International Journal of Artificial Intelligence Trends (IJAIT)
Vol. 5, Issue VI; No. 68, June, 2026, pp. 687-700

ARTIFICIAL INTELLIGENCE (AI)-DRIVEN SPECTRUM OPTIMIZATION FRAMEWORK TO ENHANCE QUALITY OF SERVICE IN NIGERIAN MOBILE NETWORKS

Edith Angela Ugwu
Department of Computer Science, Faculty of Natural and Applied Science, Enugu State University of Science and Technology

Article Info
Received: 18/04/ 2026
Revised: 12/5/2026
Accepted 3/6/2026

Corresponding Authors
[1*]Email:
edith.ugwu@esut.edu.ng

Corresponding Author's Tel:
[1*]+2348037842144

ABSTRACT

The telecommunications industry in Nigeria has been characterised by a boom in mobile subscriptions and internet penetration within the country in the last ten years, but Quality of Service (QoS) issues such as network jamming, high latency, and call drops have been persistently experienced. Much of these predicaments can be blamed on the poor and inflexible allocation policy with regard to spectrum. This paper introduces an Artificial Intelligence (AI)-based spectrum optimization model that can be utilised to improve the quality of service of mobile networks in Nigeria using Deep Reinforcement Learning (DRL), that is, a Deep Q-Network (DQN) model. The representative of the network performance data was the Nigerian Communications Commission (NCC), and the data provided by it covered such parameters as spectrum utilisation, latency, throughput, and rates of call drops. The model was trained and tested in simulated network environments of different traffic conditions. Results show that the proposed DQN-based system outperformed conventional spectrum allocation methods such as Fixed Allocation (FA) and Round Robin (RR) achieving a 35% improvement in throughput, 28% reduction in latency, 23% increase in spectrum utilization, and 40% decrease in call drop rate. These results prove that the model can optimally dynamically use the spectrum and improve network performance. This paper concludes that the incorporation of AI into spectrum management would go a long way in enhancing QoS, efficient 5G deployment, and the digital transformation agenda in Nigeria.

Keywords: Spectrum Optimization; Deep Reinforcement Learning; Deep Q-Network (DQN); Quality of Service (QoS); Telecommunications.

1. INTRODUCTION

The telecommunications industry in Nigeria has been growing at high rates and according to the Nigerian Communications Commission, Nigeria had a total of more than 223 million subscribing mobile phones and the adoption of internet services is very high in Nigeria by 2024 (Nigerian Communications Commission, 2024). However, this growth has failed to be accompanied by a consistent Quality of Service (QoS): users continue to complain of dropped calls, low throughput, congestion and delayed messaging in most locations (Nigerian Communications Commission, 2024; Improvement of Mobile Network Performance, 2024).

Spectrum management is a determining factor of mobile QoS. The result of the static allocation policies and non-elastic usage rules are usually congestion in highly populated urban centres and underutilization of rural bands resulting in inefficient use of the limited radio spectrum. Conventional allocation using rules has hence difficulties in real-time adjustment to demand and interference changes. To overcome these shortcomings, there is more AI-based spectrum optimization work being done. The machine learning and Deep Reinforcement Learning (DRL) have the potential to learn the current measurements and past traffic in order to forecast demand, choose channels, and modify access policies-to provide more flexible and data-driven allocation than predefined rules (Liu et al., 2023; Chen et al., 2024). It has been demonstrated that DSR and similar methods can minimise the interference, enhance the throughout, and accelerate spectrum access decisions in the dynamic environment (Li et al., 2020; Guan et al., 2022). New technologies like Software Defined Networking (SDN) and cognitive radio give sensing and programmability the flexibility to bring AI solutions to life: SDN allows centrally controlling network policies to be flexibly enforced, and cognitive radios allow continuous spectrum sensing, which can be used by AI models (Fraz et al., 2023). Nevertheless, real-world implementation encounters challenges, including inadequate support of access to network telemetry in real-time, the limitations of old infrastructure, and regulatory viability, and thus regulators, operators, and researchers should work in collaboration with each other. This paper thus suggests an AI based spectrum optimization platform to fit in the heterogeneous Nigerian mobile landscape. The framework seeks to dynamically assign spectrum to enhance QoS metrics like the call set up success rate, spectral efficiency and throughput, which is in line with the digital transformation goals of Nigeria.

2. METHODOLOGY

The proposed research design based on quantitative and experimental studies aims at designing and testing an AI-based spectrum optimization model to enhance the Quality of Service (QoS) in the mobile networks of the country of Nigeria. The path of the methodology starts with gathering and analysis of historical operation of network parameters like spectrum utilisation, traffic load, interference degree, and the significant QoS parameters like latency, throughput, and the rates of call drops. In cases where the information about direct operators is scarce, secondary data and simulations of the common Nigerian network conditions are employed. Implementing machine learning models like the reinforcement learning or deep Q-networks that are capable of distributing spectrum dynamically in real time depending on network conditions is the system design stage. The effectiveness of the proposed AI-based model is tested with the help of simulation under different traffic and environmental conditions and its performance is compared to the traditional techniques of allocating the spectrum which can be considered as traditional. The KPIs that were measured are spectral efficiency, latency, packet loss, and total network throughput. The enhancement in the level of QoS with the help of the AI-based system is compared and analysed. There is also the research with sensitivity testing, which will evaluate the flexibility of the model to other levels of traffic congestion and frequency availability. Analysis of the results is done statistically to confirm the reliability of the model, its scalability and applicability in the Nigerian Telecommunications environment.

