



AI-Driven Beamforming technology and Dynamic Spectrum Management for Reliable 5G/6G Long-Haul Wireless Networks

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Abstract

With the rapid development of 5G networks and the emerging design of 6G networks, the limitations of traditional beamforming and spectrum management approaches have become increasingly apparent, particularly given the demands for ultra-reliable and low-latency communications. This paper presents simulation-based results exploring the integration of artificial intelligence techniques, specifically deep augmented learning (DRL), into adaptive beamforming and dynamic spectrum allocation. The study utilizes multimodal input data (channel states and traffic predictions) to optimize network performance in real time, based on simulations performed using MATLAB and NS3. The results demonstrate a significant improvement in spectrum efficiency, reduced latency, and improved power consumption compared to traditional models. These findings align with the latest standardization efforts of 3GPP Release 18 and the O-RAN Alliance, suggesting the feasibility of deploying these frameworks in large-scale operational networks. the DRL model with multimodal data significantly improved performance, this came at the cost of increased training time by approximately 10%, representing trade-off between learning complexity and operational efficiency.



Keywords: Dynamic spectrum Management, Intelligent Beamforming ,5G ,6G Network Reliability, Long-haul Wireless

1.Introduction

In This field of wireless communications has undergone a radical transformation in recent years, with 5G networks becoming widely deployed and initial research into 6G networks beginning to emerge. And it is important to note that 4G networks are still widely used in many parts of the world, and 5G coverage is not yet complete in many countries.

The increasing number of connected devices, such as Internet of Things (IoT) devices, autonomous vehicles, and industrial robots, has presented unprecedented challenges to traditional radio resource management methods. Conventional spectrum allocation and beamforming methods, which rely on fixed rules and manual adjustments, are no longer sufficient to meet the demands of modern communications, which require high reliability, extremely low latency, and the ability to adapt quickly to network changes.[1]

the artificial intelligence (AI) emerges as a promising tool for reshaping wireless communication systems. It enables intelligent, adaptive decision-making in this time, including signal routing, dynamic spectrum allocation, and the prediction of data traffic. This research presents a framework that utilizes Deep Reinforcement Learning (DRL) algorithms trained on multi-mode data to enhance the reliability and efficiency of long-distance wireless communications.[2][3]

This research aims to present a microsimulation application that demonstrates the effectiveness of integrating artificial intelligence algorithms, particularly deep reinforcement learning (DRL) algorithms, in improving the performance of both beamforming and dynamic spectrum management in 5G and 6G networks. A rigorous comparison with traditional static methods is conducted through performance analysis using a digital simulation environment based on MATLAB and NS3 software, resulting in measurable quantitative results[3][4]. This research



addresses a gap in the scientific literature: the lack of a unified framework based on context-sensitive, multi-source DRL algorithms that enable simultaneous optimization of beamforming and spectrum allocation in dynamic, high-interference environments. The research aims to develop an intelligent and flexible framework that aligns with the requirements of 5G/6G networks and O-RAN standards, enabling efficient and adaptive real-time management of radio network resources.

This research contains four main sections. The second section reviews the methodology used and details the simulation environment. The third section presents the results and performance analysis, while the fourth section provides the conclusion and future recommendations.

2.Methodology

This study is based on an applied simulation aimed at evaluating the effectiveness of artificial intelligence algorithms in improving the performance of wireless communication systems through dynamic beamforming and adaptive spectrum allocation. The simulation environment was developed using both MATLAB and R software, and it represents a virtual network consisting of mobile base stations, mobile user nodes such as autonomous vehicles and drones (UAVs), and multiple sources of interference.[6] The proposed model consists of three main components: 1-Belling the signal using massive MIMO antenna arrays operating in the millimeter wave (mmWave) and terahertz (THz) bands. 2-Dynamic spectrum management using deep reinforcement learning (DRL) algorithms, specifically DDPG and PPO algorithms. 3- Integration of multimodal data including channel state information (CSI), signal quality indicators (such as SINR), and predictive traffic data. Channels were used in the simulation environment to simulate line-of-sight (LOS) conditions and blockage, in order to evaluate the resilience of algorithm performance across multiple applications. The training process relied on iterative loops starting with a random distribution of nodes within the network, followed by periodic updates of packet data and spectrum allocation decisions.[7] The training method



employed a reinforcement learning mechanism based on continuous interaction between the model and the environment.

