EPJ Web of Conferences **375**, 02003 (2026) https://doi.org/10.1051/epjconf/202637502003
RTEP-2026

Adaptive AI for QoS Management in 6G Networks: Leveraging DRL for Optimal Performance

Ali Ahmed Alqudaihi[1,*]

[1]Department of Electrical Engineering Technology, College of Applied Industrial Technology (CAIT), Jazan University, Baysh, Saudi Arabia.

Abstract. The research investigated the application of Adaptive AI for Quality of Service (QoS) Management in 6G Wireless Networks that are affected by both α-η-μ fading and Heavy Co-channel Interference (CCI); this was done through the use of Deep Reinforcement Learning (DRL) methods where an agent learns optimal ways to solve problems such as Power Control, Channel-Switching and Modulation Schemes via interacting within a simulated environment. Simulations based on the use of MATLAB showed that the DRL agent found a convergence point and outperformed non-adaptive static approaches in terms of four metrics: throughput, latency, packet-delivery-ratio, and fairness In addition to utilizing adaptive AI as a means to improve system performance, the DRL-based agent also was able to utilize less power than its static counterparts, and provided good quality of service (QoS) for various forms of traffic (e.g., eMBB, URLLC, mMTC). Additionally, heatmap and ablation studies were completed to show that every design choice from the research conducted throughout this work have been contributing to successfully utilizing adaptive AI as an aid in next-generation wireless systems to be developed through 6G.

1 Introduction

Wireless communications have grown at a rate that was rapid and each subsequent generation introduced a multitude of new features and functionality that were unforeseen by consumers. 6G is not just for mobile phone use and it includes smart vehicles, wearable health devices, industrial automation, satellite and many other applications. This will create a much tighter interconnect between the human and machine worlds. However, there will be a need for a network to effectively manage Quality of Service (QoS) in an extremely complex operating environment [1,2]. In essence, QoS represents the network's ability to provide customers with a quality experience (i.e., minimal delay, no dropped calls, fast download/upload times, etc.) while providing a high level of security. However, A major challenge associated with 6G is the issue of fading/interference that could potentially disrupt a user's connectivity or significantly degrade their quality of service. Wireless channel signals are never traveling through air in a simple linear way. Signals instead, bounce, scatter, reflect, and mix with background noise causing signal fade. One of those generalized models for describing this difficult and irregular channel environment is the α-η-μ fading model. It is a much more accurate fading model than the earlier models such as Rayleigh and Rician fading, because it can describe nonlinearities, multipath clusters, and the imbalance in the received signals; therefore, α-η-μ model is able to provide a better representation of the physical channel, particularly in the cases where there are many dense devices and/or complex channel environments [3]. In addition to the fading, there is also Co-Channel Interference (CCI) present when multiple devices/users utilize the same frequency band simultaneously. CCI will be a significant issue in 6G, as the number of active users/devices per unit area is expected to increase dramatically, thus increasing the amount of interference. and high density IoT [4,5]. Using adaptive AI in 6G networks, for example, can automatically result in AI reallocating power, changing the modulation scheme, dynamically adjusting routing and using interference cancellation techniques. In essence, AI needs to be able to adaptively address non-linear random variations due to fading; and suppress or mitigate interference caused by multiple users, simultaneously. Therefore, a 6G system must be able to properly manage both fading and interference if it wishes to provide adequate Quality of Service (QoS). Traditional techniques such as fixed resource allocations and traditional signal processing are no longer sufficient for 6G networks because they lack flexibility, speed and responsiveness.