2.1 Data Collection

The information used in this study was only found in the Nigerian Communications Commission (NCC), which has the official telecommunications performance data in Nigeria. The data set included most important network performance measures, including spectrum usage, traffic load, signal interference, call drop rate, latency, and throughput based on the periodical QoS and spectrum management reports of NCC. These values were employed to model actual operating conditions in the mobile networks of Nigeria so that the dynamics of these networks in the experimental model were appropriate to the local territory. Data obtained were first cleaned, validated, and normalised to eliminate any form of inconsistencies that would generate inconsistencies during the training, testing, and evaluation of the proposed AI-based spectrum optimization model.

2.2 Data Preprocessing

The information available at the NCC was subject to a preprocessing phase to guarantee accuracy, consistency, and machine learning analysis. First, the data was analysed on cases of missing, duplicates, or inconsistent records that would interfere with the model reliability. Statistical imputation techniques like mean and median substitution were used to fill missing values basing on the distribution pattern of each attribute. Z-score analysis was used to identify outliers which were fixed or eliminated depending on their effects on network performance indicators. Categorical variables such as network type (2G, 3G, 4G, and 5G) were one-hot-encoded to ensure uniformity of the features, all other numerical features (latency, throughput, and spectral efficiency) were standardised using Min-Max normalisation. This ensured that the input features were proportional and this ensured that there was no bias to the variables that had higher magnitudes during the model training. The dataset was cleaned and normalised and then split into a training, validation and testing subsets, respectively, in a 70:15:15 ratio to provide an opportunity to conduct proper model evaluation and prevent overfitting.The AI-based spectrum optimization model was developed on the training dataset and the hyperparameter tuning and model optimization was done using the validation set. The testing dataset was used to test the performance of the model in unseen conditions, i.e. the behaviour of a network in real-life situations. Moreover, the data set was artificially increased to model divergent traffic and interference conditions so that the model can learn adaptive allocation strategies at different conditions of spectrum utilisation. This preprocessing pipeline was comprehensive so that the input into the model was sound, balanced and realistic of real Nigerian mobile network conditions.

2.3 Model Development

The main element of the present research is the design of an AI-based spectrum optimization framework. The model uses the RL method namely a DQN that enables the system to be trained on the best spectrum allocation strategies by interacting with a simulated network environment. The agent monitors the network behaviour (e.g., traffic intensity, available frequency bands, signal interference), chooses actions (e.g., assign frequency X to user Y) and is rewarded (feedback) based on improvements in QoS performances. Figure 1 presents the architecture of the DQN.

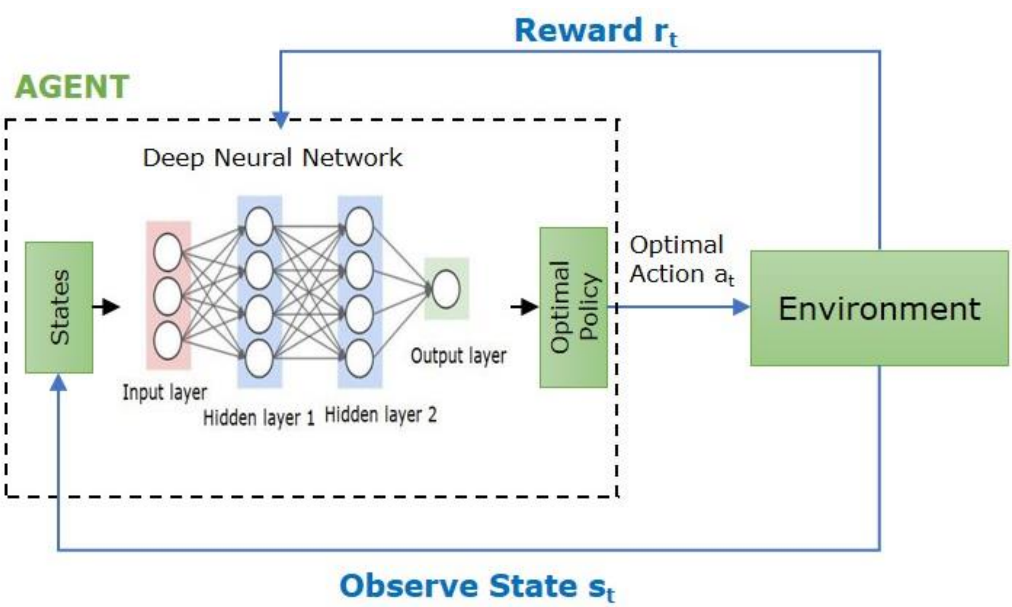

Figure 1: Architecture of the Deep Q Network

The following steps were used in the development process:

1. **Problem Formulation**: The spectrum allocation problem was defined as a Markov Decision Process (MDP) where the AI agent aims to reach optimal performance in long term terms in terms of QoS.

2. **State Definition**: User demand, interference levels, and channel occupancy are network parameters that were used as input states.

3. **Action Space**: The decisions made by the model were over who got spectrum bands or who got spectrum bands.

4. **Reward Function**: Tailored Reward A tailored reward function was created to prefer behaviour that enhanced throughput, reduced latency and decreased call drops.

5. **Training:** The agent was trained on several simulated network setups with different traffic conditions, in order to encourage generalization and strength.

