Volume 5, Issue III, March, 2026; No. 86, pp. 1090-1105
Submitted 2/2/2025; Final peer review 7/4/2026
Online Publication 12/4/2026
Available Online at http://www.ijortacs.com

# AI-DRIVEN SPECTRUM MANAGEMENT IN 5G NETWORK TECHNOLOGY TO IMPROVE NETWORK EFFICIENCY

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**Abstract**

Spectrum management has become a burning problem in the Fifth-Generation (5G) wireless networks as a result of growing traffic load, scarcity of spectrum, and very dynamic network conditions. The conventional approach to the allocation of the spectrum, static, cannot adapt to these obstacles and leads to poor utilisation of the available resources and worsens Quality of Service (QoS). This paper will suggest an AI-based spectrum management system that combines Extreme Gradient Boosting (XGBoost) to predict network traffic and spectrum demand with Deep Q-Network (DQN) to predict dynamic spectrum allocation. A practical network traffic dataset was deployed to study and test the proposed system in a virtual 5G environment. The experimental findings indicate that the XGBoost model has a high prediction accuracy as evidenced by a high $R^2$ score of 0.93 that will be used to conduct proactive spectrum planning. The DQN-based allocation strategy demonstrated effective learning, achieving a spectrum utilization of 87.6%, compared to 62.3% obtained using static allocation. There were also noticeable enhancements in the average throughput, latency, packet loss as well as overall QoS. The results affirm that AI-based spectrum management is an efficient and dynamically adaptable tool that can be used to optimise spectrum utilisation and improve the network in 5G networks.

**Keywords: AI-Driven Spectrum Management; 5G Networks; XGBoost; Deep Q-Network (DQN); Dynamic Spectrum Allocation.**

## 1. INTRODUCTION

The increasing data rate, ultra-low latency, and enormous connectivity demanded by the mobile communication and the spread of devices with connexions have been fuelled by their rapid increase. The 5G networks are tailored to these needs, and they provide improved mobile broadband, ultra-reliability, and low-latency, as well as massive machine-type communications (Mao et al., 2026). Nevertheless, the growing population of users and a variety of applications exert a lot of pressure on the radio band that is a scarce and highly valuable resource. Spectrum management is such an important issue that it has become a critical problem to bring the full potential of 5G networks to life (Ansari and Singh, 2025).

The existing spectrum allocation techniques are largely fixed or even operated manually and cannot adapt to dynamic traffic profiles and changing service demands, particularly in 5G networks. The result of this inefficiency is usually spectrum underutilization, user interference, and worse QoS (Islam Rony et al., 2021). Since the 5G networks can still support various tasks, such as high-definition video streaming and Internet of Things (IoT) devices and autonomous systems, there is a pressing need to implement smart mechanisms to optimise spectrum utilisation in real-time (Cullen et al., 2023).

The dynamic spectrum management in the 5G networks can be promising when Artificial Intelligence (AI) and Machine Learning (ML) methods are used. Analysing past and current network data, AI can forecast the demand in the spectrum, identify the trends of interference, and efficiently allocate the resources compared with the traditional approaches (Hussien et al., 2025). Reinforcement learning, deep learning, and supervised prediction models, among other techniques, allow networks to be adaptive, which enhances throughput, reducing latency and maximising the overall spectrum efficiency (Elmorsy et al., 2025). This is the way AI can be integrated into the spectrum management to offer an automated, data-driven solution to the challenges of contemporary wireless communication (Patil et al., 2025).

Recent research emphasises the effectiveness of reinforcement learning to dynamic environments, which allows one to quickly adapt to traffic changes and nuisance (Giwa et al., 2025). Deep learning models have been found to be highly accurate in spectrum sensing and interference detection, which is more accurate than traditional methods (Guel et al., 2024). Furthermore, AI-enabled cognitive radio systems can automatically detect unoccupied spectrum and optimally distribute it, which can then be further used (Verma et al., 2025).

Demand forecasting using AI has been used to forecast traffic carrying capacities and optimise rollout plans to operators (Bikkasani and Yerabolu, 2024). On the same note, convolutional neural networks are an AI-based approach to identifying interference that has provided better reliability in dense deployments (Alnfiai, 2025). Federated learning-based spectrum sharing networks are anticipated to become scalable systems in a multi-operator environment (Eldeeb and Alves, 2025). Moreover, the traffic prediction based on AI will improve the spatiotemporal distribution of resources in order to guarantee the QoS of various applications (Havolli and Fetaji, 2025).