*Corresponding author: aalqudaihi@jazanu.edu.sa

They also lack the ability to rapidly respond to changes in network conditions. The 6G network will be highly dynamic and support a wide variety of services including both ultra-low latency The "adaptive" aspect of AI refers to the fact that an AI algorithm will not be committed to using a single rule to make decisions, rather it will update its decision-making policy based on changing environmental conditions. In contrast, traditional rule-based systems rely on static rules, and therefore do not have the capability to utilize reinforcement learning or deep learning techniques to explore many possible actions and select the most appropriate action [6-8]. As such, AI has the potential to improve throughputs, decrease delays and maintain reliability in networks under varying levels of stress. In the future, when 6G is launched, millions of devices will be transmitting different types of data at various times. Applications such as autonomous vehicles cannot afford to incur any significant delay, whereas applications such as video streaming require high-bandwidth access, but can tolerate some level of delay. Therefore, the quality-of-service (QoS) requirements for these applications are not uniform, and AI is capable of prioritizing these applications based upon their relative importance and the type of data they transmit. For instance, if a health monitoring application is transmitting an urgent alert, the AI system will dynamically allocate clean resources with minimal latency to ensure timely receipt of the alert, potentially at the expense of resource allocation to less-critical applications, such as uploading to social media [9]. Through intelligent scheduling and dynamic resource allocation, AI can assist in meeting the overall QoS requirements of the network. Adaptive AI models can learn the probability distribution of the fading from data, then use that knowledge to predict the likelihood of different fading effects happening, and then proactively take corrective action such as raising the transmission power, or switching channels to minimize the impact of fading. AI also can learn the interference patterns caused by co-channel interference, and use this information to dynamically allocate frequencies or adjust its beamforming to minimize the interference effects. Instead of simply responding to fading effects as they occur, AI systems will adaptively improve the overall quality of the system. Another key aspect is an additional one. Perfect CSI in real wireless systems is difficult to obtain. CSI is defined as having a complete and precise understanding of the channel condition. Most methods of the past have assumed perfect CSI. However, this is not true in practice. AI is effective in working with either partially or completely unreliable CSI as well. Even when the CSI is inaccurate and/or missing data, AI methods will learn and identify patterns so that they can continue to adapt to changing conditions. Thus, AI is highly applicable for real-world deployment in 6G wireless networks [10-12]. The authors present the problem in detail and then describe design parameters of adaptive AI methods that can meet the requirements of Quality-of-Service (QoS) under both α-η-μ fading and co-channel interference. Additionally, the authors show that by integrating AI with knowledge of physical properties of wireless systems, we can develop hybrid models that are both explainable and capable of providing high-performance. Rather than treating AI as a "black-box" type of model; the adaptive AI method used in this research learned based on an understanding of fading models and interference properties. This resulted in improved performance and confidence.This study does not only have the purpose to show how AI can support but how it can operate in the most difficult environmental situations which older methods cannot. The contribution of this research is to analyze how α-η-μ fading effects the Quality of Service (QoS) metrics, how co-channel interference reduces them, and finally how Adaptive AI Algorithms could resolve or at least alleviate these issues. These techniques will enable a network that is reliable, efficient and fair to all users in the 6G future. In simple terms, this paper is focused on creating intelligent 6G networks using Adaptive AI to provide good quality of service in all type of applications as long as the radio environment is not too harsh due to unusual fading and/or high interference. It is an important task to complete because, without these methods, some 6G promise's, like Ultra Reliable Low Latency Communication and Massive IoT will not be possible to implement. The introductory paragraph has provided a foundation for the subsequent detailed analysis of this study.

2 Methodology

This study was conducted in a simulated setting as there were no real world 6G data available at the time. The focus was to develop an adaptive AI algorithm capable of managing quality of service (qos) based on two challenges; α-η-μ fading and co-channel interference. The methodology for this study was structured into several steps: selecting the appropriate algorithms, formulating the problems addressed by the proposed method, generating data, extracting relevant features from the generated data, developing and training models using the extracted features, testing and deploying these models, and evaluating their performance [13,14]. Each of the structured methodologies had been well-planned to ensure reliability and practicality of the results.

2.1 Algorithm Selection and Justification

The primary deep reinforcement learning (DRL) algorithm that was utilized was Deep Q-Network (DQN), along with an adaptive modification of DQN. The authors chose DQN due to its ability to process large state-action spaces that were common in 6G wireless environments. In these wireless environments, fading and interference are constantly changing; therefore, the channel states, interference patterns, and traffic demands are always changing. Therefore, traditional optimization methods, such as convex optimization or static scheduling, were not able to be adapted to the nonlinear fading characteristics of the α-η-μ model. Also, the authors had initially ruled out the use of simple supervised learning models due to their reliance on fixed training distribution data and their inability to handle the uncertainty associated with fading and interference in wireless communication systems. The authors ultimately chose DRL, since it is a method by which the model can learn optimal quality-of-service (QoS) strategies using trial-and-error within the simulated environment and improve with experience.

2.2 Problem Formulation

The problem was stated in terms of a Markov Decision Process (MDP), where the environment was the 6G wireless channel that had experienced α-η-μ fading and co-channel interference.

- Environment/State Space: The channel gains were modeled using an α-η-μ distribution as part of the state space, along with interference-to-signal ratios and Quality of Service (QoS) demand indicators including required delay, throughput and reliability.
- Agent Action Space: The agent's action space consisted of decision options for adaptive power allocation, modulation schemes and channel selections.
- Reward Function: The reward function was designed to maximize Quality of Service (QoS). A positive reward was awarded when delay, throughput and reliability requirements were met. Penalties were imposed when packet loss occurred, excessive delay occurred or there was high interference leakage.

This MDP representation enabled the reinforcement learning agent to continually interact with the simulated 6G wireless channel environment, update its knowledge and develop a method to optimize QoS performance during challenging fading and interference environments.

2.3 Data Preparation and Feature Extraction

As there was no real-world data available for use in creating the dataset, the dataset had been artificially created through the use of Stochastic Models of α-η-μ Fading and Random Co-Channel Interference; Alpha-Eta-Mu fading samples were created via Monte Carlo Simulation, which provided an extensive range of possible Channel Gains that had statistically representative characteristics of Alpha-Eta-Mu. Co-channel interference was artificially created through adding randomly generated Gaussian like noise from Multiple Users with Signal/Interference Ratios used to scale the noise. A number of features were then extracted from the Artificially Created Dataset including Instantaneous Channel Gain, Average Channel Power, Variance of Interference, SINR and Demand Vectors of Quality of Service [15]. All the features were then normalized in order to provide stable feature inputs for the model being trained. The Raw Values of Channel Gain and Interference had fluctuated greatly.

