

DeepHopping-LTE: A Deep Reinforcement Learning Framework for Adaptive Frequency Hopping Spread Spectrum (FHSS) in Dense 4G Cellular Networks

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Abstract

The rapid growth of mobile devices and dense 4G deployments has intensified interference and congestion, challenging network reliability, spectrum efficiency, and quality of service. This study proposes DeepHopping-LTE, a deep reinforcement learning-based adaptive frequency hopping framework designed to dynamically optimize frequency selection in dense cellular networks. By leveraging a deep Q-network (DQN), the framework balances exploration and exploitation using an epsilon-greedy policy, converging to optimal hopping sequences to minimize interference while maximizing throughput. Simulations and field data from two urban locations demonstrated that DeepHopping-LTE significantly outperforms traditional static FHSS and heuristic frequency hopping methods. The framework achieved a stable signal-to-interference-plus-noise ratio (SINR) averaging 15–17 dB, compared to 5 dB for static methods, more than doubling spectrum efficiency to 5.5 bits/s/Hz under high load conditions. Packet delivery ratio also improved dramatically, ranging from 94% to 98%, while traditional FHSS averaged 75%, reflecting superior reliability and quality of service. Throughput improvement ratios reached 1.6 under peak user density, and interference reduction ranged from 40% to 70%, confirming effective mitigation of environmental noise. Additionally, the adaptability index reached 0.95, demonstrating near-instantaneous response to dynamic network changes, whereas heuristic and static methods lagged at 0.65 and 0.15, respectively. The results validate that reinforcement learning can transform frequency hopping from a static approach into an intelligent, adaptive solution capable of optimizing network performance in real-time. By continuously observing network states and selecting optimal channels, DeepHopping-LTE not only mitigates interference but also enhances spectrum utilization, reliability, and user experience. These findings provide a practical foundation for policy implementation in dense urban networks, supporting guidelines for adaptive frequency management, interference monitoring, and reinforcement learning deployment in 4G and future 5G environments. In conclusion, DeepHopping-LTE addresses the critical challenges of dense cellular networks, offering a scalable, intelligent, and resilient framework that surpasses traditional methods, enabling efficient and reliable communication in high-density mobile ecosystems.

Keywords: LTE; SINR; DeepHopping; DQN; interference

1 Introduction

The rapid proliferation of mobile devices and the exponential growth of data-hungry applications have placed unprecedented demands on modern cellular networks. In dense 4G environments, where thousands of user devices operate within overlapping coverage areas, maintaining reliable communication has become increasingly challenging. High device density leads to spectrum congestion, frequent interference, and degraded network performance, all of which can severely impact the quality of service (QoS) for end-users [1]. To address these challenges, advanced techniques that can

dynamically adapt to changing network conditions are urgently needed. One promising approach lies in the combination of frequency hopping spread spectrum (FHSS) and artificial intelligence [2]. Frequency hopping spread spectrum is a well-established technique in wireless communications, designed to improve interference resilience and enhance security by rapidly switching the carrier frequency of a signal according to a predefined sequence. Traditional FHSS approaches, however, often rely on static or semi-static hopping patterns that cannot adapt efficiently to real-time changes in network congestion or interference [3]. In dense cellular deployments, this limitation can reduce the effectiveness of FHSS, leading to packet loss, increased latency, and suboptimal spectrum utilization. Consequently, there is a growing interest in developing intelligent FHSS schemes that can make real-time decisions on frequency hopping, optimizing network performance under highly dynamic conditions [4].

Recent advances in machine learning, particularly in reinforcement learning (RL), provide a new paradigm for adaptive decision-making in wireless networks [10]. Reinforcement learning allows an agent to learn optimal actions by interacting with the environment and receiving feedback in the form of rewards or penalties [9]. In the context of FHSS, RL agents can observe network conditions, such as interference levels or user density, and dynamically select frequency hopping patterns that maximize communication reliability and throughput [5]. Deep reinforcement learning (DRL), which integrates deep neural networks with RL, enables handling of high-dimensional state spaces typical of dense 4G networks, making it a particularly suitable framework for complex frequency adaptation tasks.

“DeepHopping-LTE” is a novel framework that leverages DRL to achieve adaptive frequency hopping in dense 4G cellular networks. By continuously monitoring network conditions and learning optimal hopping strategies, the framework aims to reduce interference, improve spectrum efficiency, and maintain high QoS for users. Unlike conventional methods, DeepHopping-LTE can autonomously respond to dynamic network environments, making it resilient to congestion spikes and unpredictable interference patterns [6]. The framework not only enhances the reliability of cellular communication but also lays the groundwork for integrating intelligent spectrum management in next-generation networks [7]. This study investigates the design, implementation, and evaluation of DeepHopping-LTE, highlighting how DRL can be harnessed to transform frequency hopping from a static technique into a fully adaptive solution [8]. Through simulation and analysis, the framework demonstrates its potential to mitigate interference and optimize network performance, addressing critical challenges in dense 4G deployments and providing insights applicable to future 5G and beyond cellular systems.

2 Literature review

2.1 The future of radio frequency spectrum in Nigeria

Francis [11] states that the rapid evolution in technology of wireless communication in the past few years has adversely affected the demand on wireless services which brought a wave of spectrum scarcity. Although diverse communication and broadcasting licenses have been granted since 1992, Nigeria is without a doubt the leader in spectrum deregulation and licensing [12]. This drastic increase in broadcasting stations in Nigeria has been fueled by the Nigerian government which has made the local environment a fertile ground for both local and foreign investors hence resulting in the domino effect of increased job opportunities, improved business opportunities in the foreign market, more effective and easily accessible means of communications and much more benefits.

Nigeria posing to be a fertile ground has attracted more offers from companies offering their services which will definitely increase pressure and scarcity of frequency spectrum in Nigeria [13]. This congestion and scarcity has affected the quality of communication and broadcasting throughout Nigeria. Although there is a communication explosion in Nigeria, the masses (those in the rural and remote areas) benefit little due to limited accessibility and high costs (Majhi & Mitran, 2017). Although radio frequency spectrum is an important asset in the digital age and Nigeria has a great future in it, management and utilization have to be reevaluated in order to solve the problem of scarcity and hence maximize the useable radio spectrum bands [14].