The proposed study is expected to explore the use of AI-controlled spectrum management in 5G networks with the aim of enhancing the efficiency of the network. Particularly, it dwells upon deploying machine learning and reinforcement learning algorithms to forecast the spectrum usage patterns, maximise allocation, and minimise interference in real time (Gowda and Panchaxari, 2023). The studies focus on the theoretical and practical dimensions of AI adoption, such as the architecture of the system, its performance indicators, and possible issues (Cullen et al., 2023). Finally, the research aims to show how smart spectrum management can ensure network performance, support multiple 5G services, and be a platform of future advancements in next-generation wireless networks (Bronson, 2025).

## 2. RESEARCH METHODOLOGY

Figure 1 represents the block diagram of the proposed system.

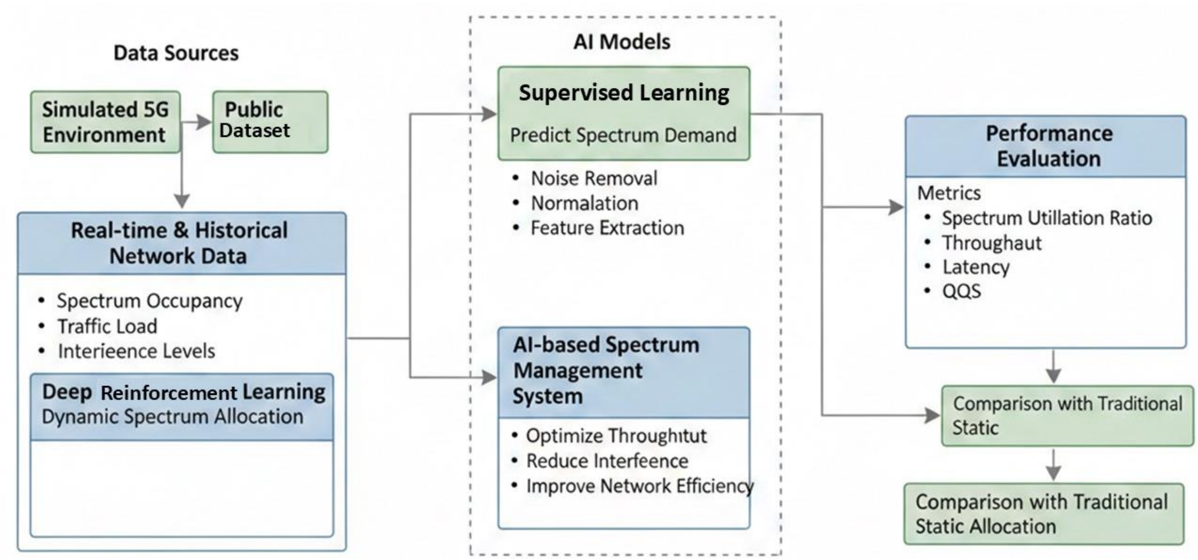


Figure 1: Block Diagram of the proposed System

The present research paper will take a quantitative and experimental research approach to examine the AI-enforced spectrum management in the 5G networks. The use of simulated 5G networks and publicly available data gathers real-time network information along with historical network information, such as spectrum occupancy, traffic load, and the level of interference. The data go through a pre-processing step to eliminate noise, standardise values and derive useful characteristics before being processed by machine learning and deep reinforcement learning systems. The prediction of spectrum demand is achieved with the help of supervised learning and the dynamic allocation of spectrum to maximise throughput, mitigate interference, and enhance network efficiency is provided by reinforcement learning algorithms. The improvements in the proposed AI-based spectrum management system are measured based on the spectrum utilisation ratio, throughput, latency, as well as the quality of service (QoS) and its performance is evaluated against the traditional methods of assigning the spectrum, based on the key metrics.

### 2.1 Data Collection

For this study, the primary data source is the Network Traffic Dataset obtained from Kaggle (https://www.kaggle.com/datasets/ravikumargattu/network-traffic-dataset). This is a set of 394, 137 network traffic instances that were recorded using Wireshark on a live network and the data is in Comma Separated Values (CSV) format. Each record contains the critical attributes; timestamp, source and destination IP addresses, type of protocol, length of packets and other traffic attributes and offers specific details of the traffic behaviour in the conditions of the real network. These high-traffic characteristics can provide detailed analysis of the usage behaviour, time dynamics, and communication pattern, and thus the dataset is very useful in training AI models to forecast spectrum demand and classify network conditions applicable to spectrum management in 5G networks.