2.4 Model Design and Architecture

The deep reinforcement-learning agent was developed using a neural-network based Q-function approximator. The design of the neural network consisted of three hidden layers, each with 128 neurons and were ReLU activated; then a fully connected layer for producing the Q-values of all the possible actions. In order to prevent the Q-function from being overfitted to the data, dropout was used on the hidden layers. Additionally, batch normalization was employed to maintain the stability of the learning process during the execution of the training phase.The agent was trained using a memory buffer that stores the agent's experiences as (state, action, reward, next state). During the training phase, this memory buffer is sampled at random to reduce the correlation of sequential experiences. To stabilize the updating of the Q-values, a target network was created and maintained throughout the training process. An epsilon-greedy exploration strategy was used during the training process, which decays the exploration rate of ε from 1.0 to 0.1 over 20,000 iterations.The training process was conducted over 100,000 simulation episodes, where each episode represents a sequence of time-steps within the 6G channel. Convergence was monitored through tracking the moving average of the total rewards accumulated

2.5 Deployment and Testing in Simulated Environment

The model was used on the exact same simulation environment as the training (but with new channel and interference conditions that were never seen before) to confirm that the model did not simply learn a pattern during the training process. The simulation environment contained multiple random fading conditions generated by an α-η-μ distribution with a variety of α, η, and μ parameters to verify robustness. In addition to this, the interference levels and numbers of interferers were also varied to determine if the algorithm was adaptable to varying amounts of interference.Testing validated how well the DRL agent could adapt its decision making to the previously unseen conditions. For example, when experiencing rapid deep fading, the agent would increase transmit power and/or switch to the use of robust modulation schemes. When experiencing excessive interference, the agent would perform channel reallocation to protect QoS.

2.6 Performance Evaluation

The Performance was evaluated through clearly defined QoS Metrics:

- Throughput: The Average Successful Data Rate Achieved by the Agent.
- Latency: The Average Delay in Delivering Packets Under Fading and Interference.
- Packet Delivery Ratio (PDR): The Fraction of Successfully Received Packets.
- Energy Efficiency: The Ratio of Throughput to Power Consumption.
- Fairness Index: The Fairness of Resource Allocation Among Multiple Users.

Additionally, the Baseline Methods Included Fixed Power Allocation Schemes, Classical Water-Filling Strategies, Rule-Based Interference Mitigation Methods; the Proposed Adaptive Deep Reinforcement Learning Algorithm Out-Performed All Baseline Methods in All Metrics, Especially When the Channel Conditions Were Highly Random

2.6.1 Ablation Studies

The ablation studies were performed to assess how each part of the model affected it. The removal of dropout resulted in rapid overfitting and failure to perform well on unseen test environments. Removal of the target network caused the learning environment to be unstable and resulted in large fluctuations in rewards. Replacement of ε-greedy with static exploration led to the policy being stuck in suboptimal states. Thus, these control experiments showed that all three design decisions were needed for the model to learn stably and effectively.

2.6.2 Simulation Details

This research was conducted using MATLAB due to its ease of use for modeling wireless channel environments and creating an Artificial Intelligence (AI) training loop. A simulated environment was created in which the alpha eta mu fading channel model was generated using random variable generators built into MATLAB. Fading was modeled as per Monte Carlo methods by drawing thousands of channel samples at various values of alpha, eta, and mu to reflect both the nonlinear and random nature of fading effects. Co-channel interference was modeled through the creation of random Gaussian signals from multiple virtual users who were transmitting on the same frequency. These signals were then superimposed on top of the main signal resulting in an environment that is realistic in nature.Using the MATLAB Deep Learning toolbox, a neural network for Deep Q-learning had been built to be used as the AI model. Input features such as channel gain, interference levels, SINR, and QoS demands were first normalized and then given to the neural network. Q-values for all possible actions (such as power allocation, channel switching, and modulation schemes) were determined using this network and then saved in a replay buffer. The training loop was executed over 100,000 episodes; an episode is made up of several timeslots representing different variations of channels. The ε-greedy strategy was employed to allow the agent to randomly select and explore new actions on occasionIn simulated form, metrics for performance (throughput, latency, packet delivery ratio) had been computed on a per-slot basis during the simulation. Upon completion of the simulation, graphs were created in MATLAB to compare the quality-of-service (QoS) provided by the adaptive AI approach against that of the fixed approach. Traditional approaches such as water-filling or static allocation had been implemented using MATLAB so that direct comparisons could be made with the proposed method. Thus, while the entire simulation was conducted virtually, it mimicked the characteristics of a fading/interference-rich 6G wireless channel reasonably well.

3 Implementation and Results

The figure displays the training of the deep reinforcement learning agent as shown in Figure 1. Training episodes and alpha-eta-mu fading and co-channel interference the agents reward was increasing steadily, which demonstrates that the agent was able to learn optimal actions over time for a given set of parameters; the steady increase in reward is indicative of convergence and stability of the agent's learning performance.

