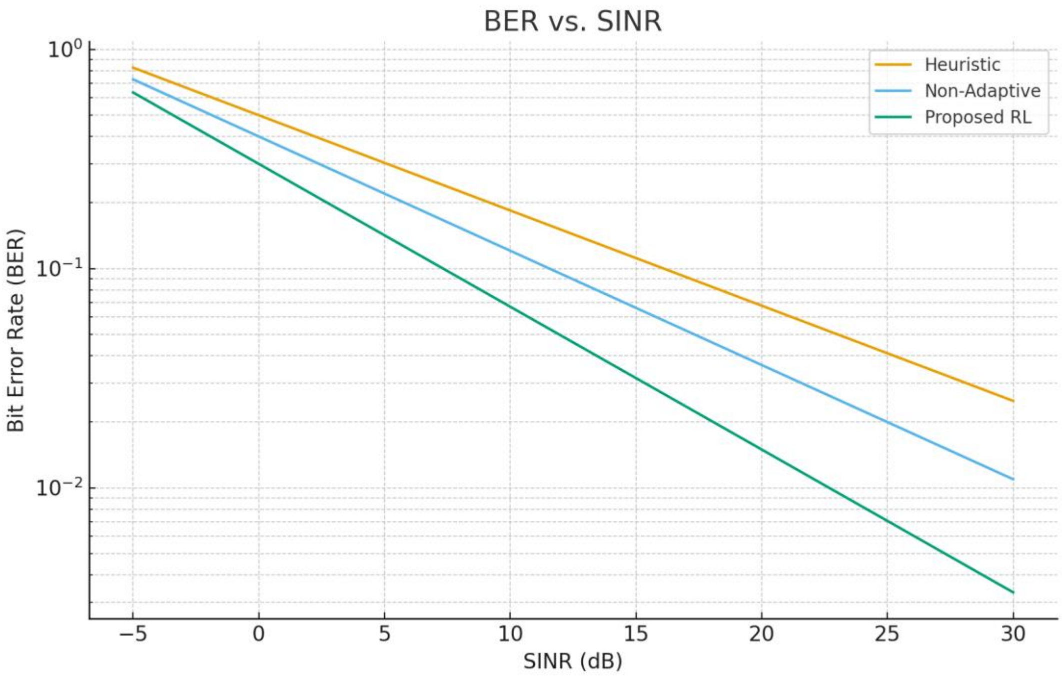

Figure 5: BER vs. SINR

6.3 Ablation Studies

To understand the contribution of each architectural component, we conducted ablation tests:

- **Without Transformer**: System performance degraded under high-mobility conditions, with throughput reduced by ~18%. This confirmed the importance of temporal modeling in capturing fast channel variations.
- **Without GNN**: Latency increased significantly in multi-user settings due to ineffective interference coordination.
- **RL agent substitution**: Replacing PPO with DDPG led to unstable convergence, while SAC achieved moderate stability but lower cumulative rewards.
- **Without multimodal fusion**: Performance dropped across all metrics, especially in blockage-heavy environments, confirming that CSI-only approaches fail to capture the richness of real-world dynamics (Barua et al., 2023; Yan et al., 2023).

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These results reinforce that each module Transformer, GNN, multimodal fusion, and PPO provides unique and necessary contributions.