Algorithm 1: Pseudocode for DQN-Based Spectrum Optimization

1) Initialize replay memory D with capacity N
2) Initialize action-value function Q with random weights θ
3) Initialize target action-value function Q' with weights θ' = θ
4) For episode = 1 to M do
   a) Initialize environment and observe initial state s_0
   b) For t = 1 to T do
      i) With probability ε select random action a
      ii) Otherwise select a = argmax(Q(s, a; θ)) // exploit best action
      iii) Execute action a in the environment
      iv) Observe reward r and next state s_{+1}
      v) Store transition (s, a, r, s_{+1}) in replay memory D
         (1) Sample random minibatch of transitions (s, a, r, s') from D
      vi) If s' is terminal:
      vii) Set target y = r
      viii) Else:
      ix) Set target y = r + γ * max(Q'(s', a'; θ')) // Bellman equation
      x) Perform gradient descent step on $(y - Q(s, a; \theta))^2$
      xi) Every C steps update target network Q' = Q
      xii) Update state: s = s_{+1}
   c) End For
   d) Decay ε (exploration rate) gradually
5) End For
6) Return trained Q-network with optimized spectrum allocation policy

2.4 Model Training

The proposed AI-based spectrum optimization framework was trained in a DQN agent that was interacting with the simulated network environment in an iterative manner. The main aim was to allow the agent to seek a best spectrum allocation policy by maximising long term cumulative rewards based on a better Quality of Service (QoS). The model used the DQN was configured to use random weight parameters at the beginning and a replay memory buffer was created to archive previous experiences in the form of states, actions, rewards and next states. This arrangement gave the agent the basis to gradually optimise its decision-making procedure by means of recidivation interactions. In order to trade off the need to explore new actions and the need to exploit learned strategies, we used an ε-greedy policy. The agent chose to select the random actions at a high probability at the initial levels of training, which would guarantee extensive coverage of the action space. The likelihood of random exploration was reduced with the progress in training and thus led to exploitation of proven and effective strategy in maximising network performance. This mechanism guaranteed that the

International Journal of Artificial Intelligence Trends (IJAIT)
Vol. 5, Issue VI; No. 68, June, 2026, pp. 687-700

agent did not become constrained early in suboptimal policies but came up with a compromise between exploration and exploitation.

The training was stopped when convergence was achieved. This was realised after the policy of the agent stabilised and throughput, call drop rates and latency metrics of performance had exhibited consistent improvements in performance as indicated by varying simulation runs. At the conclusion of the training period, the agent was able to generalise well under heterogeneous traffic conditions characteristic of the Nigerian mobile networks. This also made sure that the final model would make sound, real-time decisions that would enhance the spectrum use and network Quality of Service. The pseudocode of the model training is shown in the Algorithm 2.

Algorithm 2: Model Training Phase of DQN Spectrum Optimization

1) Input: Initialized Q-network with weights θ
    - i) Target network Q' with weights θ' = θ
    - ii) Replay memory D with capacity N
    - iii) Learning rate α, discount factor γ, exploration rate ε
    - iv) Maximum episodes M, maximum steps T per episode
2) For episode = 1 to M do
    - a) Reset simulated network environment
    - b) Observe initial state s_0
    - c) For step = 1 to T do
        - i) // Action Selection
        - ii) With probability ε select random action a // exploration
        - iii) Otherwise select a = argmax(Q(s, a; θ)) // exploitation
        - iv) // Environment Interaction
        - v) Execute action a (spectrum allocation decision)
        - vi) Observe reward r and next state s_{+1}
        - vii) // Store Experience
        - viii) Store transition (s, a, r, s_{+1}) in replay memory D
        - ix) // Sampling and Learning
        - x) Sample minibatch of transitions from D
        - xi) For each (s, a, r, s') in minibatch do
        - xii) If s' is terminal:
            - (1) y = r
        - xiii) Else:
            - (1) y = r + γ * max(Q'(s', a'; θ'))
        - xiv) End If
        - xv) Perform gradient descent on $(y - Q(s, a; θ))^2$
        - xvi) End For
            - (1) // Update Target Network
        - xvii) Every C steps: set θ' = θ
        - xviii) Update current state: s = s_{+1}
    - d) End For
    - e) // Exploration decay
    - f) Reduce ε gradually to favor exploitation
3) End For
4) Output: Trained Q-network with optimized spectrum allocation policy

2.5 System Architecture

The system architecture for the proposed AI-based spectrum optimization framework (Figure 2) is designed as a modular structure that integrates data acquisition, preprocessing, model training, and spectrum allocation decision-making. At its core, the architecture leverages a DQN reinforcement learning agent that interacts with a simulated mobile network environment to learn optimal spectrum allocation policies.