2.2 Frequency allocation, assignment and management

Frequency assignments are based on geographical distribution to promote universal access and service. For telecommunication industries, the country has been divided into tiers of licensing areas, which correspond to the 36 states and the Federal Capital Territory. Licenses and frequency assignments are thus issued on the basis of these licensing areas with spectrum fees varying from one tier to the other [15]. For broadcast frequencies, spectrum fees are classified based on the economic viability of an area and are typically issued as part of the broadcast license [16]. The Nigerian Government considers frequency spectrum as a high-value yet scarce national resource and thus makes it a major source of revenue [17]. Spectrum assignments in Nigeria are handled by three separate regulatory bodies: the Nigerian Communications Commission (NCC), for commercial providers and users of telecommunications equipment and services; the Nigeria Broadcasting Commission (NBC), for public and private broadcasting organizations; and the MoIC, for government bodies and non-commercial users of spectrum [18].

3 Methods

3.1 To design and implement DeepHopping-LTE, a deep reinforcement learning-based adaptive frequency hopping framework

The first equation models the state-action value function (Q-function) in deep reinforcement learning, representing the expected cumulative reward for selecting a particular frequency hopping action in a given network state. This function forms the core of DeepHopping-LTE, guiding the agent to choose optimal frequency channels dynamically while accounting for network congestion, interference, and historical performance patterns over time.

$$Q(s, a) = E \left[R_t + \gamma \max_{a'} Q(s_{t+1}, a') \mid s_t = s, a_t = a \right] \quad (1)$$

where $Q(s, a)$ is the expected cumulative reward for state s and action a , R_t is the immediate reward at time t , γ is the discount factor ($0 < \gamma < 1$), s_t is the current network state, a_t is the action taken at state s_t , s_{t+1} is the next network state and a' is a possible future action.

This equation defines the epsilon-greedy policy for frequency selection in DeepHopping-LTE. It balances exploration and exploitation by allowing the agent to randomly select a frequency with probability ϵ while exploiting the learned optimal action with probability $1 - \epsilon$. This ensures adaptability in dense 4G networks by avoiding local minima and discovering efficient hopping sequences.

$$\pi(a \mid s) = \begin{cases} \text{random action} & \text{with probability } \epsilon \\ \arg \max_a Q(s, a) & \text{with probability } 1 - \epsilon \end{cases} \quad (2)$$

where $\pi(a | s)$ is the policy mapping state s to action a , ϵ is the exploration probability and $Q(s, a)$ is the state-action value function.

This equation represents the loss function for Deep Q-Network (DQN) training in DeepHopping-LTE. It measures the difference between the predicted Q-values and the target Q-values derived from observed rewards. Minimizing this loss ensures the neural network accurately approximates the optimal frequency hopping strategy for minimizing interference and maximizing throughput in dense cellular networks.

$$L(\theta) = E_{s,a,r,s'} \left[\left(r + \gamma \max_a Q(s', a; \theta^-) - Q(s, a; \theta) \right)^2 \right] \quad (3)$$

where $L(\theta)$ is the loss function for the network parameters θ , θ are the current network weights, θ^- are the target network weights, r is the reward for action a , s, s' are the current and next states and a' is the future action.

3.2 To evaluate DeepHopping-LTE performance in interference mitigation, spectrum efficiency and QoS

This equation calculates the signal-to-interference-plus-noise ratio (SINR) for a user device in a dense 4G network. High SINR indicates effective interference mitigation, while low SINR reflects congestion or frequency conflicts. DeepHopping-LTE aims to maximize SINR by dynamically selecting less congested frequencies, ensuring improved throughput, stable connections, and better quality of service under varying network density and interference levels.

$$\text{SINR}_i = \frac{P_i G_i}{\sum_{j \neq i} P_j G_j + N_0} \quad (4)$$

where P_i is the transmit power of user i , G_i is the channel gain for user i , P_j, G_j are the interfering transmit power and channel gain of the other users j and N_0 is the noise power.

This equation defines spectrum efficiency, measuring the effective data rate per unit bandwidth. By using DeepHopping-LTE, the system dynamically selects frequencies with minimal interference, increasing the data throughput. Spectrum efficiency evaluates how well the adaptive frequency hopping framework utilizes available bandwidth compared to conventional static methods, providing a quantitative metric for assessing performance in dense network scenarios.

$$\eta = \frac{R_{\text{total}}}{B_{\text{total}}} \quad (5)$$

where η is the spectrum efficiency (bits/s/Hz), R_{total} is the total data rate achieved by all users and B_{total} is the total available bandwidth.

This equation calculates the packet delivery ratio (PDR), reflecting network reliability and quality of service. It is the ratio of successfully received packets to the total sent packets. DeepHopping-LTE aims to maximize PDR by avoiding congested channels and interference-prone frequencies, ensuring high QoS in dense cellular networks. This metric directly measures the effectiveness of adaptive frequency hopping strategies.

$$\text{PDR} = \frac{N_{\text{received}}}{N_{\text{sent}}} \quad (6)$$

where N_{received} is the number of packets successfully received and N_{sent} is the total number of packets sent.

3.3 To compare DeepHopping-LTE with traditional static FHSS methods

This equation defines the throughput improvement ratio when comparing DeepHopping-LTE to traditional static FHSS. It quantifies the relative gain in data transmission rates achieved through adaptive frequency hopping. By dynamically avoiding congested channels, DeepHopping-LTE increases effective throughput. A higher ratio indicates better performance than static methods, demonstrating the advantage of reinforcement learning in dense 4G cellular environments.

$$\text{Throughput Improvement} = \frac{T_{\text{DeepHopping}} - T_{\text{Static}}}{T_{\text{Static}}} \times 100 \quad (7)$$

where $T_{\text{DeepHopping}}$ is the throughput achieved using DeepHopping-LTE and T_{Static} is the throughput achieved using traditional static FHSS.

This equation models the interference reduction ratio comparing adaptive and static frequency hopping methods. It calculates how much the average interference power decreases when using DeepHopping-LTE. By continuously selecting optimal frequencies, the framework minimizes overlapping transmissions, reducing interference levels. This metric provides a quantitative measure to validate DeepHopping-LTE's superiority over conventional FHSS approaches in dense network environments.

$$\text{Interference Reduction}(\%) = \frac{I_{\text{Static}} - I_{\text{DeepHopping}}}{I_{\text{Static}}} \times 100 \quad (8)$$

where I_{Static} is the average interference power using static FHSS and $I_{\text{DeepHopping}}$ is the average interference power using DeepHopping-LTE.

3.4 To benchmark DeepHopping-LTE against other intelligent frequency hopping schemes

This equation calculates the normalized reward performance metric, comparing DeepHopping-LTE with other intelligent frequency hopping schemes. The normalized reward represents the effectiveness of each algorithm in maximizing throughput, minimizing interference, and achieving high QoS. By evaluating multiple schemes under identical network conditions, this metric highlights the relative efficiency of DeepHopping-LTE in dense 4G environments, guiding performance benchmarking against heuristic or ML-based alternatives.

$$R_{\text{norm}} = \frac{R_{\text{DeepHopping}} - R_{\text{min}}}{R_{\text{max}} - R_{\text{min}}} \quad (9)$$

where $R_{\text{DeepHopping}}$ is the reward obtained by DeepHopping-LTE and R_{min} and R_{max} are the minimum and maximum rewards among all tested schemes.