Kaggle had data that was downloaded and then stored securely in order to have reproducibility as well as proper documentation. All the records during collection were kept with their original attributes in order to maintain the integrity and time-structure of traffic. The heterogeneous characteristics of the dataset permit supervised learning and time series modelling methods, which permits the study to exploit the historical tendencies and real time fluctuation of the network traffic to AI based spectrum allocation. Before analysis, metadata data source, capture time and feature descriptions were recorded to ensure easy preprocessing, feature selection, and model training.

### 2.2 Data Preprocessing

The network traffic dataset was thoroughly pre-processed before it could be used in the AI-driven spectrum management to guarantee the quality and consistency of the information. All value gaps, redundancy and erroneous entries were detected and fixed or eliminated to avoid bias during model training. Categorical attributes, e.g. protocol type were numerically coded using the one-hot encoding in order to get these attributes into the machine learning algorithms.

Continuous variables such as the length of packets and timestamps were normalised or scaled to make them similar and to avoid the domination of the learning process by some features. The data was further divided into training, validation and testing to aid the supervised learning and model testing. Models that required time analysis e.g. LSTM or reinforcement learning methods were generated using time-based sequences to capture the time dynamics of traffic. The dimensionality reduction techniques were used to select features and predict spectrum demand, as well as to classify traffic by using the most informative features. This preprocessing makes sure that the data set is prepared to be trained into efficient models and enables the AI algorithms to learn the patterns that will maximize the spectrum allocation in 5G networks and enhance the efficiency of the network.

### 2.3 AI Modelling/Spectrum Management Approach

This paper will use XGBoost and Deep Q-Networks (DQN) to decide how to allocate the spectrum and enhance network performance in the 5G network. XGBoost is a gradient boosting algorithm that is applied to predict network traffic trends and spectrum demand using the already pre-processed dataset. The model examines variation like packet length, type of protocol, volume of traffic and time stamp that would determine the high demand periods and the possibility of congestion. Due to its capability of large and heterogeneous datasets and having high accuracy it is applicable in predicting spectrum requirements in dynamic 5G setting. In the case of real-time spectrum allocation, the DQN, which is a deep reinforcement learning algorithm, is used. The 5G network environment is structured as a state of current traffic and spectrum states, actions as available strategies in allocation, and rewards as performance measures, such as throughput, reduction in latency, and spectrum utilisation. The DQN agent is educated on the best policy of allocating resources by means of interaction with the network, adapts to varying traffic patterns, and minimises user interference. The combination of XGBoost to predict traffic and DQN to dynamically allocate spectrum offers the system an example of an intelligent, proactive way of managing the spectrum to improve network efficiency and enable a variety of 5G services.

#### 2.3.1 The XGBoost Model

Extreme Gradient Boosting model (XGBoost) is the model used in this research to forecast network traffic behaviour and spectrum demand in a 5G environment. XGBoost is an effective ensemble learning model that is grounded on gradient boosting decision trees and boasts a high predictive accuracy, scalability, and efficiency in dealing with large and complicated data.

XGBoost is applied in this study to learn patterns based on spectrum utilisation and traffic congestion with features of pre-processed network traffic including packet length, protocol type, volume of traffic, and time of the day. Through these predictions, the high-demand periods can be identified beforehand and this is what is needed when planning the spectrums. This model is trained on labeled historical traffic data and the hyperparameters of the model, which include learning rate, maximum tree depth, number of estimators and the subsampling rate are carefully tuned to avoid overfitting and improve generalization. Analysis is also carried out to the feature importance to establish the most significant parameters that influence the spectrum demand. The XGBoost model output is an input into the spectrum management model in that it gives precise traffic predictions upon which the DQN uses to make the best possible real-time spectrum allocation decisions. With this integration, the spectrum utilisation is better, there is less interference and overall network efficiency is increased in the 5G systems. The pseudocode of the proposed XGBoost Model on traffic and spectrum demand prediction is presented in Algorithm 1.

