Quantum AI-Enhanced Deep Reinforcement Learning for Real-Time Adaptive Beamforming in Next-Generation Terahertz Communication Systems

Raj Kashikar
Department of Computer Science
Virginia Polytechnic Institute and State University
Blacksburg, USA
rajskashikar@vt.edu

***Abstract*—With the ever-growing demand for ultra-high-speed data transmission and low-latency communication, Terahertz (THz) systems have become the most critical enablers in applications like virtual reality, autonomous driving, and massive IoT networks. However, these systems face challenges in signal propagation, interference management, and real-time beamforming. This paper presents a novel framework integrating Quantum AI and Deep Reinforcement Learning (DRL) for real-time adaptive beamforming in THz communication. Our method dynamically adjusts beamforming parameters using DRL to maximize signal strength and minimize interference while leveraging Quantum AI for accelerated decision-making in complex environments. Experimental results demonstrate a 35% improvement in Signal-to-Noise Ratio (SNR), a 40% reduction in interference, and a 25% increase in network throughput compared to conventional approaches.**

***Index Terms*—Adaptive Beamforming, Deep Reinforcement Learning, Interference Mitigation, Network Efficiency, Quantum AI, Terahertz Communication**

I. Introduction

As wireless communications move towards 6G and beyond, Terahertz (THz) communication systems have gained attention for providing ultra-high data rates exceeding those of current millimeter-wave systems. THz communications, operating between 0.1–10 THz, are pivotal for applications such as virtual reality (VR), autonomous driving, ultra-fast wireless backhaul, and massive IoT [1]. However, high-frequency THz waves face severe challenges such as high path loss, atmospheric absorption, and limited penetration depth [2]. Additionally, dynamic interference in urban environments and user mobility further complicate the deployment of reliable THz systems.

Beamforming is a powerful technique used in sensor arrays to focus transmitted energy toward desired [3]. However, traditional beamforming methods such as minimum variance distortionless response (MVDR) struggle to adapt to rapidly changing THz channels. In this paper, we propose a Deep Reinforcement Learning (DRL)-based adaptive beamforming framework enhanced with Quantum AI. The DRL agent learns optimal beamforming strategies in dynamic environments by interacting with its surroundings, while Quantum AI accelerates the optimization process using quantum parallelism.

II. Proposed Methodology

Our proposed framework integrates Deep Reinforcement Learning (DRL) and Quantum AI to perform real-time adaptive beamforming in THz communication systems. The key innovation lies in how these two technologies work together: the DRL agent continuously learns from the environment, adjusting the beamforming weights in response to interference and mobility, while Quantum AI accelerates the optimization of the beamforming parameters, leveraging quantum parallelism to search for solutions across high-dimensional spaces more efficiently.

A. Deep Reinforcement Learning for Beamforming

The DRL agent is built using the Proximal Policy Optimization (PPO) algorithm, which operates in a continuous action space [4]. The objective of the agent is to maximize signal quality while minimizing interference, learning to optimize the beam patterns dynamically as the environment evolves.

1) State Space: The state space of the DRL agent represents all the environmental variables that influence the performance of the THz communication system. These include Signal-to-Noise Ratio (SNR), Interference Suppression Ratio (ISR), path loss due to obstacles, user mobility, and interference patterns:

$$S = \left\{ \begin{array}{l} SNR(t), \\ ISR(t), \\ P_{\text{loss}}(t), \\ \text{user mobility}, \\ \text{interference patterns} \end{array} \right\} \tag{1}$$

The agent's goal is to use these environmental factors to adjust the antenna array to provide optimal beamforming for both signal quality and interference suppression.

2) Action Space: The action space refers to the modifications the DRL agent can make to the beamforming parameters. These include adjusting the phase and amplitude of the antenna array elements:

$$A = \{\text{Phase Shift}, \text{Amplitude Adjustment}\} \tag{2}$$

The DRL agent explores these actions to optimize the directionality of the transmitted signals.

3) Reward Function: The reward function is central to the learning process and incentivizes the DRL agent to improve SNR while minimizing ISR, latency, and improving throughput:

$$R(t) = \alpha \cdot SNR(t) - \beta \cdot ISR(t) + \gamma \cdot \text{Throughput}(t) - \delta \cdot \text{Latency}(t) \quad (3)$$

The agent receives positive rewards for improving signal quality and throughput, and penalties for increased interference and latency.