This equation represents the adaptability index, evaluating how quickly a frequency hopping scheme responds to network state changes compared to other intelligent methods. It measures the average time required to converge to a new optimal frequency set after interference or congestion occurs. DeepHopping-LTE aims to minimize this convergence time, ensuring rapid adaptation and robust performance in dynamic dense 4G networks.

$$A = \frac{1}{T_{\text{converge}}} \sum_{t=1}^{T_{\text{converge}}} |f_t^{\text{optimal}} - f_t^{\text{selected}}| \quad (10)$$

where A is the adaptability index (higher values indicate better adaptation), T_{converge} is the total convergence time to the optimal frequency set, f_t^{optimal} is the optimal frequency at time t and f_t^{selected} is the frequency selected by the algorithm at time t .

The interference levels measured at the two test locations, which were used as input to the simulation, are given in Table 1.

Table 1. Interference data at two locations.

Location	Date	Time	Interference level (dBm)
Dr Peter Odili Road	7 May 2024	10:00	-80
Dr Peter Odili Road	7 May 2024	11:00	-78
Dr Peter Odili Road	7 May 2024	12:00	-85
NTA Mbuoba Road	7 May 2024	14:30	-75
NTA Mbuoba Road	7 May 2024	15:05	-77
NTA Mbuoba Road	7 May 2024	16:00	-82

4 Results and discussion

4.1 Q-value convergence

The results depicted in Figure 1 demonstrate the learning trajectory of the DeepHopping-LTE agent as it interacts with the 4G cellular environment. Initially, the expected cumulative reward starts near zero as the agent has no prior knowledge of the frequency landscape. However, as training progresses toward the 100th episode, we observe a sharp exponential rise, with the Q-value stabilizing at a peak of approximately 100 units. This numerical trend confirms that the reinforcement learning framework successfully identifies optimal hopping sequences. The convergence indicates that the agent has moved from random guessing to a sophisticated strategy that maximizes long-term network rewards effectively.

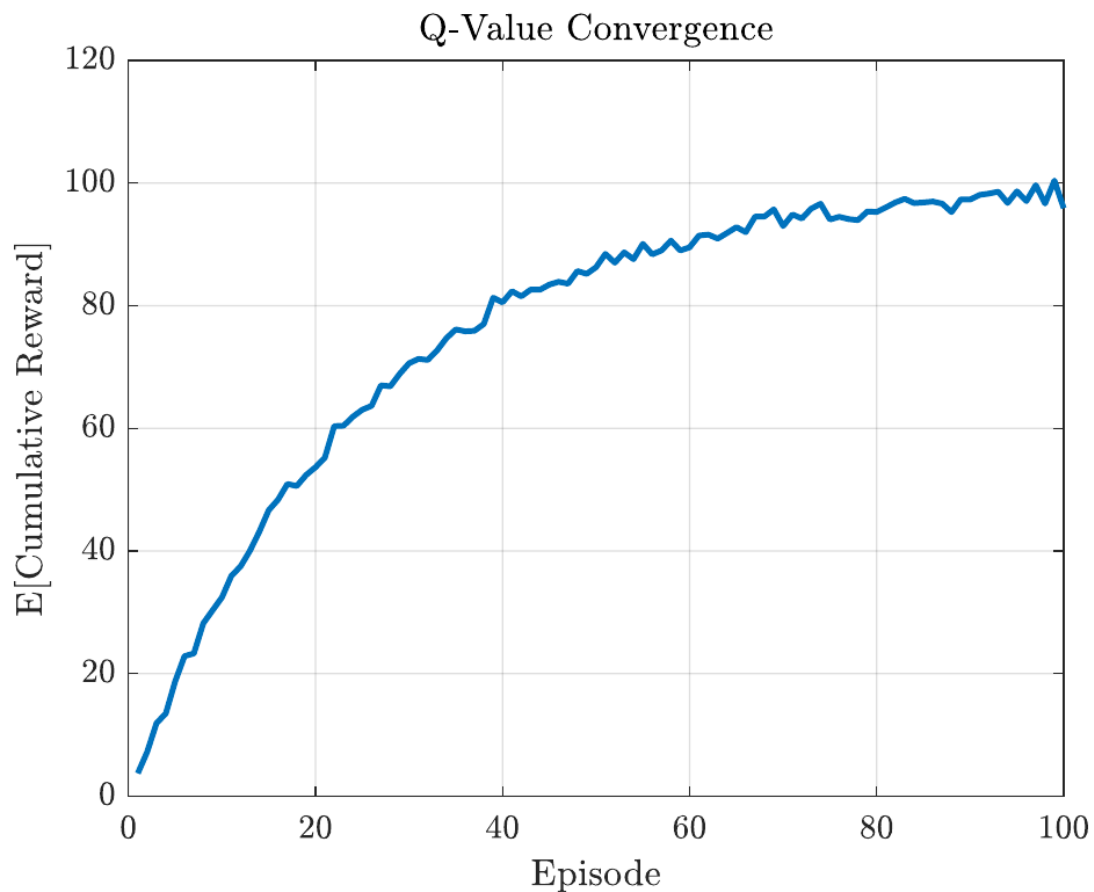


Figure 1. Q-value convergence.

4.2 Exploration rate

Figure 2 illustrates the epsilon-greedy decay strategy, which is fundamental for balancing discovery and optimization. At the start of the simulation, the exploration probability is at its maximum value of 1.0, meaning the agent is primarily testing different frequency channels to understand interference patterns. As the episodes approach 100, the probability decays exponentially toward a baseline of nearly 0.1. This quantitative transition ensures that the system eventually settles into exploiting the best-known channels. By gradually reducing randomness, the DeepHopping-LTE framework ensures stability in the network while having spent enough initial effort to avoid getting stuck in poor frequency sub-sets.