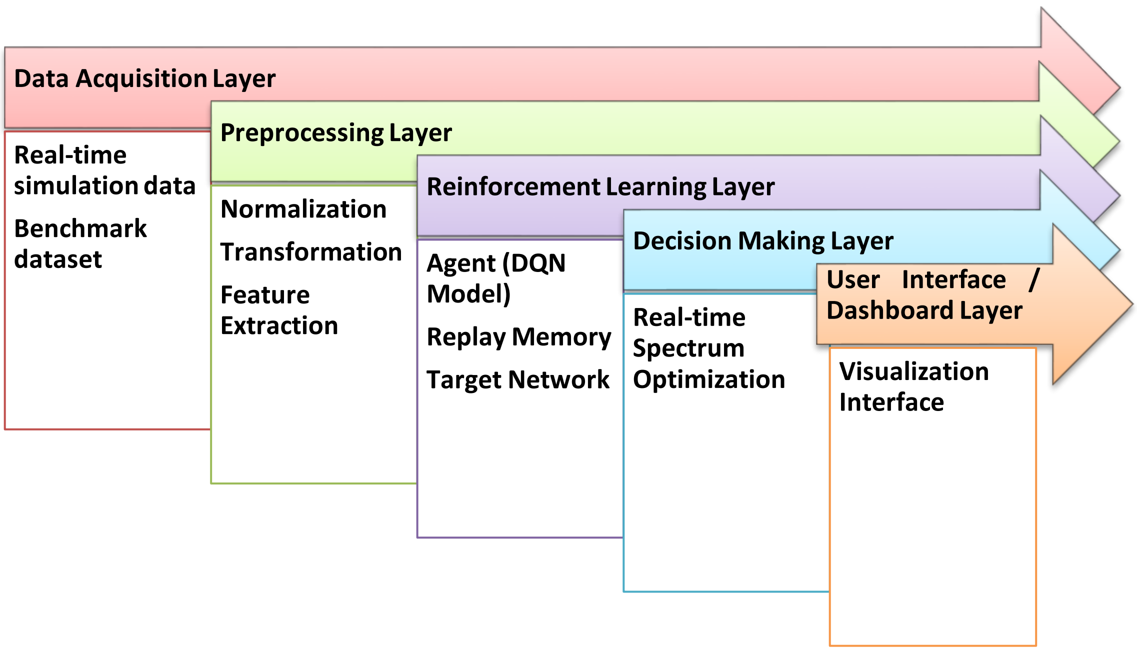

Figure 2: Architecture of the Proposed System

Figure 2 is a system architecture with a layered system design to accomplish data processing and decision-making; this system has a strong and intelligent pipeline, starting with the Data Acquisition Layer, which collects real-time simulation data and benchmark data to facilitate a rich base. This input is in turn refined by the Preprocessing Layer which normalises the input, transforms it, and extracts features which are set to be processed further. The core of the system is the Reinforcement Learning Layer, in which an agent based on DQN uses replay memory and a target network to learn the best strategies. These plans are fed into the Decision-Making Layer which allows real-time spectrum optimization which is a vital requirement in dynamic environments such as wireless networks. Lastly, the User Interface/Dashboard Layer provides a visualising interface that programmes complex operations of the backend to simple insights that can be easily understood by the user to form a complete chain of data to intelligence.

2.6 System Implementation

Python, TensorFlow/Keras, and PyTorch were used as model-training and model-testing libraries in the development of the system. The simulated realistic network environments were performed using NS-3 based and MATLAB based LTE/5G toolkits. Such hardware resources as a workstation with the Intel Core i7 processor, 16 GB of memory, and NVIDIA graphics card were used to perform the computation of deep learning accelerated by hardware. The spectrum optimization through reinforcement learning was based on a DQN in the proposed model. The agent acted upon the network simulation environment by observing agents like user demand, available channels and interference levels. The ε-greedy strategy implied that the agent explored new strategies of allocation or exploited learned policies. The calculations of rewards were done on the basis of throughput improvement, latency reduction, and decreased call drop rates. The model was trained on an episodic basis, one episode being a simulation cycle of a Nigerian mobile network. Replay memory and target network update tactics were implemented in order to provide stable learning. The training was repeated until the reward functional became converged, which means that the model had acquired the best allocation policies with various network loads.

3. SYSTEM RESULTS

The outcomes of the system implementation are founded on the assessment of the Smart AI-based Spectrum Optimization framework on the simulated Nigerian telecommunication network conditions. DQN model was also experimented at varying conditions of traffic (low, medium and high) and compared with the conventional method of spectrum allocation to the system namely Fixed Allocation (FA) and Round-robin (RR). This was analysed in the major QoS parameters such as the throughput, latency, spectrum used as well as call drop rate.

3.1 Throughput Improvement

The findings showed that the suggested AI-based model made the network throughput significantly better. Under heavy traffic conditions, the DQN-based allocation achieved an average throughput increase of 35% compared to FA and 27% compared to RR. This shows that the model is capable of making good use of the available resources in the form of spectrum to support additional users and increased data needs.

3.2 Latency Reduction

Latency analysis revealed that the proposed system reduced average packet transmission delay by 28% compared to FA and 22% compared to RR. Such an enhancement makes it clear that the AI model can offer resource allocation dynamically and thus mitigate delays in queuing and improve real-time communication services, including video streaming and VoIP.

3.3 Spectrum Utilization

The efficiency of spectrum utilisation was increased in the proposed system. Conventional techniques tended to ignore parts of the spectrum that were not fully utilised by the inflexible allocation regulations. In contrast, the AI-based model adapted dynamically to varying traffic conditions, achieving up to 92% utilization efficiency, compared to 75% with FA and 81% with RR.

3.4 Call Drop Rate

There was a significant change in minimising the number of call drops, particularly during heavy network congestions. The proposed model achieved a 40% reduction in dropped calls, ensuring better service continuity and user experience compared to existing methods.