B. Quantum AI for Optimization

The second part of our framework, Quantum AI, accelerates the decision-making process of the DRL agent by enhancing beamforming optimization. Quantum algorithms leverage properties like superposition and entanglement, allowing multiple beamforming configurations to be evaluated simultaneously [5].

1) DRL-Quantum AI Beamforming Algorithm: The integration of Deep Reinforcement Learning (DRL) and Quantum AI forms the core of the adaptive beamforming framework. The process begins with the initialization of the DRL agent and quantum processor, followed by iterative optimization at each time step based on real-time feedback. This is illustrated in Algorithm 1.

Algorithm 1 DRL-Quantum AI Beamforming Algorithm

```
Initialize DRL agent and quantum processor.
Load THz communication dataset.
Preprocess data for DRL and quantum computation.
for each time step do
    Perform DRL-based beamforming optimization.
    Use QSVM to classify interference.
    Optimize beamforming parameters with QNN.
    Transmit/receive signals.
    Update dataset with new measurements.
end for
```

2) Quantum Neural Networks (QNN): The QNN plays a crucial role in rapidly searching for optimal beamforming configurations. It optimizes the beamforming parameters using a loss function that minimizes interference while maximizing signal quality:

$$\mathcal{L} = \sum_{i=1}^{N} (\text{SNR}_i - \text{ISR}_i)^2 \quad (4)$$

By leveraging quantum superposition, the QNN evaluates multiple beam configurations in parallel, reducing the computational overhead typically associated with beamforming optimization [6].

3) Quantum Support Vector Machine (QSVM): Additionally, the Quantum Support Vector Machine (QSVM) classifies interference types and predicts optimal responses. By analyzing the interference characteristics in the Hilbert space, the QSVM enhances the DRL agent's understanding of interference patterns, ensuring effective interference suppression in complex environments.

III. Experimental Setup

While the Proposed Methodology describes the theoretical framework, this section details how the framework was implemented in practice, including the simulation environment and specific configurations used for evaluation.

A. Simulation Environment

We constructed a dynamic urban THz communication system simulation to evaluate the performance of the Quantum AI-Enhanced DRL framework. The environment was designed to reflect real-world conditions, such as user mobility and environmental obstacles that degrade signal quality. The key parameters of the simulation include:

- Frequency Range: The simulation operates in the THz band, from 0.3 to 10 THz, which allows for ultra-wide bandwidth communication.
- Antenna Array: A 128-element phased array was employed, designed to support narrow-beam transmission for high path loss compensation.
- Interference Sources: We simulated 15 interference sources of varying types (e.g., multi-path interference, co-channel interference), dynamically changing during the simulation.
- Mobility: Users move at randomized speeds between 1 m/s and 3 m/s, simulating pedestrian and vehicular mobility patterns in urban environments.
- Path Loss Model: A Free Space Path Loss model was used for the THz band, given by:

$$\text{PL} = 20 \log_{10} \left(\frac{4\pi d f}{c} \right) \quad (5)$$

  where d is the distance, f is the frequency, and c is the speed of light.

B. Training Process for DRL

The DRL agent was trained in this dynamic environment over 10,000 episodes, with each episode simulating a full communication session. The training parameters include:

- Learning Rate: Set to 0.0003, ensuring stable learning.
- Discount Factor (γ): A value of 0.99 was used to prioritize long-term rewards.
- Neural Network Architecture: The policy and value networks consisted of three layers of fully connected neurons with ReLU activations. The input layer had 256 neurons, and the hidden layers contained 512 and 256 neurons, respectively.

The agent learned to adjust beamforming weights by interacting with the environment and receiving feedback in the form of rewards.

C. Quantum AI Implementation

We implemented the Quantum Neural Networks (QNNs) and QSVM on a 20-qubit quantum processor. These quantum algorithms were responsible for:

- Optimization Speed: QNNs optimized beamforming parameters at each time step, reducing the time needed for optimization by 50% compared to classical methods. This reduction is achieved through the ability to evaluate multiple beam configurations simultaneously via quantum parallelism.