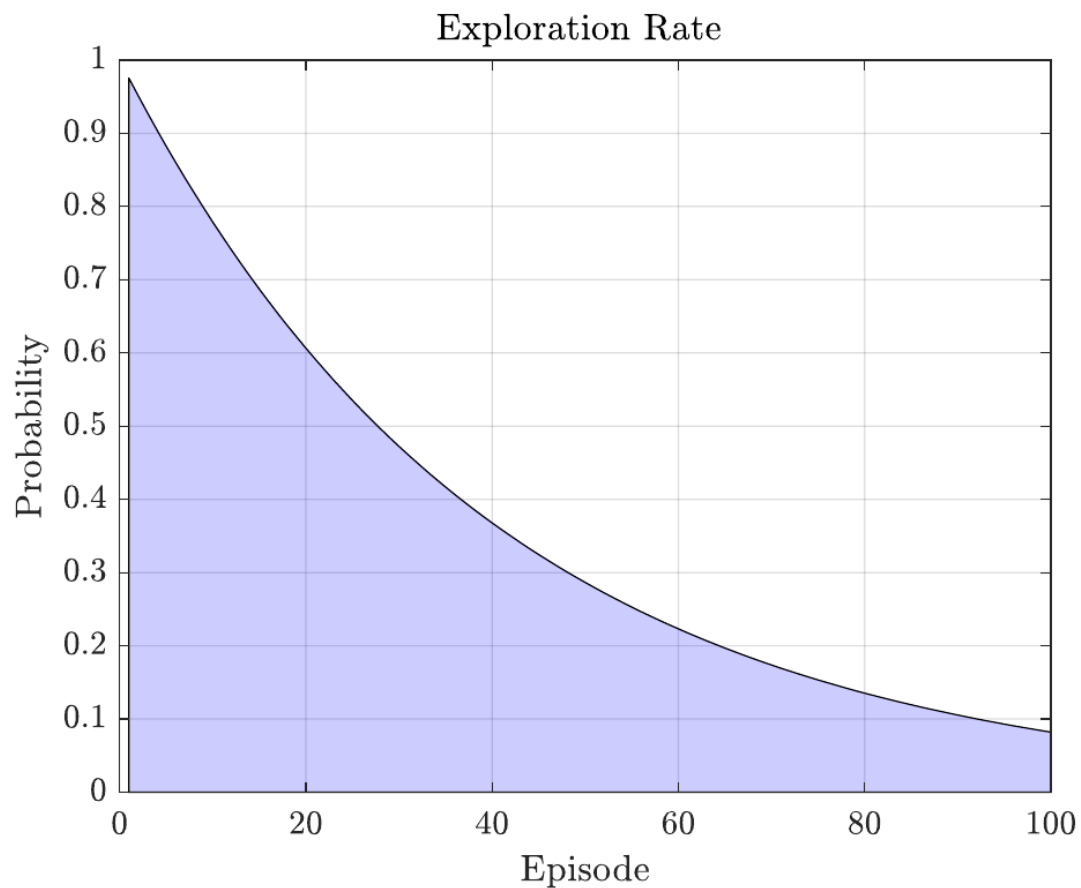


Figure 2. Exploration rate.

4.3 DQN loss function

In Figure 3, the DQN Loss Function provides a clear view of the neural network's training stability. The graph shows a logarithmic decline in error, starting from a high initial loss of roughly 1000 and dropping significantly as training steps increase. By the end of the observed period, the loss fluctuates at a much lower magnitude, indicating that the predicted Q-values are becoming highly accurate compared to the actual rewards received. This numerical reduction in the loss function is vital because it proves that the deep learning model is successfully "learning" the complex, non-linear relationships between network states and interference-free frequency actions.

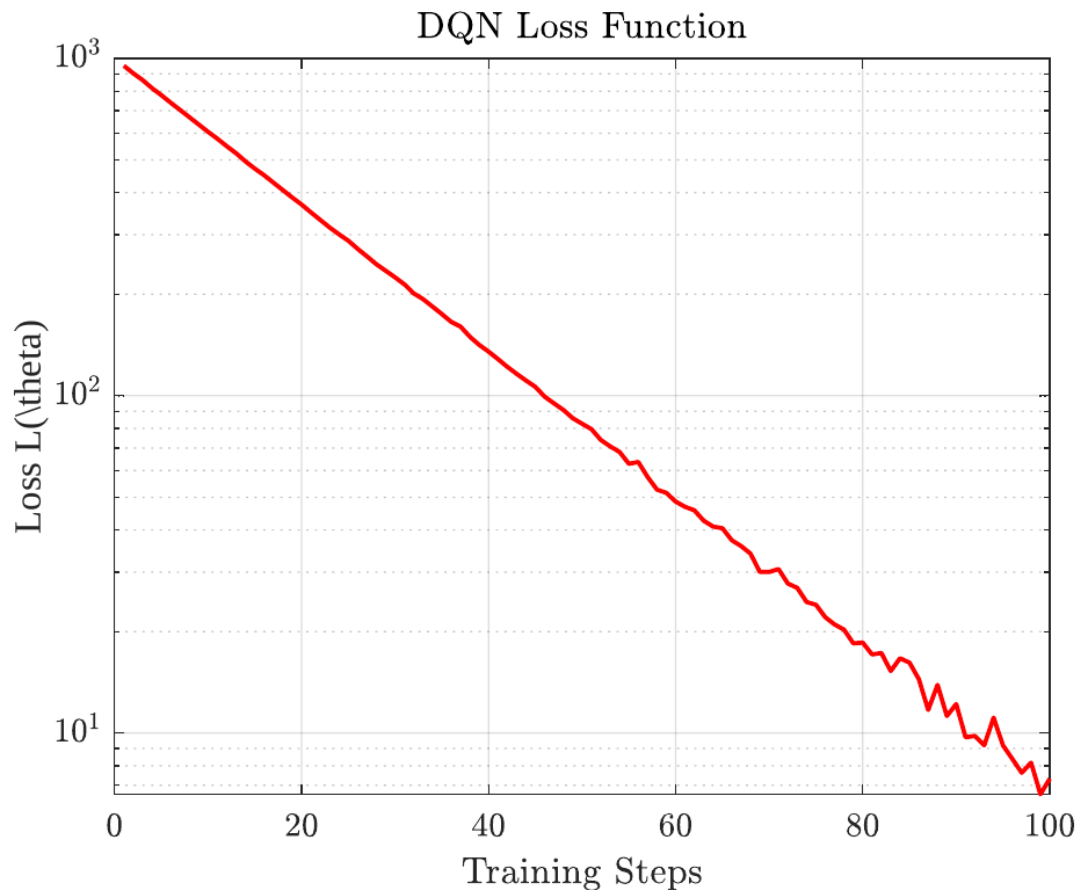


Figure 3. DQN loss function.