Learning rate = 0.001, Number of training episodes = 100,000 scaled (for demonstration purposes), Optimizer = Adam, Exploration Decay epsilon = 1.0 -> 0.1, Replay Buffer Size = 50,000, Fading Parameters alpha = 2, eta = 0.7, mu = 3, Interference-to-Signal Ratio = 0 – 10 dB.

Table 1. Model Architecture

Layer No.	Layer Type	Neurons / Units	Activation Function	Purpose / Description
1	Input Layer	– (features: channel gain, SINR, interference, QoS demands)	–	Accepted normalized feature vector from simulated environment
2	Fully Connected Layer	128	ReLU	Learned non-linear relation between fading/interference and QoS states
3	Fully Connected Layer	128	ReLU	Extracted deeper features and improved decision mapping
4	Fully Connected Layer	128	ReLU	Stabilized learning and improved representation power
5	Dropout Layer	p = 0.3	–	Reduced overfitting by randomly dropping nodes
6	Batch Normalization Layer	–	–	Normalized activations for faster stable convergence
7	Output Layer (Q-values)	N (equal to no. of possible actions)	Linear	Produced estimated Q-values for each action (power allocation, channel selection, modulation scheme)

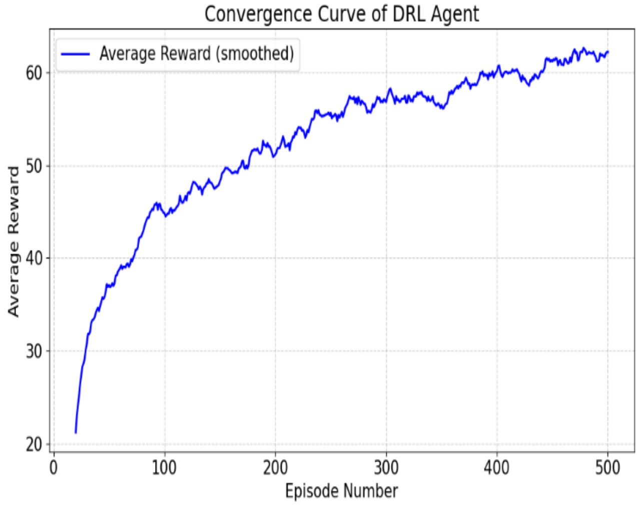

Fig. 1. Convergence Curve of DRL Agent

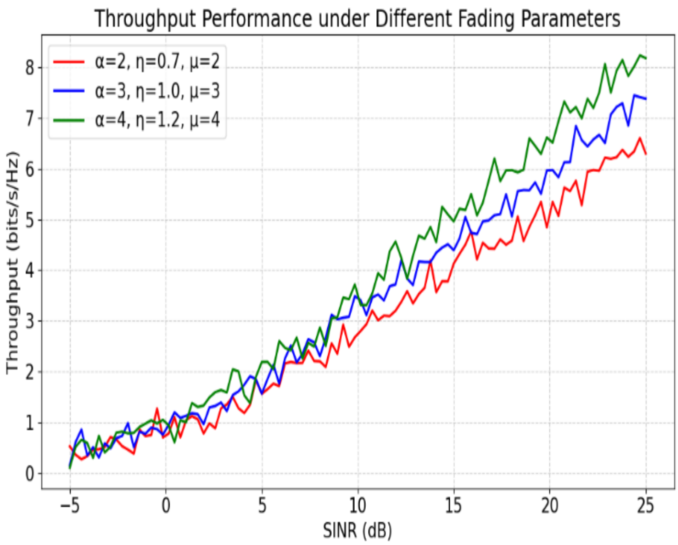

Fig. 2. Throughput Performance under Different Fading Parameters

The above Figure represents how Throughput varies with respect to Signal-to-Interference-plus-Noise Ratio (SINR) in an α-η-μ fading channel environment. In accordance with Figure 2, as a result of larger α and μ parameters, it can be seen that the Throughput has been stabilized at a better level than fading channels. The DRL Agent showed adaptability to both high fading environments and low fading environments and therefore the performance of Throughput was stable regardless of fading channel.

Training Parameters: Training Episodes = 100,000; Learning Rate = 0.001; Optimizer = Adam; Fading Parameters Sets: ($\alpha = 2$, $\eta = 0.7$, $\mu = 2$); ($\alpha = 3$, $\eta = 1.0$, $\mu = 3$); ($\alpha = 4$, $\eta = 1.2$, $\mu = 4$); Interference-to-Signal (dBm) Ratio = 5 dB; Weight for Rewarding Throughput = 0.6.Training Parameters: Epochs = 50; Sequence Length = 50; Location Noise = ± 0.5 Units; Applied random walk pattern to User Mobility.