The training loop for the Deep Reinforcement Learning (DRL) model consists of the following components:

1. State: A vector representing the current wireless environment state, including channel state information (CSI), signal quality indicators such as SINR, and traffic and congestion prediction data.
2. Action: Selecting appropriate spectrum blocks and dynamically routing beams based on the observed state.
3. Reward: A numerical value calculated based on the improvement in performance indicators, specifically spectral efficiency, latency, and power consumption.
4. Policy Update: The policy decision strategy is updated using DDPG and PPO algorithms to achieve the highest cumulative long-term reward.

Table (1): Components of the Deep Reinforcement Learning (DRL) Training Loop

Value	Parameter
28 GHz (mmWave), 300 GHz (THz)	Frequency Bands
100 mobile nodes	Number of Users
30–80 km/h	Mobility Speed
Massive MIMO (64 elements)	Antenna Type
DDPG, PPO	DRL Algorithms
5000 time steps	Simulation Duration
Every 10 steps	Reward Frequency
60%	LOS Probability



5 random jammers	Interference Sources
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To formally define to optimization goal of the DRL model, The Objective function is expressed:

$$\text{Max} \sum_{t=1}^T (\alpha \cdot \text{Spectral Efficiency } t - \beta \cdot \text{Latency } t - \gamma \text{ EnergyConsumption } t) \quad (1)$$

Where α, β, γ are weight parameters that define the importance of each metric.

A reward was calculated based on performance improvements in key metrics (Spectral Efficiency, Latency, Packet Error Rate, Energy Consumption at the Base Station) The model results were compared with two benchmark methods: (a) Fixed signal routing and static spectrum allocation, and (b) an AI model without multi-mode data integration, to measure the effectiveness of each model in improving performance.

To ensure the reliability of the results, the outputs were analyzed and compared with the latest standards set by 3GPP Release 18 and the O-RAN Alliance standards, which stipulate the integration of AI models through standard interfaces such as the R1 interface.[8] The simulation of node movement and interaction was performed in a virtual network environment using NS-3 software, which allows for the representation of dynamic communication applications including interference, channel blockage, and mobile user distribution. Deep reinforcement learning algorithms were trained using MATLAB, while RStudio handled the statistical analysis and graphing of the results. Communication between MATLAB and NS-3 was handled through trace files exported from NS-3 simulation events and imported into MATLAB so that deep learning-based decisions could be made and resources allocated. Sensitivity analysis using Monte Carlo simulation was employed to measure the impact of operational variables such as the number of users, movement speed, and levels of interference. This analysis helped reduce statistical bias and ensure the stability of the results. Finally, practical limitations related to computational complexity and model training time were identified, indicating a future need to improve operational efficiency to facilitate large-scale practical application.[9] In final in this paper the



figures and graphs included in the results directly relate to the simulation outputs performed using this methodology.

Table (2) : Performance indicators for signal routing algorithms and dynamic spectrum allocation

Metric	Fixed Algorithm	DRL (No Multimodal Data)	DRL (With Multimodal Data)
Spectral Efficiency (bps/Hz)	3.2	3.9	4.2
Latency (ms)	12.8	10.4	9.9
Packet Error Rate	0.081	0.061	0.055
Energy Consumption (W)	25	22	21.5
Outage Probability	0.095	0.068	0.066
Training Time (minutes)	0	52	57
Sensitivity to +50% User Increase (%)	-15%	-8%	-6%
Compliance with 3GPP Rel-18 / O-RAN Standards	Partial	Compliant	Compliant