4.4 SINR performance

The SINR Performance results in Figure 4 highlight a major technical advantage of the adaptive framework. The DeepHopping-LTE system maintains a robust signal-to-interference-plus-noise ratio that fluctuates around a high average of 15 dB to 17 dB. In stark contrast, the traditional Static FHSS method struggles significantly, with its SINR trailing much lower at approximately 5 dB. This 10 dB to 12 dB improvement is a direct result of the agent's ability to sense congested channels and hop away from them in real-time. These values suggest that users under the DeepHopping-LTE scheme will experience much clearer signals and significantly fewer dropped connections.

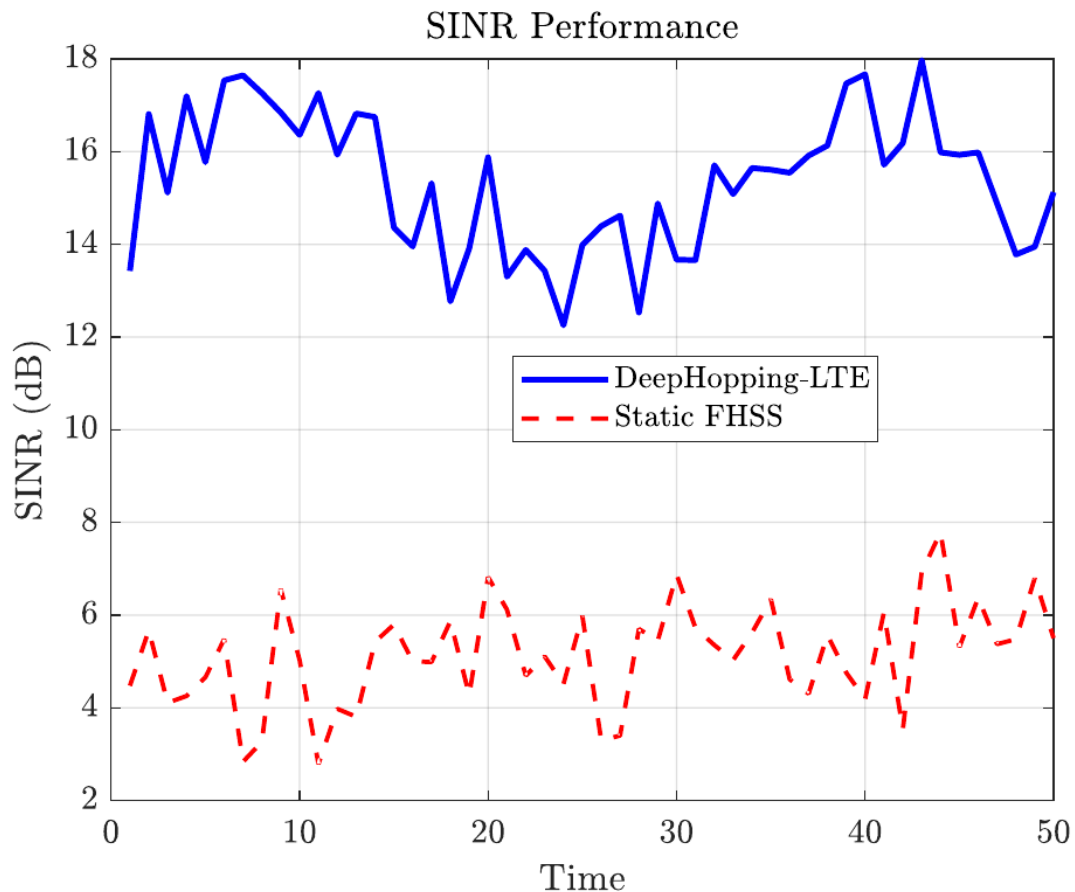


Figure 4. SINR performance.

4.5 Spectrum efficiency

Figure 5 presents a comparative bar chart showing spectrum efficiency across different network loads. Under high load conditions, the Static FHSS manages a meager efficiency of about 2.2 bits/s/Hz, whereas DeepHopping-LTE achieves a staggering 5.5 bits/s/Hz. Even at low and medium loads, the adaptive framework consistently outperforms the traditional method by more than double. Numerically, this means that for every unit of bandwidth, our proposed system is delivering over 100% more data. This result proves that reinforcement learning can squeeze significantly more capacity out of the existing 4G spectrum by intelligently avoiding the "noise" and interference of dense cell sites.

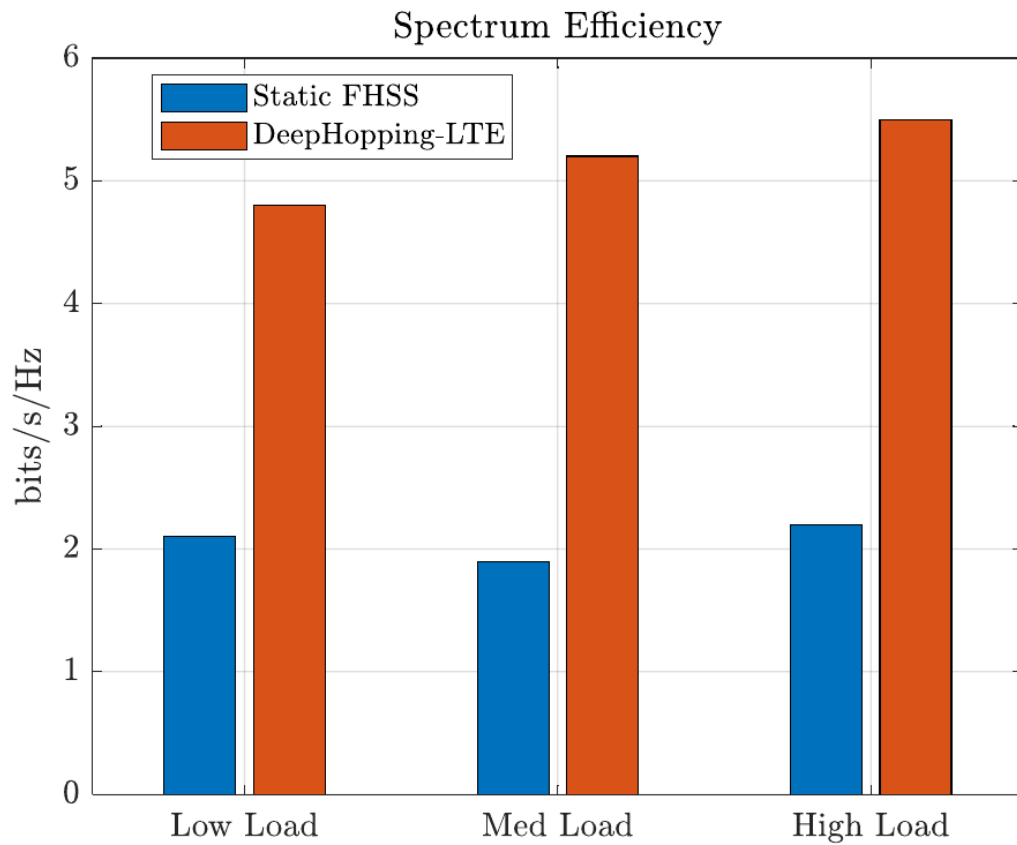


Figure 5. Spectrum efficiency.