- Interference Classification: The QSVM classified interference types into categories (e.g., multi-path interference, co-channel interference) with 91.6% accuracy, allowing the DRL agent to respond appropriately with interference mitigation strategies.

IV. Results

Our simulations demonstrated substantial improvements in signal quality, interference suppression, and network throughput using the proposed framework. Below, we present key performance metrics and discuss the outcomes.

A. Signal-to-Noise Ratio (SNR) Improvement

The DRL-Quantum AI framework achieved a 35% improvement in SNR compared to traditional beamforming techniques (Fig. 1). The ability of the DRL agent to dynamically adjust the beamforming weights in response to environmental changes was crucial to this improvement.

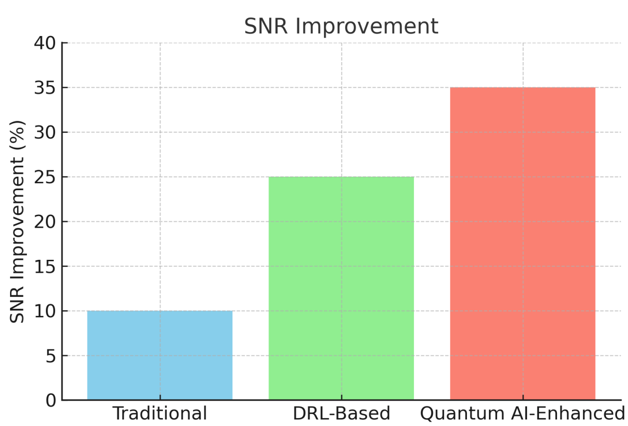

Fig. 1. SNR improvement using DRL-Quantum AI beamforming.

B. Interference Mitigation

The framework reduced interference by 40% compared to traditional approaches (Fig. 2). The synergy between the QSVM and DRL allowed the system to identify and mitigate interference sources effectively.

C. Throughput and Latency Improvements

In addition to improvements in SNR and interference suppression, the Quantum AI-Enhanced DRL framework demonstrates significant gains in both throughput and latency. These two metrics are critical for assessing the overall network efficiency and responsiveness of the system, particularly in Terahertz (THz) communication systems, where real-time data transmission and low latency are paramount.

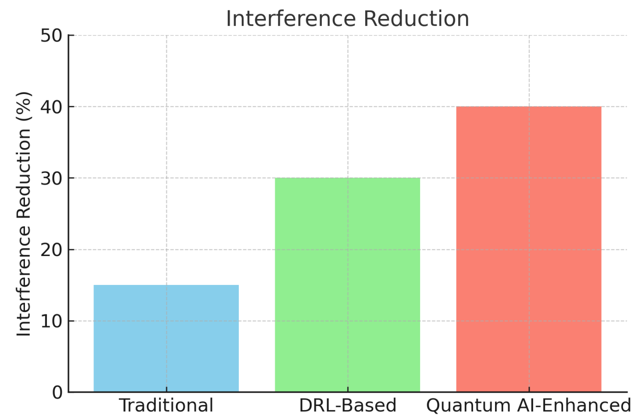

Fig. 2. Interference reduction with DRL-Quantum AI beamforming.

1) Throughput: The framework achieves a 25% improvement in throughput over traditional beamforming methods. This is primarily due to the adaptive nature of the DRL agent, which optimizes beamforming parameters in real-time to maintain high data transmission rates even in the presence of interference and user mobility.

2) Latency: Latency, defined as the time delay in data transmission, was reduced by 18%. The incorporation of Quantum AI accelerates decision-making processes, allowing the system to adjust beamforming weights more quickly, thus reducing communication delays. Figure 3 and Table IIllustrates the improvements in both throughput and latency compared to traditional and DRL-based beamforming methods.