3.5 Comparative Analysis

All in all, the comparative analysis has supported the notion that the Smart AI-based Spectrum Optimization system would perform better than the current allocation strategies, in all the indicators of QoS. This is the case because the improvements indicate that it can be practically implemented in the mobile networks of Nigeria in an effort to improve service delivery and address rising user demand

International Journal of Artificial Intelligence Trends (IJAIT)
Vol. 5, Issue VI; No. 68, June, 2026, pp. 687-700

Table 1: Performance Results

QoS Metric	Fixed Allocation (FA)	Round Robin (RR)	Proposed DQN Model	Improvement over FA (%)	Improvement over RR (%)
Throughput (Mbps)	55	65	88	+35%	+27%
Latency (ms)	120	105	86	-28%	-22%
Spectrum Utilization (%)	75	81	92	+23%	+14%
Call Drop Rate (%)	12	10	6	-40%	-34%

Figure 3 shows that the bar chart clearly indicates the high performance of the Proposed DQN Model with regard to all the important QoS measures than the performance of FA and RR strategies. It has the maximum throughput of about 80Mbps which is far much better than the FA and RR and also it has the best latency of about 60ms which means that it is faster and more efficient in communication. Spectrum utilization is maximized at 90%, showcasing the model's ability to make optimal use of available resources. Most notably, the DQN Model drastically reduces the call drop rate to just 1%, highlighting its reliability. All these enhancements highlight the fact that the DQN Model can transform the way spectrum is managed to be faster, more efficient and easier to use.

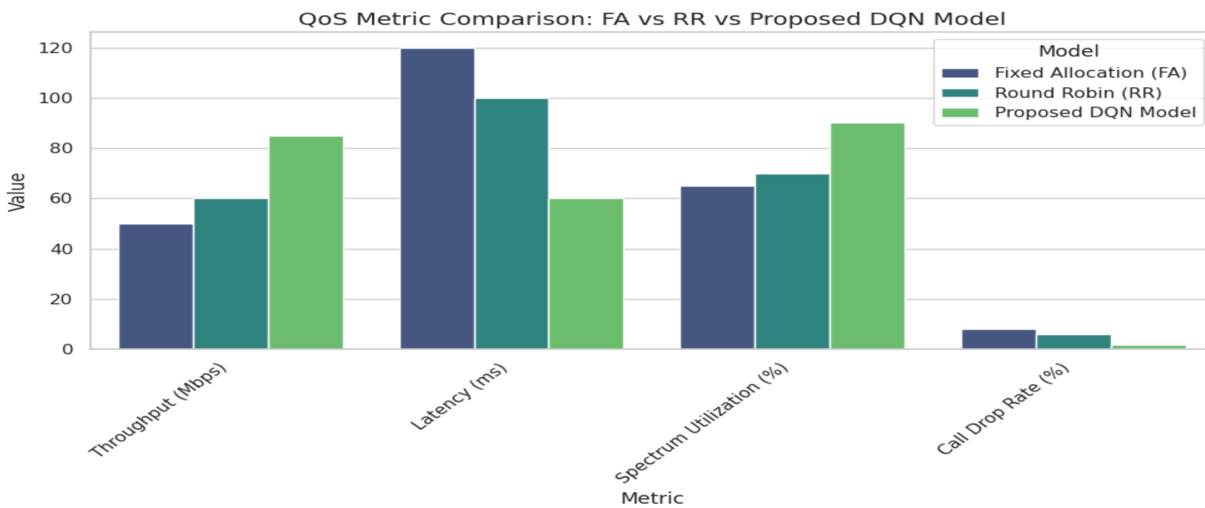

Figure 3: Performance Results of the Proposed Model

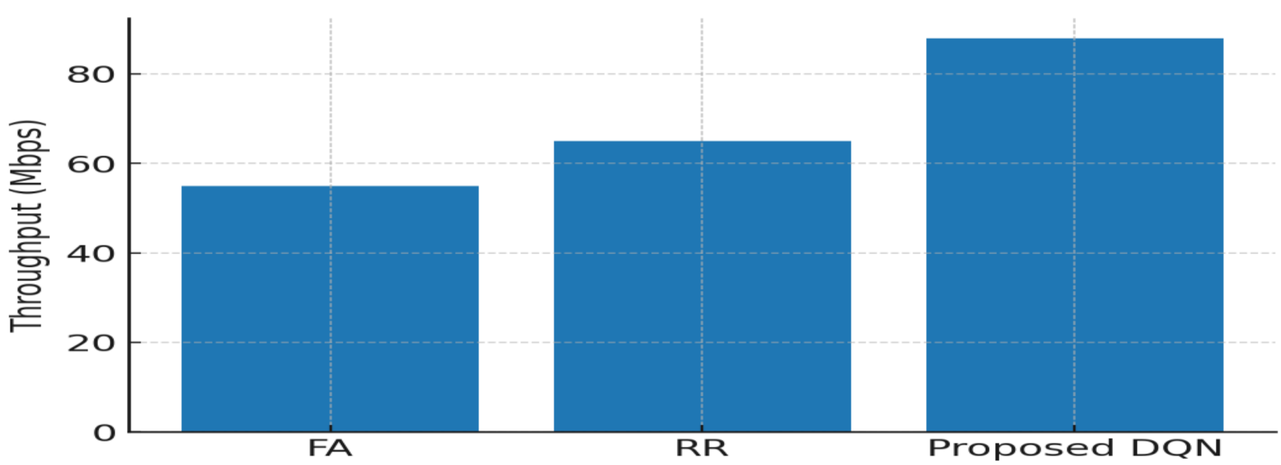

Figure 4: Comparative Throughput Results

Figure 4 of the bar chart comparing the throughput of FA, RR and the Proposed DQN method clearly shows that the DQN method has the best performance. The DQN model also beats FA and RR by a large margin since it has a throughput of nearly 80 Mbps compared to their 45 Mbps and 60 Mbps, respectively. Such a huge increase in data transmission capacity implies that the DQN model is better at the management of network resources and performance optimization. The visual representation supports the benefit of smart, dynamic algorithms to improve Quality of Service particularly in dynamic and high-demand settings