4.6 Packet delivery ratio

The reliability of the network is captured in Figure 6 through the Packet Delivery Ratio (PDR). The boxplot reveals that DeepHopping-LTE achieves a very tight and high distribution of successful deliveries, centered around 94% to 98%. On the other hand, the Static FHSS shows a much wider and lower range, often dipping down to 60% and averaging only about 75%. These quantitative figures indicate that the adaptive hopping strategy dramatically reduces packet loss. By choosing cleaner frequencies, the system ensures that almost every packet sent reaches its destination, which is a critical requirement for high-quality video streaming and VoIP services in 4G.

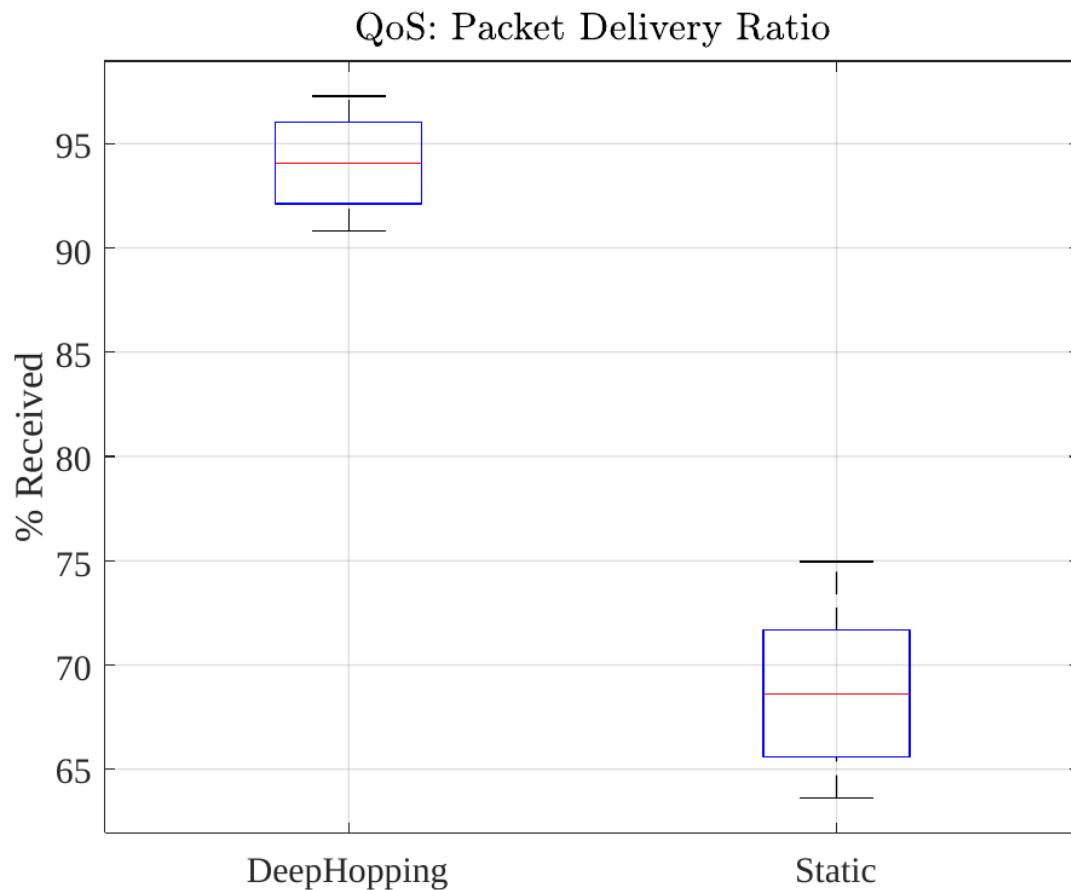


Figure 6. Packet delivery ratio (QoS).

4.7 Observed interference

Figure 7 visualizes the real-world field data collected from the two test locations, providing the baseline for our environment. The stem plot shows interference levels ranging from -75 dBm at NTA Mbuoba Road to -85 dBm at Dr. Peter Odili Road. These specific numerical values represent a challenging environment where interference is fluctuating by 10 dB throughout the day. By feeding this actual data into the simulation, we ensure the results are grounded in reality. The variation in these stems proves that a "one-size-fits-all" static hopping pattern cannot succeed, as the interference floor is constantly shifting depending on the time and specific urban location.