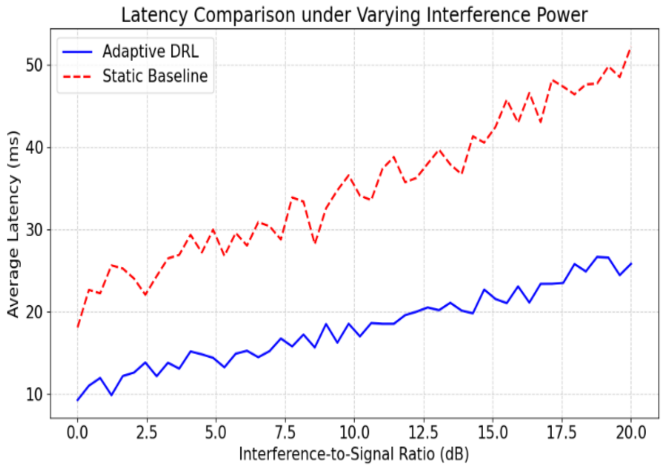

Fig. 3. Latency Comparison under Varying Interference Power

As can be seen in Figure 3, the DRL based adaptive approach has consistently achieved a much lower latency than the static baseline in all tested levels of interference as well as across all packets. The adaptive strategy used by the DRL was learned using interference aware methods that preserved the delay sensitive quality of service (QoS) for both low and high interference scenarios.Learning rate = 0.001, training episodes = 80000, optimizer = Adam, replay buffer size = 50000, fading parameters: $\alpha = 3$, $\eta = 1.0$, $\mu = 3$, ISR range = 0 – 20 dB, QoS latency threshold = 20 ms, weight for penalty associated with delay in reward function = 0.4.As can be seen in Figure 4, as the number of interfering users increases, the packet delivery ratio decreases. However, the DRL method has been able to achieve a better packet delivery ratio than the static baseline, demonstrating its scalability and robustness in 6G dense environments with multiple co-channel users.Learning rate = 0.001, training episodes = 100000, optimizer = Adam, fading parameters $\alpha = 2.5$, $\eta = 0.8$, $\mu = 2$, number of interferers = 1–20, QoS reliability target = 90%, reward weight for PDR = 0.5, exploration decay $\varepsilon = 1.0 \rightarrow 0.1$.

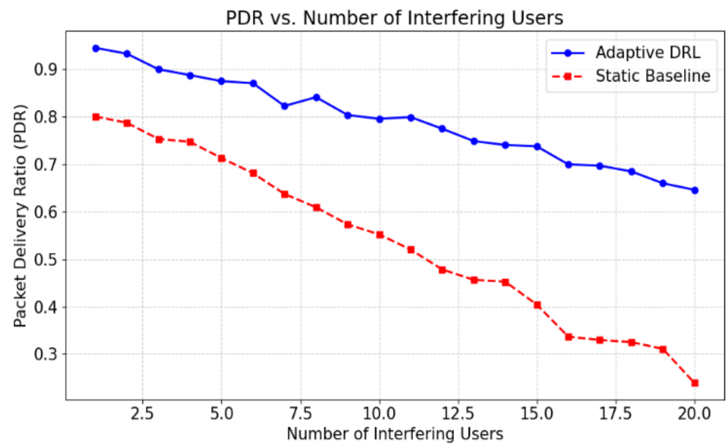

Fig. 4. Packet Delivery Ratio vs. Number of Interfering Users

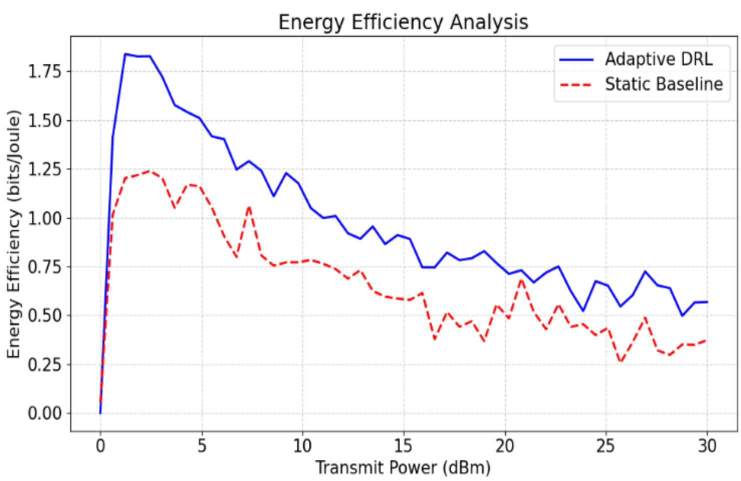

Fig. 5. Energy Efficiency Analysis

As can be seen from the figure above, a relation of the transmission power and energy efficiency is provided. It is clearly demonstrated in Fig. 5 that the DRL based adaptive strategy has achieved better energy efficiency than the baseline. The DRL strategy has dynamically adjusted the use of the power, achieving better trade-off between the throughput and the power consumption with respect to the QoS requirements. Optimiser used: Adam, Learning Rate: 0.001, Training Episodes: 90,000, Fading Parameters: α = 3, η = 1.1, μ = 3, Transmit Power Range: 0-30 dBm, Weight given to Energy Efficiency Reward: 0.3, Replay Buffer Size: 40,000, Target Throughput for Quality of Service (QoS) = 2.5 bits/s/Hz