**Algorithm 1: Pseudocode of the XGBoost-Based Traffic and Spectrum Demand Prediction**

Input D = $\{(x1, y1), (x2, y2), \ldots, (xn, yn)\}$//Pre-processed network traffic dataset
x = Feature vectors (packet length, protocol type, traffic volume, timestamp, etc.)
y = Target variable (spectrum demand / traffic load)
T = Number of boosting rounds
η = Learning rate
$max\_depth$ = Maximum tree depth

Output F(x) = Predicted spectrum demand

Begin 1. Initialize model with constant prediction:

$$F0(x) = argmin\, \Sigma\, L(yi, c)$$

2. For t = 1 to T do

a. Compute gradients and Hessians:

$$gi = \partial L(yi, F(xi)) \,/\, \partial F(xi)$$
$$hi = \partial^2 L(yi, F(xi)) \,/\, \partial F(xi)^2$$

b. Construct a regression tree ft(x) by:
- Splitting nodes based on maximum information gain
- Using gi and hi to evaluate split quality
- Limiting tree depth to $max\_depth$

c. Compute optimal leaf weights:

$$wj = -(\Sigma gi) \,/\, (\Sigma hi + \lambda)$$

d. Update the model:

$$Ft(x) = Ft - 1(x) + \eta \times ft(x)$$

3. End For

4. Output final prediction model:

$$F(x) = FT(x)$$

End

This XGBoost model Algorithm 1 is an iterative decision tree ensemble construction, with each successive tree reducing the error of the last prediction model by gradient descent optimization. The model is able to predict the spectrum demand by learning complex nonlinear relationships in network traffic data and hence direct the DQN to make real-time spectrum allocation decisions.

### 2.3.2 The Deep Q-Network (DQN) Model

This paper uses the DQN model to accomplish real-time dynamic spectrum allocation in a 5G network setting. DQN is a deep-learning algorithm that integrates Q-learning with deep neural networks, and thus allows it to operate via large and continuous state spaces, which is typical of wireless networks. The environment state in this study is described as the existing network conditions which are predicted traffic demand using the XGBoost model, level of spectrum occupancy, interference value and QoS index. Action space is the set of potential strategies in the allocation of the spectrum between available frequency bands, and the reward function would be to maximise the spectrum utilisation and throughput and minimise the latency and interference. The DQN agent interacts with the network environment in a continuous manner by monitoring the current condition, choosing actions with an e-greedy policy to reduce both exploration and exploitation, and being provided with feedback, which is in the form of rewards. They include experience replay and a target network to enhance stability and convergence of learning. The neural network will estimate the optimal Q-value function, such that after time, the agent will be able to learn optimal spectrum allocation policies. The DQN framework allows the adaptive and dynamic control of the spectrum by incorporating the predictions of the traffic demand provided by the XGBoost model, which leads to better network utilisation and minimised load congestion as well as support a variety of 5G applications. The DQN pseudocode of the dynamic spectrum allocation is shown in the Algorithm 2.

**Algorithm 2: Deep Q-Network (DQN) for Dynamic Spectrum Allocation**

Input S = State space (traffic demand, spectrum occupancy, interference, QoS metrics)
A = Action space (possible spectrum allocation strategies)
$\alpha$ = Learning rate
$\gamma$ = Discount factor
$\varepsilon$ = Exploration probability
M = Replay memory size
B = Mini-batch size
C = Target network update frequency
N = Number of training episodes

Output $\pi$* = Optimal spectrum allocation policy
Begin 1. Initialize replay memory D with capacity M
2. Initialize primary Q-network $Q(s,a;\ \theta)$ with random weights θ
3. Initialize target Q-network $Q'(s,a;\ \theta')$ with θ′ ← θ
4. For episode = 1 to N do
a. Initialize environment $state\ s_0$
b. For each time step t do
i. With probability ε select a random action a
Otherwise select a = argmax Q(s, a; θ)
ii. Execute action a and observe:
- Reward r
- Next $state\ s_{+1}$
iii. Store transition $(s,a,r,s_{+1})$ in replay memory D
iv. Sample random mini-batch from D:
(s, a, r, $s_{+1}$)
v. Compute target Q-value:
y= r + γ max Q′($s_{+1}$, a′; θ′)
vi. Update Q-network weights θ by minimizing:

$$L(\theta)\ =\ (y\ -\ Q(s,a;\ \theta))^2$$

vii. Update state:
s← $s_{t+1}$
viii.If t mod C == 0 then
$\theta'\ \leftarrow\ \theta$ // Update target network
c. End For
5. End For
6. Output optimal policy:
$\pi$*(s) = argmax $Q(s,a;\ \theta)$
End

Algorithm 2: As in the 5G network, the DQN agent of the Algorithm 2 learns optimal spectrum allocation policy through interaction with the 5G network environment and the continuous updating of its Q-value estimates with experience replay and target networks. Reward function of the system is used to motivate high spectrum utilisation, high throughput, less interference and latency. The DQN makes it possible to implement proactive spectrum management and adaptive spectrum management by integrating traffic demand forecasts of the XGBoost model into the state representation.