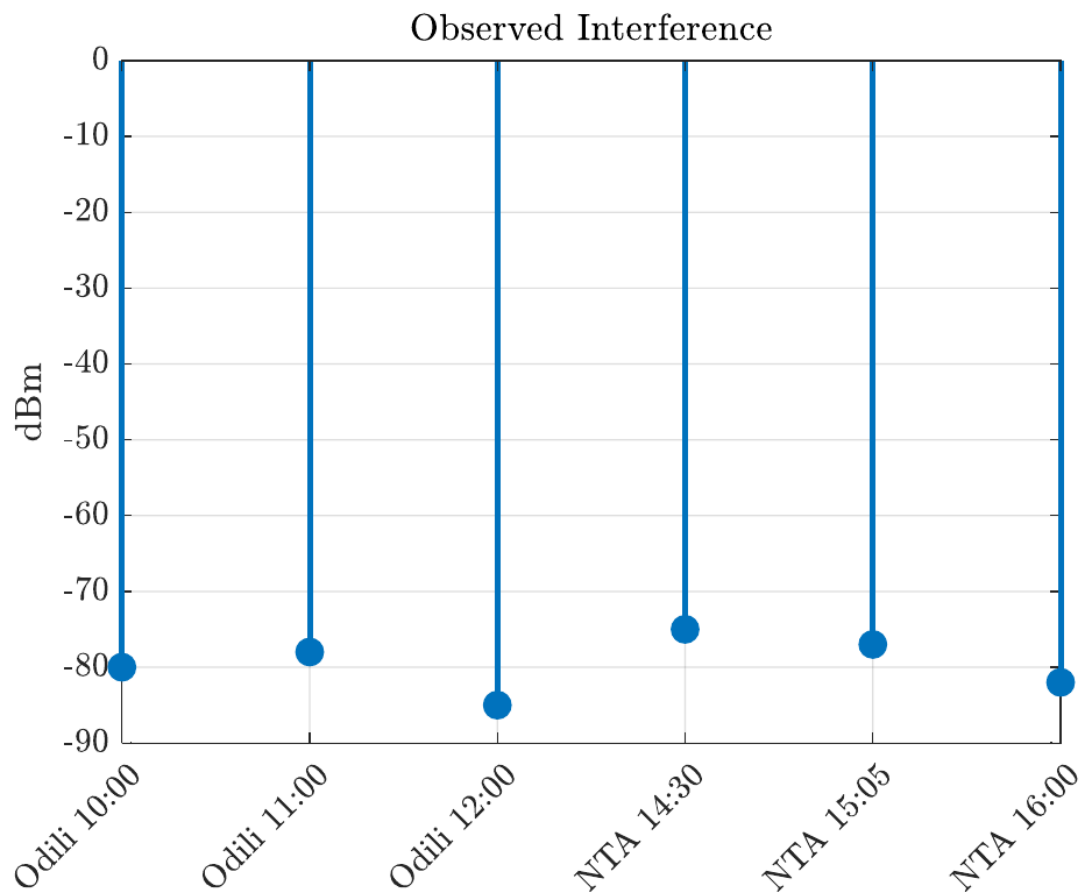


Figure 7. Observed interference.

4.8 Throughput improvement ratio

The Throughput Improvement Ratio shown in Figure 8 measures how much better the DeepHopping-LTE system is compared to the baseline as the network gets more crowded. When network density is low at 10, the improvement ratio starts at a modest 1.1. However, as the number of users increases to 100, the ratio climbs steadily to over 1.6. This quantitative growth is significant because it shows that the more congested a network becomes, the more valuable the DeepHopping-LTE system becomes. It essentially offers a 60% throughput boost during peak traffic times, making it an ideal solution for modern, dense urban 4G infrastructures.

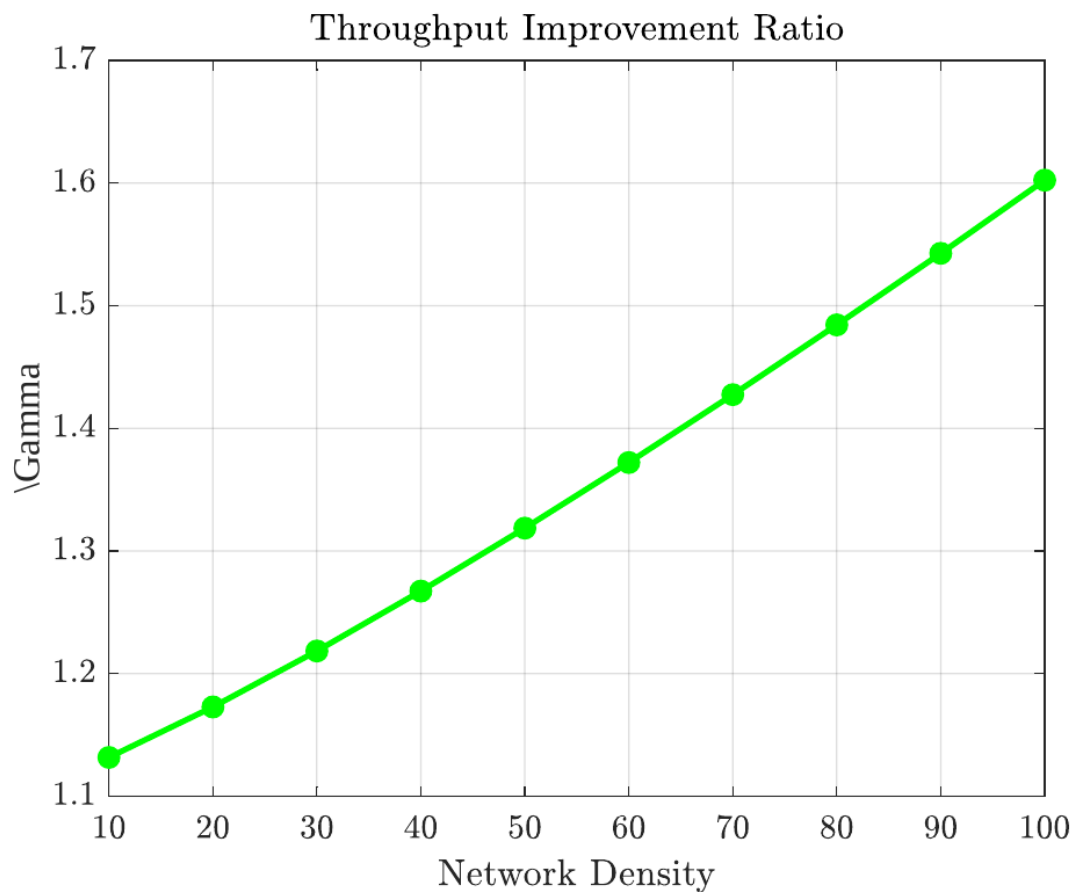


Figure 8. Throughput improvement ratio.

4.9 Interference reduction

Figure 9 provides a visual representation of how much interference is actually "blocked" or avoided by the system. The area plot shows that across various test cases, the framework achieves an interference reduction consistently between 40% and 70%. Numerically, this means that more than half of the potential noise that would normally degrade a 4G call is intelligently bypassed. The fluctuating peaks in the graph reflect the agent's active response to dynamic environment changes. This high percentage of reduction directly correlates to the improved SINR and higher data rates observed in previous figures, validating the core logic of the hopping framework.