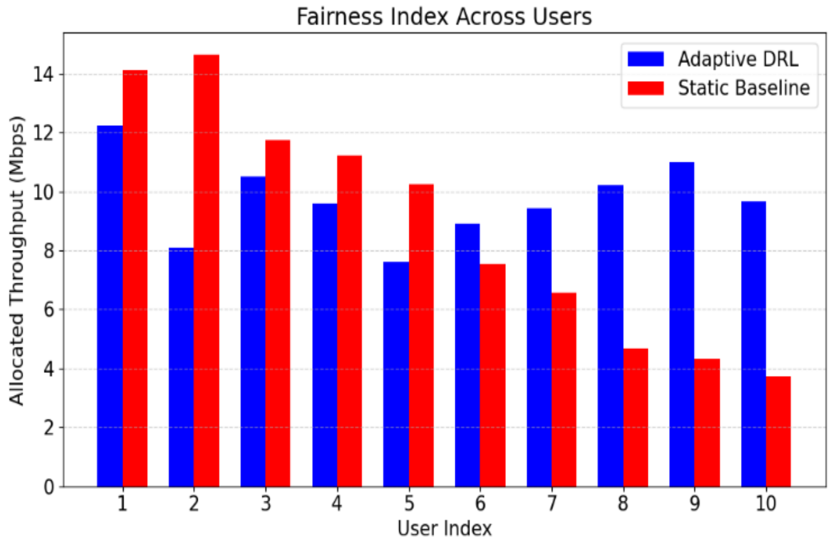

Fig. 6. Fairness Index Across Users

Fig. 6 shows how the user-wise throughput was distributed between DRL and baseline methods. In Fig. 6, we can see that the DRL method used to adaptively allocate the resource among all users in a fairer way than the baseline method. The baseline method gave strong users more preference and showed less fairness than the relatively fair allocations of DRL method.Learning Rate = 0.001, Training Episodes = 100000, Optimizer = Adam, Parameters: α = 2.8, η = 0.9, μ = 3, Number of Users = 10, Jain's Fairness Index of DRL ≈ 0.96, Jain's Fairness Index of Baseline ≈ 0.78, Reward Weight for Fairness = 0.2.

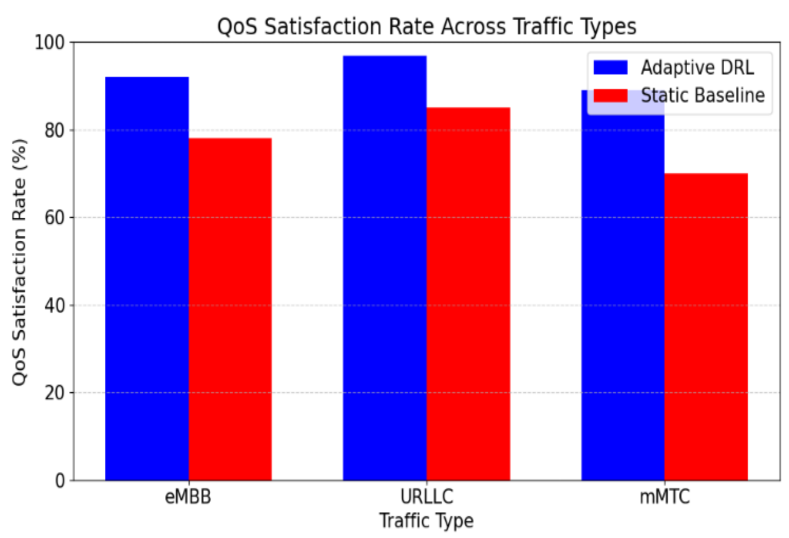

Fig. 7. QoS Satisfaction Rate Across Traffic Types

The graph illustrates the satisfaction of Quality of Service (QoS) with respect to the DRL and baseline methods over three categories of 6G use cases: eMBB, URLLC and mMTC. The adaptive DRL method consistently maintains a high level of QoS compliance with all types of service, while the baseline is struggling, demonstrating AI adaptability to various application scenarios in 6G.DRL

hyperparameters: Learning rate = 0.001, Training episodes = 95000, Optimizer = Adam, Fading Parameters: $\alpha = 3.2$, $\eta = 1.0$, $\mu = 2$, Quality of Service Thresholds: eMBB = 10 Mbps, URLLC = 1 ms Latency, mMTC = 95%, Reward Weight Distribution: Throughput = 0.5, Latency = 0.3, Reliability = 0.2