### 2.3.3 Model Training

In this research, the training of the model will be conducted in two consecutive steps with the XGBoost and DQN models. The XGBoost model is initially trained with the processed network traffic data to understand the trends related to the traffic volume and spectrum utilisation. This training and testing set is split along with the model parameters, learning rate, estimators count, maximum tree depth, and subsampling ratio are optimised through cross-validation to improve the accuracy of prediction and to avoid overfitting the model. The trained XGBoost model produces traffic and spectrum demand predictions which are input features to the reinforcement learning environment.

The second stage is training the DQN model based on continuous communication with the virtual 5G network environment. The state space encompasses the real-time network status, as well as the projected traffic demand based on the XGBoost model whereas the action space is the possible spectrum allocation choices. Various episodes are used to train the DQN agent with the experience replay and target network update to achieve steady convergence. The reward function is meant to maximise the spectrum utilisation and throughput and minimise interference and latency. The integrated XGBoost-DQN framework trained through iterative learning is brought to an optimal spectrum management policy that yields efficiency of the overall network.

### 2.4 System Implementation

The spectrum management system proposed to be achieved with the aid of AI is developed within a modular framework that incorporates data processing, predictor modelling, and decision making based on reinforcement learning as shown in Figure 2. The system will be developed on a Python environment because it has a wide range of support on machine learning, and deep learning libraries. XGBoost is programmed through the XGBoost platform whereas the DQN is programmed through deep learning frameworks like PyTorch. The data traffic captured by Kaggle network is initially loaded into the system and data analysis module before being fed to the modelling modules. The process of implementation starts with the XGBoost model estimating the intensity of traffic and spectrum demand using the characteristics of incoming network traffic. These estimates are subsequently sent into the DQN module which is run on a simulated environment of 5G network to make dynamic spectrum allocation decisions. The environment keeps the state updated information on factors like the traffic load, the occupancy of the spectrum and the interference levels and the agent is the DQN which chooses the best action according to the learned policies. Real time monitoring of performance indicators, such as spectrum utilisation, throughput, latency and QoS is used to measure the effectiveness of the system. This combined implementation allows flexible, smart spectrum management, which proves the relevance of AI methods in enhancing the 5G network performance.