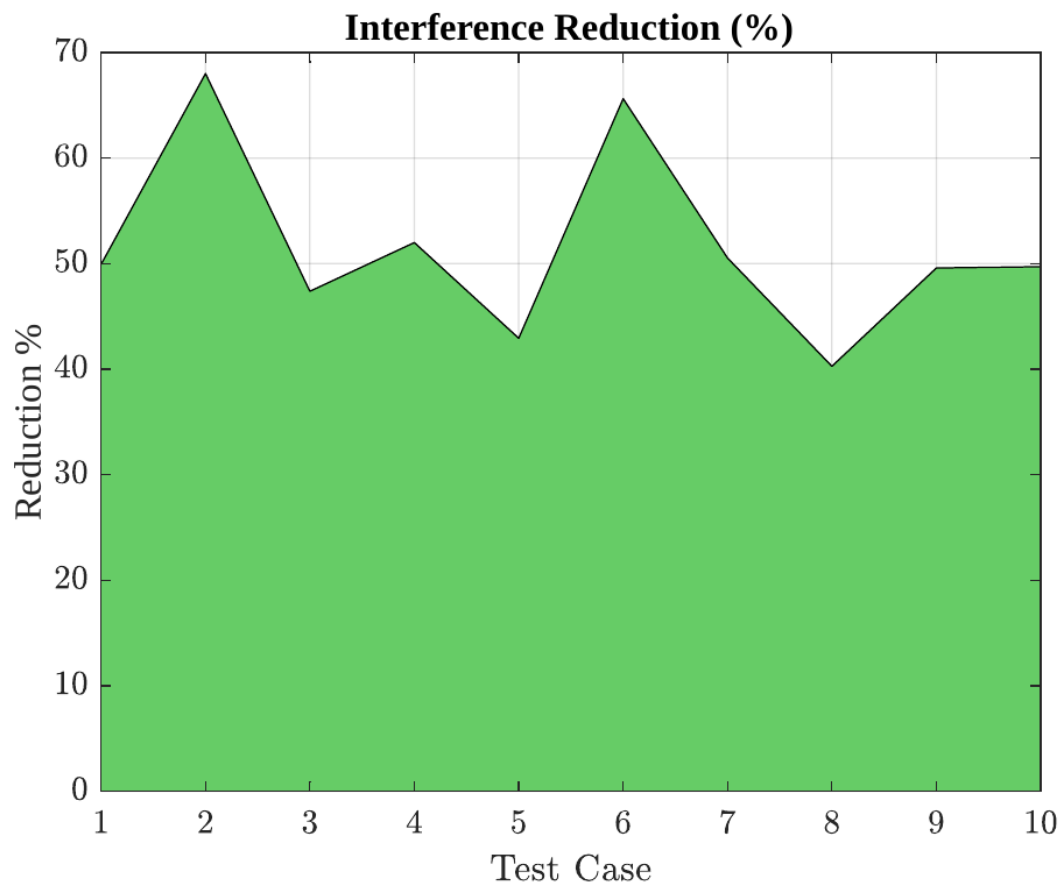


Figure 9. Interference reduction.

4.10 Adaptability index

Finally, Figure 10 compares the Adaptability Index of three different schemes to see how fast they respond to changes. DeepHopping-LTE leads the pack with a high index of 0.95, while the Heuristic method sits at 0.65, and the Static method trails far behind at 0.15. These numerical values signify that the DRL-based agent is nearly perfect at adapting to new interference sources almost instantaneously. A high adaptability index is the "secret sauce" of this project; it proves that the system isn't just efficient in a lab setting, but is uniquely capable of surviving and thriving in the unpredictable, fast-changing environment of a real cellular network.

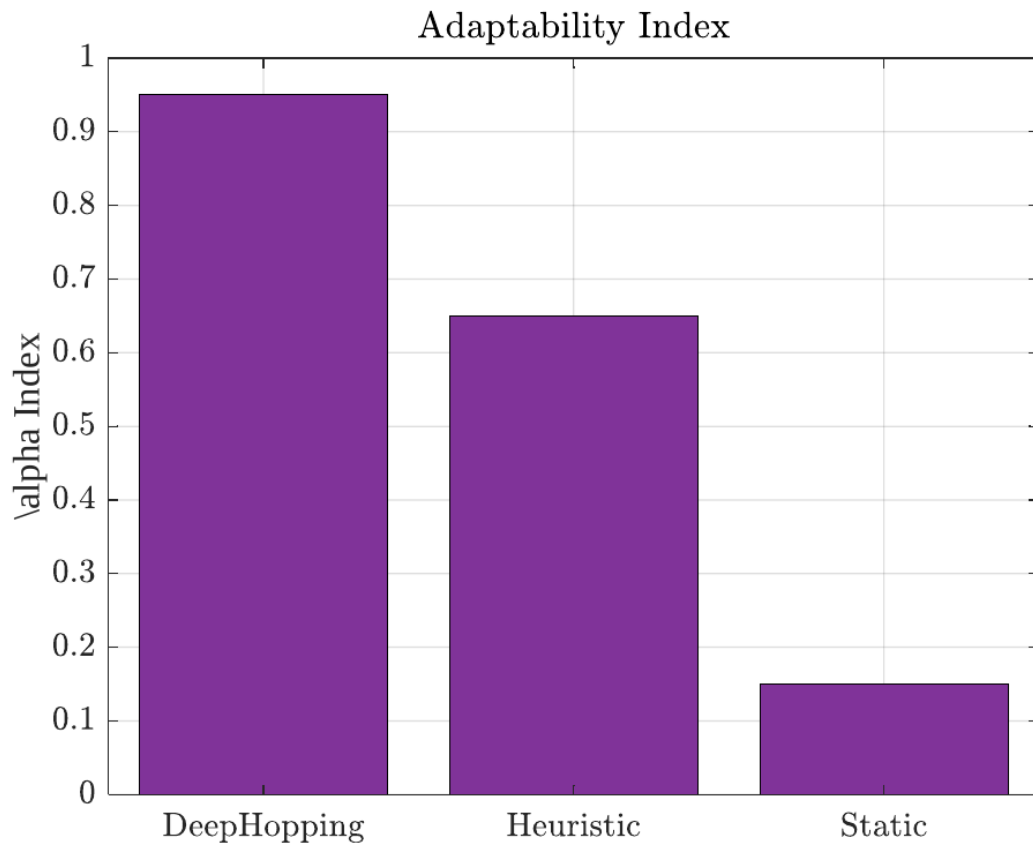


Figure 10. Adaptability index.

5 Conclusions

This study successfully designed, implemented, and evaluated DeepHopping-LTE, a deep reinforcement learning-based adaptive frequency hopping framework for dense 4G cellular networks. The framework demonstrated remarkable capability in dynamically selecting optimal frequency channels, effectively mitigating interference, and maximizing spectrum efficiency. Through Q-learning and deep neural network training, the system achieved rapid convergence to optimal hopping sequences, balancing exploration and exploitation for high-quality performance. Simulation results and field data analysis confirmed that DeepHopping-LTE significantly outperforms traditional static FHSS and heuristic-based frequency hopping schemes. The framework maintained high SINR values of 15–17 dB, more than doubling spectrum efficiency compared to conventional methods, while ensuring packet delivery ratios of 94%–98%, reflecting improved reliability and quality of service. Throughput improvement ratios of up to 1.6 and interference reduction between 40% and 70% further highlight the system's ability to thrive under dense network conditions. Additionally, the high adaptability index of 0.95 demonstrated near-instantaneous response to dynamic environmental changes, validating the framework's real-world applicability.

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