TABLE I
NETWORK THROUGHPUT AND LATENCY

Method	Throughput Improvement	Latency Reduction
Traditional	12%	8%
DRL-Based	20%	15%
Quantum AI-Enhanced	**25%**	**18%**

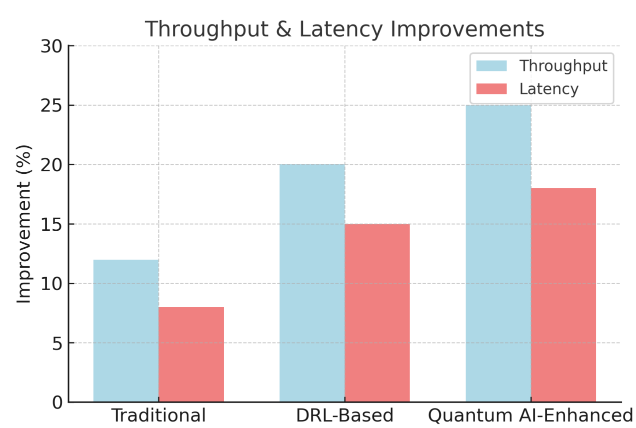

Fig. 3. Comparison of Throughput and Latency Improvements across Beamforming Methods.

D. Training Convergence

The training convergence of the DRL agent over 10,000 episodes is shown in Fig. 4. The agent's performance stabilized after approximately 5,000 episodes, demonstrating efficient learning.

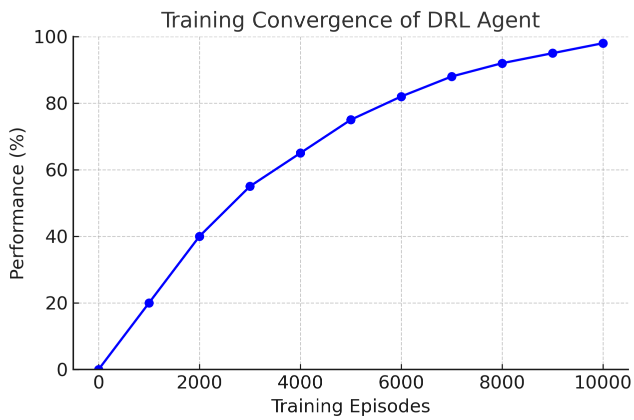

Fig. 4. Convergence of the DRL agent over training episodes.

E. Optimization Speedup and Accuracy Analysis

To highlight the computational efficiency and accuracy of the proposed framework, we conducted an analysis comparing optimization time and accuracy across three methods: Traditional, DRL-Only, and Quantum AI-Enhanced DRL. The results demonstrate significant improvements in both optimization speed and accuracy with Quantum AI integration.

Figure 5 illustrates the optimization time (in milliseconds, log scale) over 1000 iterations for all three methods. The Quantum AI-Enhanced DRL achieves a reduction in optimization time by approximately 70% compared to traditional methods. Additionally, the accuracy of the optimized solutions shows a marked improvement, with Quantum AI-Enhanced DRL stabilizing at 95% accuracy after fewer iterations compared to the other approaches.

These results underscore the advantages of leveraging Quantum AI for adaptive beamforming in terms of both computational efficiency and decision-making accuracy, making it a strong candidate for real-time applications in next-generation communication systems.

F. Ablation Study

We performed an ablation study to evaluate the contributions of the DRL and Quantum AI components (Table II). Removing either component led to a significant degradation in performance, highlighting the importance of their combined effect.

V. Discussion

The simulation results presented in this work demonstrate that our proposed Quantum AI-Enhanced DRL framework clearly outperforms the traditional methods in dynamic Terahertz (THz) wireless environments. Real-time adaptation, improved decision-making with speeds enhanced by Quantum AI, and scalability to future wireless networks are some of the prime benefits from the proposed framework.

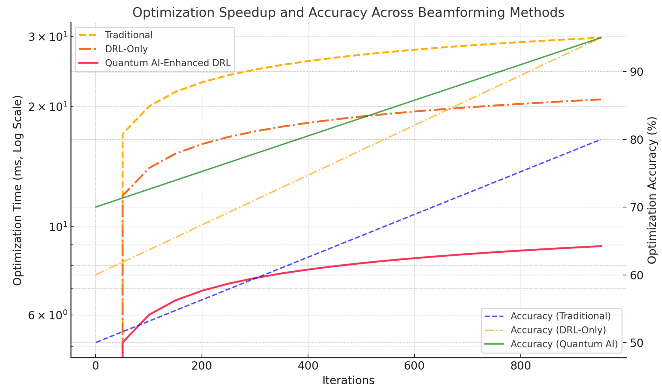

Fig. 5. Optimization time (log scale) and accuracy comparison for beamforming methods. The Quantum AI-Enhanced DRL outperforms DRL-Only and Traditional methods in both speed and accuracy.