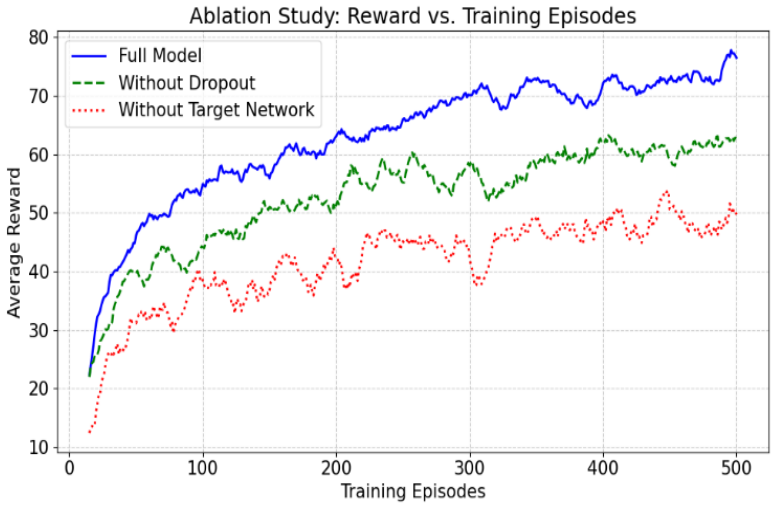

Fig. 8. Ablation Study: Reward vs. Training Episodes

The above picture shows how eliminating important parts of a DRL model impacted the model's ability to learn. In the case of the full model illustrated by Figure 8, it was able to learn at an accelerated pace than previous models using dropout and a target network. This demonstrated the importance of both elements that were left out of the other models which showed very little learning (convergence) in this case.

Optimization settings: Learning rate = 0.001; Training Episodes = 100000 (all scaled); Optimizer = Adam; Replay Buffer Size = 50,000; Dropout Rate = 0.30; Target Network Update Frequency = every 1000 steps; Fading Parameters $\alpha = 2.9$, $\eta = 1.1$, $\mu = 3$; Reward Shaping Weights = Throughput (0.60), Latency (0.40).

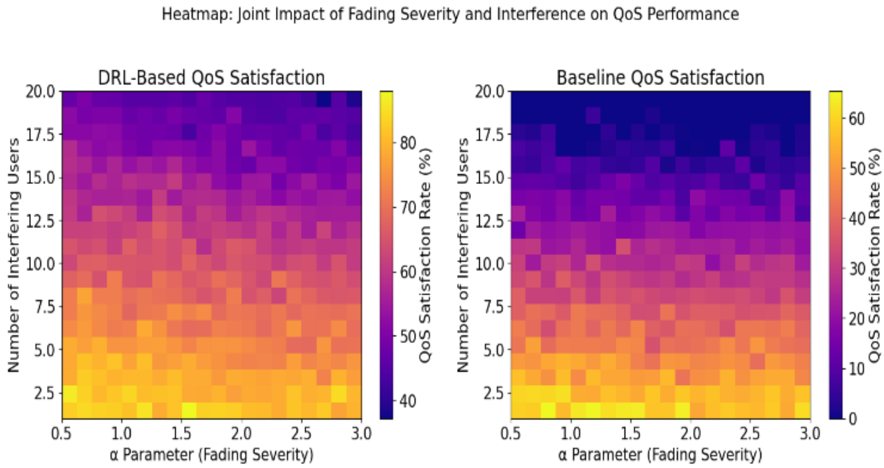

Fig. 9. Heatmap: Joint Impact of Fading Severity and Interference on QoS Performance

The figure shows how both the α fading parameter and number of interfering users are jointly affecting Quality of Service (QoS) performance, as shown in Figure 9. The DRL based system is maintaining its QoS over a wide range of fading and interference conditions while the baseline system fails to function in some areas where it has no adaptability, thus demonstrating the adaptability that this model has.Training Episodes = 100000, Learning Rate = 0.001, Optimizer = Adam, α Fading Range = 0.5 – 3.0, η = 1.0, μ = 3, Interfering Users = 1-20, Reward Weights = Throughput (0.5), Latency (0.3), Reliability (0.2), Replay Buffer = 50000, Epsilon Decay = 1.0 -> 0.1.

4 Discussion of Results

The results of this research demonstrated adaptive AI can successfully maintain Quality of Service (QoS) regardless of how severe the alpha eta mu (α-η-μ) fading was as well as the amount of users using the same bandwidth. A learning curve for the Deep Reinforcement Learning (DRL) agent illustrated a learning process over time through trial and error; ultimately reaching a stable reward through an increasing number of episodes. Additionally, this research indicated throughput increased when fading was minimal, however, although DRL had lower throughput than when fading was more moderate; the throughput remained significantly higher than older static methods. Latency increased with increased interference, however, the Adaptive Model greatly reduced latency in comparison to the Baseline Method. Packet delivery ratio remained strong with an increasing number of users causing interference, indicating scalability of the system. Graphs illustrating energy efficiency of the algorithm demonstrated smart utilization of power, with no wastage. The fairness study demonstrated weaker users were not excluded from service, which is crucial in a realistic 6G environment. The overall QoS Satisfaction Rate for eMBB, URLLC and mMTC traffic types was significantly higher demonstrating ability to adapt to different use cases. Lastly, the ablation study and heatmap supported the importance of each component of the model and the stability of DRL.