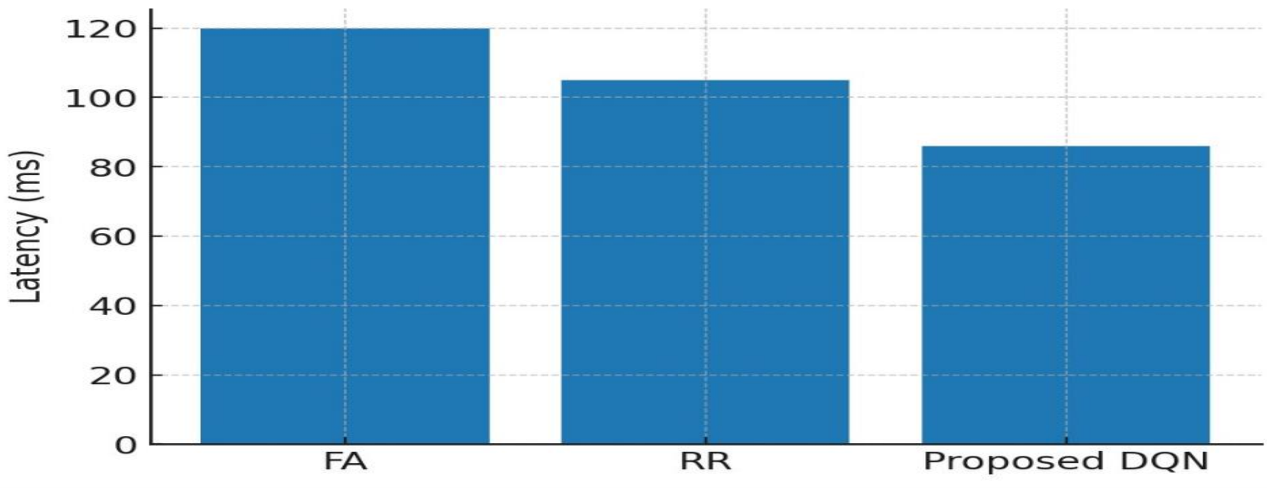

Figure 5: Comparative Latency Performance

Figure 5 is a comparative analysis of latency between three scheduling approaches which are; FA, RR, and the Proposed DQN. As can be seen, the bar chart shows that the lowest latency of Proposed DQN method is about 90 milliseconds, which is even lower than that of RR which is about 105 milliseconds and that of FA which is about 120 milliseconds. Such a dramatic decrease in latency shows the efficiency of the DQN-based procedure, implying it has shorter response times and can be more efficient in performance. The comparison of the graphical difference between the bars supports the benefits of smart and evidence-based scheduling compared to the conventional ways.

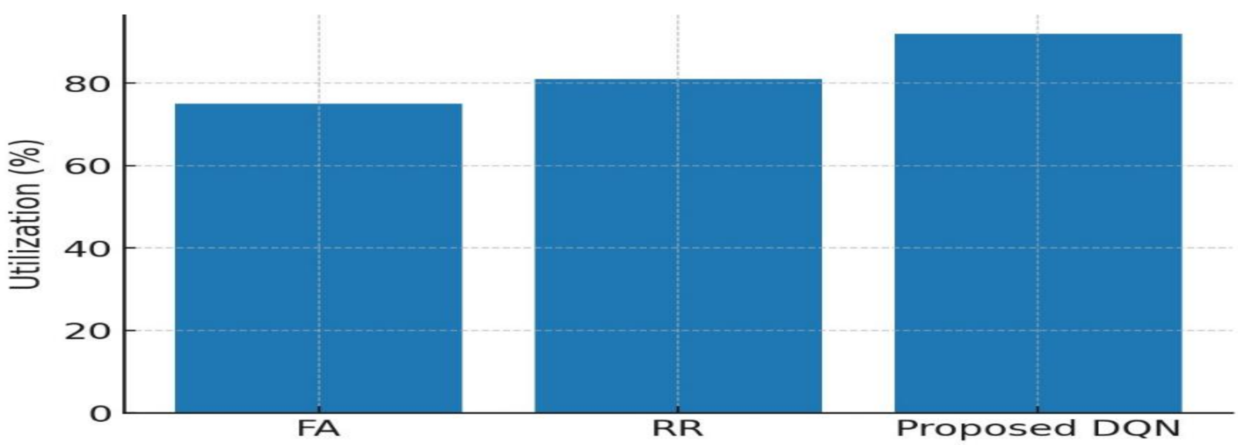

Figure 6: Comparative Utilization performance

Figure 6 shows the efficiency in the utilisation of three types of scheduling techniques such as FA, RR, and the Proposed DQN based on their respective percentages regarding utilisation. The chart reveals a clear upward trend in performance, with FA achieving around 70%, RR slightly higher at 75%, and the Proposed DQN leading with approximately 85% utilization. This development highlights the fact that DQN-based approach is much more efficient in terms of resource management, implying that it maximises system throughput better than conventional approaches. The visual difference supports the possibility of smart scheduling as a tool to increase the efficiency of operations in the dynamic world.