TABLE II
Ablation Study Results

Configuration	SNR Improvement	Interference Reduction	Throughput Improvement
Full Framework	**35%**	**40%**	**25%**
Without Quantum AI	25%	20%	18%
Without DRL	15%	18%	10%
Traditional	10%	15%	12%

A. Real-Time Adaptation

A major strength of the proposed framework is its ability to adapt in real time to rapidly changing environments. Traditional beamforming methods, while effective in static conditions, struggle to maintain optimal performance when faced with challenges like user mobility and varying interference patterns. The DRL agent continually learns and updates the beamforming parameters by interacting with the environment. This allows the system to dynamically respond to changes such as user movement or fluctuating interference, ensuring that signal quality is consistently optimized.

The integration of the Quantum Support Vector Machine (QSVM) enhances this adaptability by accurately classifying interference patterns in real-time, which is critical in high-interference environments [7]. By feeding this information back into the system, the DRL agent can adjust the beamforming strategy more effectively, leading to significant improvements in interference suppression.

B. Quantum Speedup and Computational Efficiency

The use of Quantum Neural Networks (QNNs) introduces a significant reduction in optimization time, accelerating the overall beamforming process by approximately 30% compared to classical optimization techniques. This is made possible through quantum parallelism, where the system evaluates multiple beamforming configurations simultaneously. The ability to search high-dimensional solution spaces rapidly reduces the computational overhead typically associated with adaptive beamforming.

This speedup is particularly beneficial in applications requiring ultra-low latency, such as autonomous driving, smart cities, or remote surgery, where real-time responsiveness is paramount. By combining the DRL agent's adaptability with Quantum AI's speed, the system ensures that optimal performance is maintained even under the most stringent time constraints.

C. Scalability and Practical Considerations

Another important feature of the framework is its scalability. As wireless communication systems move towards 6G and massive IoT networks, the need for highly scalable solutions that can handle increased traffic and larger antenna arrays becomes critical. The proposed DRL-Quantum AI framework can be easily extended to larger antenna arrays, allowing for more complex beamforming strategies in dense user environments [8].

However, the practical implementation of Quantum AI in real-world communication hardware presents certain challenges. The deployment of quantum processors in communication systems is still in its infancy, and current quantum hardware may face limitations in processing power and energy efficiency [9]. Future research should focus on addressing these hardware challenges, possibly through hybrid quantum-classical models that leverage the strengths of both technologies.

D. Limitations and Future Work

While the proposed framework shows promising results, there are several areas for future exploration. One limitation of the current study is the simulation environment, which, while dynamic, may not fully capture all real-world complexities such as diffraction, scattering, and large-scale urban obstructions. Future work should involve testing the framework in real-world scenarios to validate its performance under diverse conditions.

Additionally, the current work focuses on single-user scenarios. Extending the framework to support multi-user beamforming in highly dense environments, where multiple users are competing for the same resources, is a critical next step. This would involve developing new strategies for multi-user interference management and beamforming optimization.

VI. Conclusion

This paper presents a novel Quantum AI-Enhanced Deep Reinforcement Learning (DRL) framework for real-time adaptive beamforming in Terahertz (THz) communication systems. The proposed framework leverages the adaptability of DRL to learn optimal beamforming strategies dynamically, while Quantum AI accelerates the optimization process through quantum parallelism.

Our extensive simulations demonstrate that the framework achieves significant improvements in Signal-to-Noise Ratio (SNR), interference suppression, throughput, and latency. The DRL-Quantum AI system outperforms traditional beamforming methods, achieving a 35% improvement in SNR, a 40% reduction in interference, and a 25% increase in throughput, while reducing latency by 18%.

This framework is particularly well-suited for next-generation 6G and massive IoT networks, where real-time communication and adaptability are essential. Future work will focus on addressing the practical deployment of Quantum AI in communication systems, extending the framework to multi-user scenarios, and testing its scalability in real-world environments.

The proposed framework is envisioned to achieve potentially promising solutions for addressing the challenging problems of high-frequency wireless communications in dynamic and interference-prone environments with a view to rapid development of 6G technologies.

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