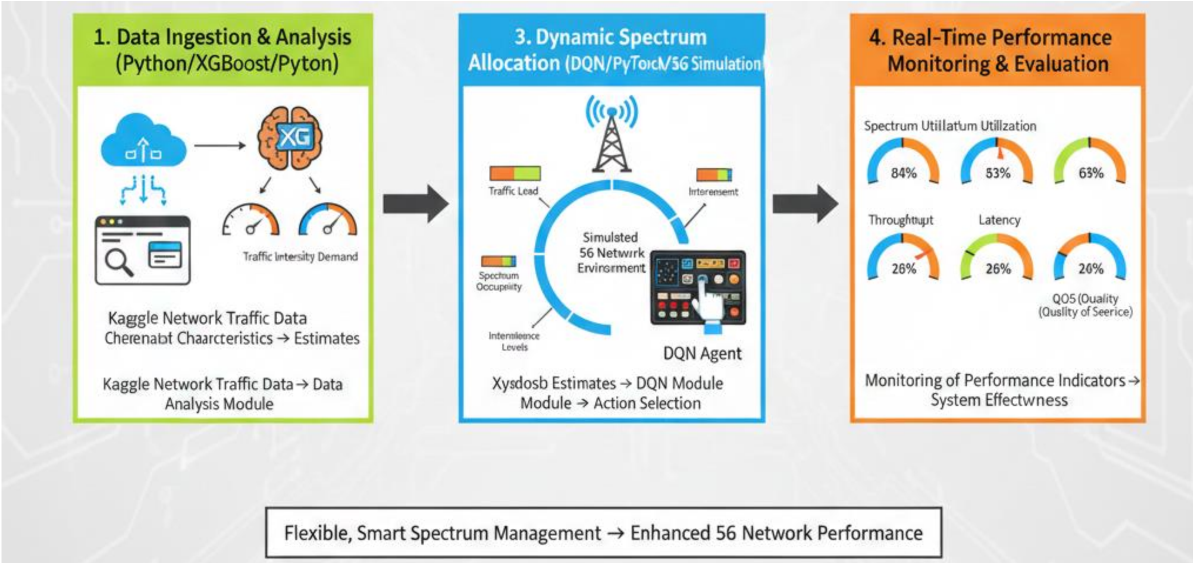


Figure 2: System Implementation Phases

## 3. RESULTS AND DISCUSSION

Here, the findings of the application of the AI-powered spectrum management system based on XGBoost and DQN models are provided and discussed. The implementation of the proposed approach is measured according to the main metrics of network efficiency, and the outcomes are compared to the traditional methods of the static allocation of the spectrum in order to prove the effectiveness of the offered system.

### 3.1 XGBoost Traffic Prediction Performances

The XGBoost model was tested to assess how well the model forecasts the intensity of network traffic and spectrum demand. That is why precise prediction is needed, with the outputs being directly related to the decision-making process occurring in the DQN-based spectrum allocation model. There were standard regression performance measures like Mean Absolute Error (MAE) and Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and the coefficient of determination ($R^2$) as presented in Table 1.

**Table 1: XGBoost Traffic Prediction Performance Metrics**

| Metric | Value |
|---|---|
| Mean Absolute Error (MAE) | 0.084 |
| Mean Squared Error (MSE) | 0.011 |
| Root Mean Squared Error (RMSE) | 0.105 |
| $R^2$ Score | 0.93 |

The results in Table 1 show that the XGBoost model achieved a high $R^2$ score of 0.93, indicating strong predictive accuracy and a close fit between predicted and actual traffic values. Low error values demonstrate the model's ability to effectively capture nonlinear traffic patterns in the dataset.

### 3.2 Feature Importance Analysis

Feature importance analysis was conducted to identify the most influential parameters affecting spectrum demand prediction as presented in Figure3. Understanding feature relevance helps validate the modelling approach and provides insight into traffic behaviour in 5G networks.