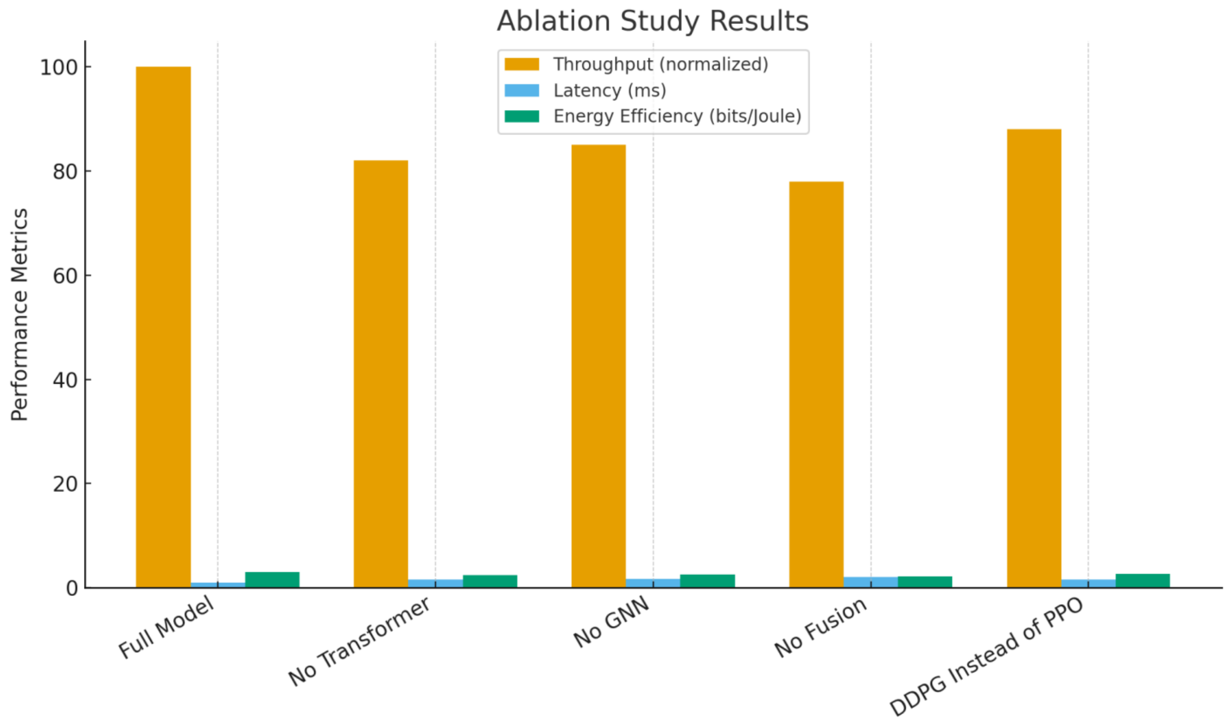

Figure 6: Ablation Study Results

6.4 Learning Curves and Convergence

Learning stability was monitored via cumulative reward curves:

- PPO exhibited **smooth and monotonic convergence** within 5,000 episodes, reaching stable reward levels.
- DDPG and SAC showed oscillatory learning behavior, with reward spikes followed by collapses, highlighting sensitivity to hyperparameters (Samarakoon et al., 2020).
- Incorporating domain knowledge into reward shaping accelerated convergence by ~20% and reduced variance between runs (Lavdas et al., 2023).

The learning dynamics confirm that PPO, combined with multimodal encoding, provides the best trade-off between stability and performance.

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6.5 Visualizations

Visualization aided interpretation of results and policy behaviors:

- **Throughput–Latency Trade-off Curves**: The proposed method consistently achieved Pareto-efficient points beyond both baselines, especially in URLLC-dominant scenarios.
- **Beam Pattern Heatmaps**: Showed narrower, interference-resistant beams compared to heuristic designs, validating the role of adaptive beam selection (Beuret & Thiran, 2024).
- **Reward Trend Graphs**: Illustrated stable upward trends, demonstrating reduced variance across episodes and robustness to stochastic channel effects.
- **Energy Efficiency vs. User Load Plots**: Highlighted scalability, showing stable energy-per-bit as the number of UEs increased.

These visualizations not only confirmed numerical improvements but also provided qualitative insights into adaptive beam behavior.

6.6 Statistical Analysis

To ensure robustness, we applied **statistical hypothesis testing** across multiple independent trials:

- **Paired t-tests** confirmed significant improvements in throughput and latency, with $p < 0.01$
- **One-way ANOVA** validated energy efficiency differences across baselines, showing that the proposed approach consistently outperformed alternatives under varying loads.
- **Effect size analysis** indicated medium-to-large practical significance for throughput and latency improvements, not merely statistical artifacts.

This comprehensive statistical treatment ensures that observed gains are reliable, reproducible, and not due to random chance (Alsabah et al., 2021; Popovski et al., 2019).