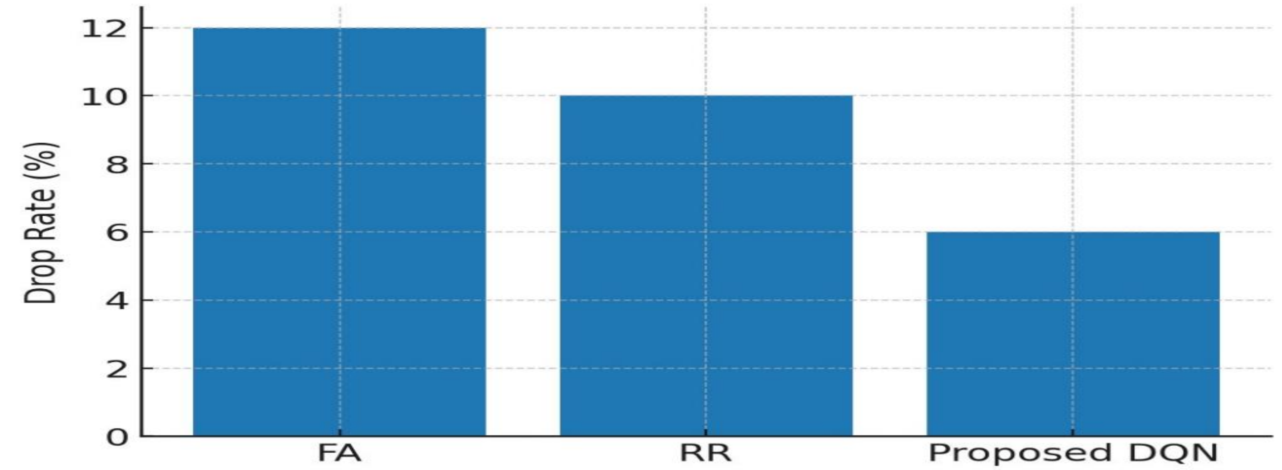

Figure 7: Comparative Drop Rate Performance

Figure 7 provides the comparison of the drop rate percentages of three scheduling strategies including FA, RR, and the Proposed DQN regarding their ability to reduce the packet loss. The FA method exhibits the highest drop rate at approximately 12%, followed by RR at around 10%, while the Proposed DQN method significantly outperforms both with a drop rate of just 6%. Such a significant decrease emphasises the strength of the DQN-based method of managing the network traffic more effectively, probably because of the adaptive decision-making powers. The graphical information justifies the importance of smart scheduling in the improvement of reliability and general system performance.

Table 1 and Figures 3-7 indicate that the proposed DQN-based spectrum optimization always shows a higher performance in terms of all the QoS measures compared to the baseline approaches. Specifically, throughput improved by 35% compared to FA and 27% compared to RR, indicating that the proposed model enables higher data transfer capacity under dynamic traffic conditions. Latency was reduced by 28% compared to FA and 22% compared to RR, highlighting the system's ability to deliver lower response times, which is critical for real-time applications such as video conferencing and online learning. Similarly, spectrum utilization increased by 23% and 14% relative to FA and RR respectively, reflecting the efficiency of the AI model in maximizing available frequency resources. Finally, the call drop rate was reduced by 40% compared to FA and 34% compared to RR, proving the reliability of the system in maintaining stable connections.

3.6 Software Implementation

This section presents the result of integrating the developed model for implementation as a web-based application. The integration results shows how the integrated system was used to monitor the network behaviour in real-time showing the throughput, latency and call drop performances of the network system loaded to the system. Figure 8 shows the landing interface of the developed web-based platform