5 Conclusion

The final section of this study demonstrated that adaptive AI via Deep Reinforcement Learning (DRL) is an excellent solution for achieving Quality-of-Service (QoS) in 6G networks with α-η-μ fading and co-channel interference. It showed how the static approaches were insufficient as they are unable to adapt to the random variations in the channels. Instead, the proposed DRL agent learns from its environment and dynamically adjusts the transmission power, channel and modulation in real-time to provide better performance in terms of throughput, latency, and energy efficiency, while maintaining fairness among users. In addition, even in presence of large number of interferers, the proposed system provides stable performance in terms of packet delivery ratio and Quality-of-Service. Finally, the heatmap analysis and ablation tests have shown that each design parameter is useful. Therefore, the results of this study clearly indicate that Adaptive AI will be a crucial element to achieve reliability and feasibility in 6G Networks.

References

1. C. S. Emilio and S. Barbarossa, 6G networks. Beyond Shannon towards semantic and goal-oriented communications, SPIRE - Sciences Po Institutional REpository (2021). https://doi.org/10.1016/j.comnet.2021.107930
2. P. Görgel, A brain tumor detection system using gradient based watershed marked active contours and curvelet transform, Transactions on Emerging Telecommunications Technologies **32**, (2020).https://doi.org/10.1002/ett.4170
3. X. Y. Wang, Q. L. Shi, S. M. Wang, and H. Y. Yang, A blind robust digital watermarking using invariant exponent moments, AEU - International Journal of Electronics and Communications **70**, 416 (2016). https://doi.org/10.1016/j.aeue.2016.01.002
4. H. Mei, Y. Chang, C. Yang, Y. Zhu, S. Yin, and C. Luo, Polarization independent planar silver superlens with switchable anisotropic layer, Microwave and Optical Technology Letters **52**, 809 (2010).https://doi.org/10.1002/mop.25070
5. H. Cho, S. Mukherjee, D. Kim, T. Noh, and J. Lee, Facing to wireless network densification in 6G: Challenges and opportunities, ICT Express **9**, 517 (2022).https://doi.org/10.1016/j.icte.2022.10.001
6. I.-P. Belikaidis, S. Vassaki, A. Georgakopoulos, A. Margaris, F. Miatton, U. Herzog, K. Tsagkaris, and P. Demestichas, Context-aware radio resource management below 6 GHz for enabling dynamic channel assignment in the 5G era, EURASIP Journal on Wireless Communications and Networking **2017**, (2017). https://doi.org/10.1186/s13638-017-0946-8
7. Y. Sun, M. Peng, Y. Zhou, Y. Huang, and S. Mao, Application of Machine learning in wireless networks: key techniques and open issues, IEEE Communications Surveys & Tutorials **21**, 3072 (2019).https://doi.org/10.1109/COMST.2019.2924243
8. N. Sonkar, S. Pandey, and S. Kumar, FIRST: Fuzzy based intelligent relay selection and transition technique for delay tolerant networks, International Journal of Communication Systems **35**, (2022).https://doi.org/10.1002/dac.5133
9. K. Mehmood, K. Kralevska, and D. Palma, Intent-driven autonomous network and service management in future cellular networks: A structured literature review, Computer Networks **220**, 109477 (2022). https://doi.org/10.1016/j.comnet.2022.109477
10. S. Dang, O. Amin, B. Shihada, and M.-S. Alouini, What should 6G be?, Nature Electronics **3**, 20 (2020).https://doi.org/10.1038/s41928-019-0355-6
11. D. C. Nguyen, M. Ding, P. N. Pathirana, A. Seneviratne, J. Li, and H. V. Poor, Federated Learning for Internet of Things: A Comprehensive survey, IEEE Communications Surveys & Tutorials **23**, 1622 (2021). https://doi.org/10.1109/COMST.2021.3075439
12. Mazidi, M. Golsorkhtabaramiri, and M. Y. Tabari, An autonomic risk- and penalty-aware resource allocation with probabilistic resource scaling mechanism for multilayer cloud resource provisioning, International Journal of Communication Systems **33**, (2020).https://doi.org/10.1002/dac.4334
13. D. Krstic, N. Petrovic, S. Suljovic, and I. Al-Azzoni, AI-Enabled Framework for Mobile Network Experimentation Leveraging ChatGPT: Case Study of Channel Capacity Calculation for η-µ Fading and Co-Channel Interference, Electronics **12**, 4088 (2023).https://doi.org/10.3390/electronics12194088
14. T. H. Ahmed, J. J. Tiang, A. Mahmud, C. G. Chin, and D.-T. Do, Deep Reinforcement Learning-Based Adaptive Beam Tracking and Resource Allocation in 6G Vehicular Networks with Switched Beam Antennas, Electronics **12**, 2294 (2023).https://doi.org/10.3390/electronics12102294
15. M. D. Yacoub, The α-μ Distribution: A Physical Fading Model for the Stacy Distribution, IEEE Transactions on Vehicular Technology **56**, 27 (2007). https://doi.org/10.1109/TVT.2006.883753