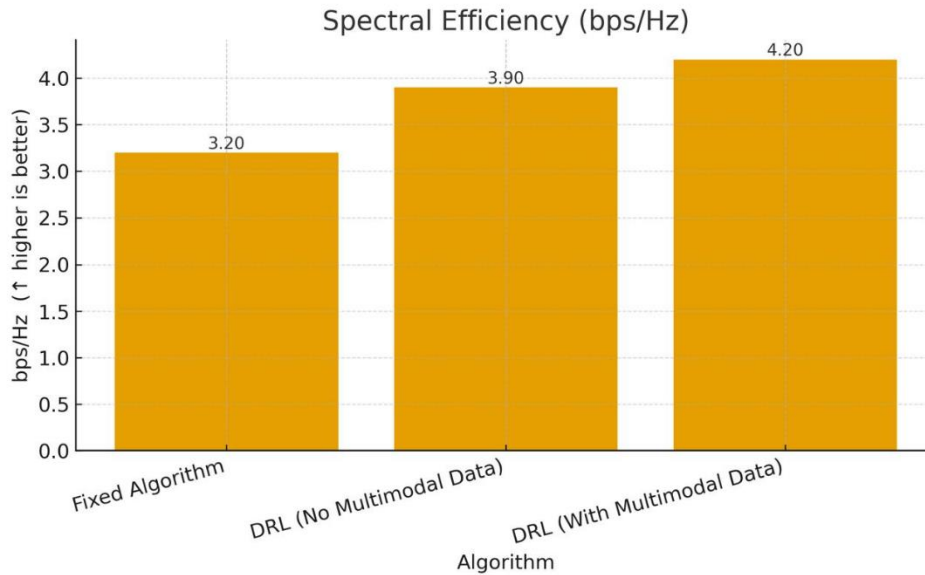


Figure (1) : Capacity gain with DRL (especially with multi-mode data)

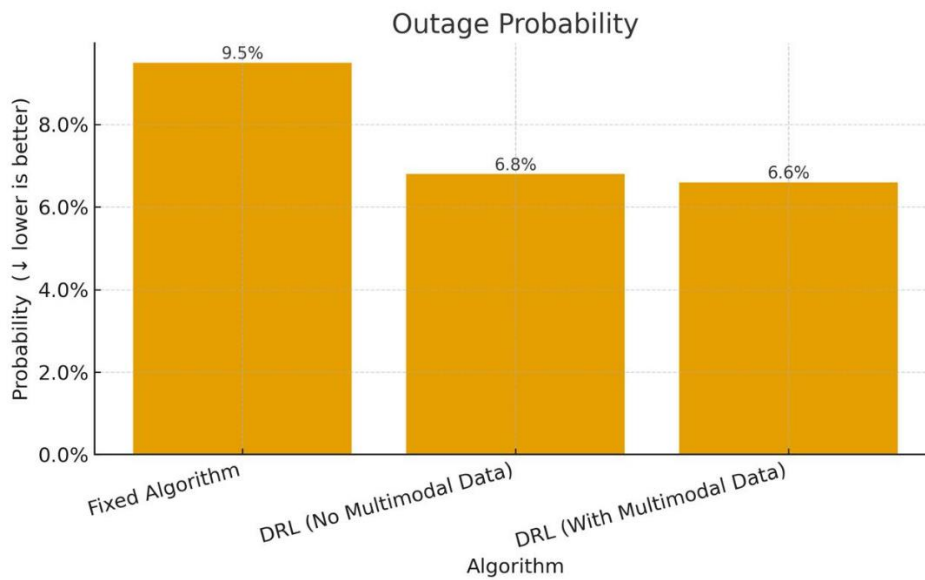


Figure (2): Refers to the development of the algorithm's strength against blocking