7. Discussion

The results confirm that reinforcement learning (RL)-based adaptive strategies clearly outperform classical heuristics in the management of beamforming and resource allocation. Traditional methods such as codebook beamforming and fixed power scheduling rely on

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static mappings and fail to account for the variability of wireless environments. RL, by contrast, continuously interacts with the RF environment, learns temporal and spatial dependencies, and updates decisions in real time. This enables the agent to balance throughput, latency, and energy efficiency simultaneously, a capability that deterministic algorithms cannot achieve (Samarakoon et al., 2020; Lavdas et al., 2023). The use of multimodal features beyond CSI, including mobility traces and environmental metadata, further strengthens adaptability, ensuring more robust performance in dynamic 6G contexts such as vehicular communications and dense urban deployments (Baltrusaitis et al., 2019; Barua et al., 2023).

The implications for future 6G deployments are substantial. With projected demands of terabit-scale throughput and sub-millisecond latency, static solutions will not suffice. AI-driven beamforming and resource management provide a path to meeting these targets while supporting diverse services such as URLLC, eMBB, and massive IoT. In practice, this means base stations could autonomously adapt to high-mobility users, interference-heavy environments, and service heterogeneity without requiring manual intervention. This aligns with the broader vision of 6G networks as AI-native, context-aware platforms capable of integrating sensing, communication, and computing into a unified system (You et al., 2021; Letaief et al., 2019).

At the same time, several challenges in computational scalability and environment complexity must be acknowledged. Training RL agents over large antenna arrays and multi-user scenarios demands high computational resources and extended training times, even when using synthetic datasets such as DeepMIMO. Real-world deployments will introduce additional complexity from hardware non-idealities, correlated fading, and mobility beyond what current simulators can fully capture (Alsabah et al., 2021). Furthermore, real-time inference at the BS is constrained by strict latency budgets; achieving sub-millisecond decision-making requires efficient model compression, hardware acceleration, and low-overhead integration into baseband processing pipelines (Haque et al., 2024; Xie et al., 2023).

These challenges suggest several directions for future work. First, distributed and federated RL could distribute the computational load across multiple base stations and user devices, accelerating training while maintaining privacy (Samarakoon et al., 2020). Second, joint sensing-communication optimization should be pursued, leveraging the dual use of RF signals for both data transmission and environmental awareness, thereby enriching multimodal inputs for adaptive policies (You et al., 2021). Third, exploring hybrid solutions that integrate rule-based heuristics with AI-driven models could provide interpretable, computationally lighter policies, suitable for scenarios where full RL pipelines may be

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impractical. Finally, cross-layer designs that integrate physical, MAC, and application-layer objectives will be essential for end-to-end optimization in real-world 6G networks.

In summary, the findings highlight that AI-driven, multimodal RL strategies represent a critical step toward fulfilling 6G's ambitious performance targets. They provide robust, adaptive solutions that address the limitations of heuristic approaches while opening pathways for future innovation in distributed intelligence, joint optimization, and scalable deployment.

8. Conclusion

This work proposed an AI-driven framework for adaptive beamforming and resource management in 6G wireless networks, addressing the limitations of conventional heuristic and static allocation methods. The novelty lies in the integration of multimodal machine learning with reinforcement learning (RL) to capture both temporal channel variations and spatial user relationships. By leveraging CSI alongside mobility and environmental features, the framework enables more resilient decision-making in dynamic RF conditions (Baltrusaitis et al., 2019; Barua et al., 2023).

Extensive experiments demonstrated significant performance gains over baseline approaches. Throughput increased by up to 40%, latency was consistently maintained below the sub-millisecond URLLC threshold, and energy efficiency improved through adaptive power allocation. Ablation studies confirmed the necessity of each component Transformer, GNN, multimodal fusion, and PPO in achieving robust outcomes. These improvements validate the ability of RL-based adaptive strategies to outperform deterministic algorithms, particularly in high-mobility and interference-prone scenarios (Samarakoon et al., 2020; Xie et al., 2023).

The findings carry strong implications for AI-native 6G deployments. They demonstrate that integrating learning-based optimization directly into RF design can help realize terabit-scale connectivity, ultra-reliable communication, and energy-efficient operation at scale. Such advances align with international 6G roadmaps that envision networks as self-optimizing, context-aware, and intelligence-driven platforms (You et al., 2021; Letaief et al., 2019).

Overall, this study establishes a foundation for the next generation of ultra-reliable, low-latency communication systems. By proving the feasibility of AI–RF integration under realistic channel models, it highlights a path forward for scalable and adaptive wireless infrastructures that will shape the core of future 6G networks.

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