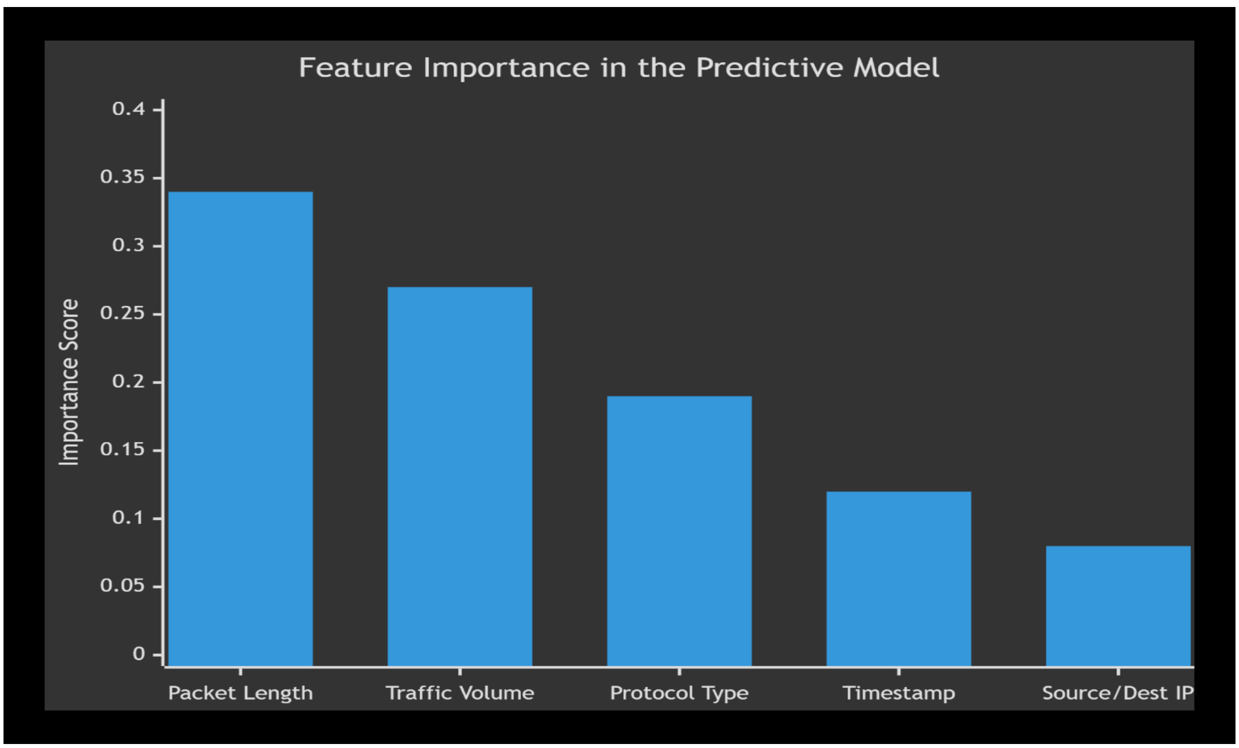


Figure 3: Feature Importance Ranking from XGBoost Model

The results in Figure 3 indicate that packet length and traffic volume are the dominant contributors to spectrum demand, confirming their relevance in dynamic spectrum management for 5G networks.

### 3.3 DQN Training and Learning Performance

The DQN model was evaluated based on its learning behaviour and convergence characteristics as shown in Table 3. The cumulative reward obtained by the agent increased steadily across training episodes, indicating effective learning of optimal spectrum allocation policies.

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**Table 3: DQN Training Performance Summary**

| Parameter | Value |
|---|---|
| Total Training Episodes | 1,000 |
| Convergence Episode | ~650 |
| Average Reward (Initial) | 18.5 |
| Average Reward (Final) | 72.4 |
| Reward Improvement (%) | 291% |

The significant increase in average reward demonstrates that the DQN agent successfully learned to allocate spectrum efficiently under varying traffic conditions.

### 3.4 Spectrum Allocation Performance Comparison

The proposed XGBoost-DQN framework was compared with a traditional static spectrum allocation method (Zhang and Li, 2021) to evaluate its effectiveness. The performance metrics such as spectrum utilization, throughput, latency, and packet loss were analysed are presented in Table 3.

**Table 3: Performance Comparison of Spectrum Allocation Methods**

| Metric | Static Allocation | Proposed XGBoost–DQN |
|---|---|---|
| Spectrum Utilization (%) | 62.3 | 87.6 |
| Average Throughput (Mbps) | 145.2 | 214.8 |
| Average Latency (ms) | 34.7 | 18.9 |
| Packet Loss Rate (%) | 4.8 | 1.6 |
| QoS Satisfaction (%) | 71.5 | 91.2 |

The results in Figure 4show that the AI-driven approach significantly outperforms the static allocation method across all evaluated metrics.