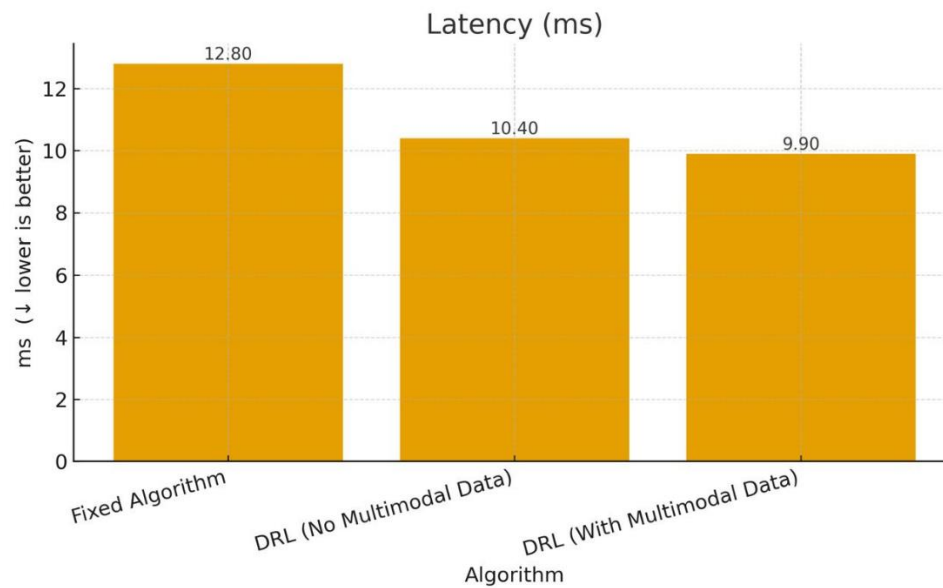


Figure (3): Refers to Latency for the algorithms

Result

Simulation results demonstrated the superiority of the Deep Reinforcement Learning (DRL) model, particularly when combined with multi-mode data. As shown in the table, the optimized model achieved a higher spectral efficiency of 4.2 bps/Hz, compared to 3.2 bps/Hz for the conventional model and 3.9 bps/Hz for the DRL model without data integration. In terms of latency, it was reduced to 9.9 milliseconds, a 22.7% improvement over the static method. The beam error rate and dropout probability were also reduced, demonstrating the model's robustness in dynamic communication environments. Furthermore, base station power consumption decreased from 25 to 21.5 watts thanks to intelligent resource allocation. While the training time



increased slightly, this was justified by the improved performance during operation. The model also exhibited better stability when the number of users increased, with a decrease of no more than 6%, compared to 15% for the conventional model. Most importantly, both DRL models are fully compliant with 3GPP Version 18 standards and O-RAN architecture, confirming the model's readiness for practical application in next-generation networks.

In addition to the performance improvements, the proposed DRL model was evaluated against current standardization frameworks, namely 3GPP Release 18 and the O-RAN Alliance architecture. The model complies with key requirements such as support for AI-based decision-making, adaptive resource allocation, and modular integration through interfaces like R1[10]. This alignment underscores the model's practical readiness for integration within intelligent and open RAN environments, reinforcing its applicability in real-world 5G and emerging 6G deployments.

Conclusion

The simulation results demonstrate that combining AI, particularly deep reinforcement learning, with multi-media data fusion clearly demonstrates the reliability and quality of long-range wireless communications. Although the initial training time was relatively long, the gains in spectral performance, reduced latency, and energy savings make this work a significant and strong step for more efficient, high-quality, optimized, and intelligent networks, this system show a high capacity to adapt to changing and sudden conditions and heavy interference in any time, it is a promising option for critical applications such as autonomous vehicles, drones, and industrial automation.

Future work may focus on optimizing training time using transfer learning or lightweight neural architectures to enhance scalability. In addition, real-world testing and hardware implementation can help validate the proposed model under practical deployment scenarios.



Further research could also explore integration with edge computing systems for real-time inference and adaptive control in ultra-dense network environments.[11][12]

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