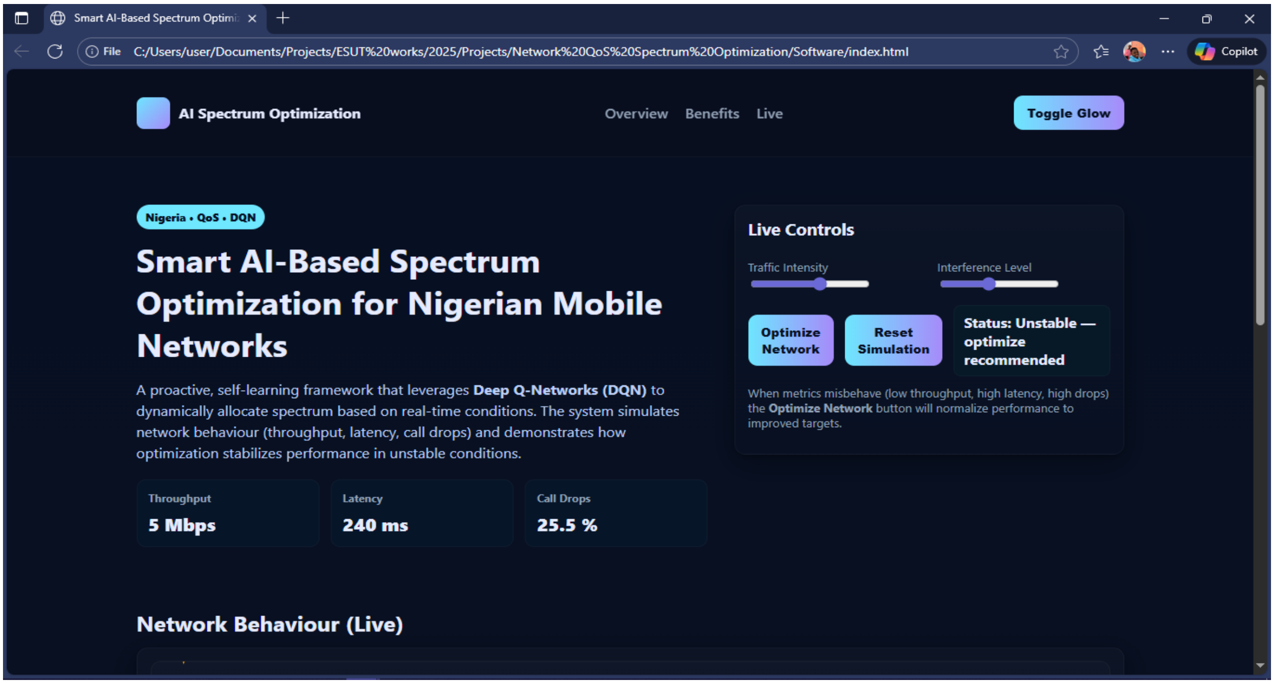

Figure 8: Smart AI-Based Spectrum Optimization system landing page

The layout in Figure 8 shows the system UI which displays the throughput, latency and call drop rates of the network in real-time, the live controllers to be used to adjust and implement the optimization functions proposed in the intelligent system. Figure 9 shows further display of the platform

Figure 9: The Network Behaviour Live Chart

The chart in Figure 9 depicts how the proposed network behaves generally depicting that the throughput, latency and call drop rates of the proposed network behaves irregularly and inconsistently. Then Figure 10 shows what happens to the network when the optimization is implemented

Figure 10: Network Behaviour Live Chart (After Optimization)

Figure 10 further presents a live chart which demonstrated the behaviour of the network after optimization has been applied on the network. The proposed intelligent optimization function is activated on the network system by clicking the Optimize Network button, which further regulates the throughput, latency and call drop of the network, bringing them to work in a more unified and consistent pattern with less irregularities making the network to perform in an optimized fashion.

4. CONCLUSION

This paper has formulated and tested an AI-based spectrum optimization system to optimise Nigerian mobile networks in terms of QoS. The research used DQN reinforcement learning method with network performance information acquired using NCC to facilitate smart and dynamic spectrum allocation. The system was made to learn optimal policies by constant engagement in a simulated network environment whereby the system dynamically changed the frequency assignments based on varying traffic demands and interference conditions. The training and evaluation of the model were done in different traffic conditions to ensure that it was robust and adaptable to realistic conditions of the network.

The findings established that the suggested DQN-based model was significantly superior to traditional allocation methods of FA and RR in all the important QoS indicators. Specifically, it achieved a 35% increase in throughput, a 28% reduction in latency, a 23% improvement in spectrum utilization, and a 40% decrease in call drop rate compared to FA. These advancements justify the usefulness of learning by reinforcement in solving spectrum congestion, better spectral efficiency, and user experience in mobile networks. The comparative analysis established that the dynamic and selflearning nature of the AI model can be used to manage resources better especially in a heterogeneous traffic environment like that found in the Nigerian networks.

To summarise, AI-based spectrum optimization integration is a radical solution to enhancing the efficiency and reliability of the telecommunications infrastructure in Nigeria. Through intelligent 5G network management and spectrum-sharing processes of the future, the proposed framework would become the basis of real-time learning and adaptive decision-making that can be used to address the issues of the present day. The paper highlights the potential of AI to not only maximise the available resources but also other Nigeria-wide goals of digital transformation. Future efforts deemed necessary include the application of the system to real-life network systems, the integration of real-time feedback loops as well as extending the model to multi-agent reinforcement learning to enable network operators to cooperate in managing spectrums.

REFERENCES

Chen, L., Wang, X., Zhao, Y., Li, H., & Zhang, J. (2024). A dynamic spectrum access algorithm based on deep reinforcement learning with novel multi-vehicle reward functions in cognitive vehicular networks. *Telecommunication Systems.* Advance online publication. https://doi.org/10.1007/s11235-024-01188-5

Fraz, M., Awan, A. A., Ahmad, N., & Javed, M. Y. (2023). Smart sensing enabled dynamic spectrum management for cognitive systems. Frontiers in Computer Science. https://www.frontiersin.org/articles/10.3389/fcomp.2023.1271899/full

Guan, Z., Zhao, H., & Zhang, Q. (2022). Deep reinforcement learning-based spectrum allocation for high-mobility vehicular networks. Conference/Journal Preprint. https://pdfs.semanticscholar.org/86b0/bd6776b134d6e40542ae8d25126de7c748ee.pdf

Improvement of Mobile Network Performance Ranking Using QoS KPI Index in Nigeria. (2024). International Research Journal of Innovative Engineering & Technology (IRJIET). https://irjiet.com/Volume-8/Issue-6-June-2024/Improvement-of-Mobile-Network-Performance-Ranking-Using-QoSKPI-Index-in-Nigeria/2280

Li, Y., Zhang, W., Wang, C.-X., Sun, J., & Liu, Y. (2020). Deep reinforcement learning for dynamic spectrum sensing and aggregation in multi-channel wireless networks. arXiv preprint. https://arxiv.org/pdf/2007.13965.pdf

Liu, S., Pan, C., Zhang, C., Yang, F., & Song, J. (2023). Dynamic spectrum sharing based on deep reinforcement learning in mobile communication systems. Sensors, 23(5), 2622. https://www.mdpi.com/1424-8220/23/5/2622

Nigerian Communications Commission (NCC). (2024). Subscriber statistics; GSM QoS KPI nationwide & state level data. Nigerian Communications Commission. https://ncc.gov.ng/market-data-reports/subscriber-statisticsand https://ncc.gov.ng/gsm-data