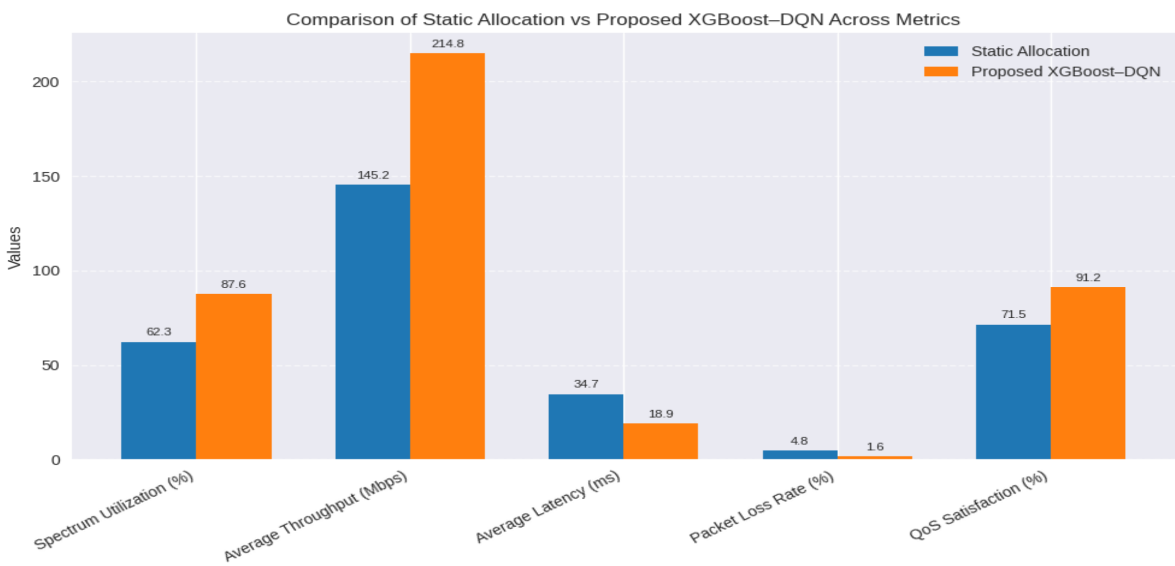


Figure 4: Comparative Performance of Static Allocation vs Proposed XGBoost-DQN

The Figure 4 chart demonstrates the high-performance of the proposed model on XGBoost-DQN compared to the old model of stationary spectrum allocation in terms of five important network performance metrics. Spectrum utilization improves dramatically from 62.3% to 87.6%, indicating more efficient use of available bandwidth. There is a significant increase in the average throughput by 145.2Mbps to 214.8Mbps and a significant reduction in the latency that was 34.7ms to 18.9ms which increases the responsiveness of real-time applications. Packet loss rate is reduced from 4.8% to just 1.6%, reflecting improved reliability, and QoS satisfaction climbs from 71.5% to 91.2%, demonstrating better overall user experience. All these findings point to the fact that AI-based spectrum management can be used efficiently to optimise the performance of 5G networks.

The stepwise analysis of performance shows that XGBoost and DQN combined are more effective to increase spectrum management efficiency in 5G networks. XGBoost provides high accuracy to predict traffic and therefore reliable prediction of traffic to support proactive spectrum planning and DQN model is effective to modify the decision on spectrum allocation in real time. The improvements in spectrum utilization (over 25%), throughput (approximately 48%), and latency reduction (over 45%) confirm the effectiveness of AI-driven spectrum management. These results are consistent with the literature and show that reinforcement learning is applicable in the management of dynamic and diverse 5G traffic conditions.

## 4. CONCLUSION

In this work, an AI-driven spectrum management framework of 5G networks based on XGBoost to predict network traffic and spectrum demand and a DQN to predict dynamic spectrum allocation was applied. It was designed and tested with a real-world network traffic data and the performance of the system compared to a conventional static spectrum allocation methodology. XGBoost model was shown to be a powerful predictive model with a root squared error of 0.105, mean absolute error of 0.084 and $R^2$ equal to 0.93, which proved to be effective in the nonlinear traffic patterns. The analysis of feature importance found that the most influential parameters that had an impact on the spectral demand were packet length, traffic volume, and protocol type.

The DQN model exhibited effective learning and convergence behaviour during training, with the average cumulative reward increasing from 18.5 at the initial stage to 72.4 after convergence at approximately 650 training episodes, representing a 291% improvement. When deployed for spectrum allocation, the integrated XGBoost-DQN framework achieved a spectrum utilization of 87.6%, significantly higher than the 62.3% obtained using static allocation. In addition, average throughput improved from 145.2Mbps to 214.8Mbps, while average latency was reduced from 34.7ms to 18.9ms, and packet loss decreased from 4.8% to 1.6%.

To sum up, the results of the implementation make it evident that AI-powered spectrum management can greatly improve the efficiency of the 5G network and QoS. The suggested framework can help overcome the problem of spectrum scarcity, traffic variability, and interference by integrating predictive allocation with intelligent reinforcement learning and precise traffic forecasting. The obtained results in terms of spectrum utilisation, throughput, latency, and QoS confirm the appropriateness of XGBoost and DQN to manage the spectrum in 5G networks intelligently and set a strong background of future research and practical implementation in next-generation wireless networks.

## 5. REFERENCES

Alnfiai, M. M. (2025). AI-powered cyber resilience: A reinforcement learning approach for automated threat hunting in 5G networks. *EURASIP Journal on Wireless Communications and Networking*. https://link.springer.com/article/10.1186/s13638-025-02497-2

Ansari, A. A., & Singh, P. (2025). AI-based dynamic spectrum allocation for hybrid satellite-5G networks. *IRE Journals*. https://www.irejournals.com/formatedpaper/1707338.pdf

Bikkasani, D. C., &Yerabolu, M. R. (2024). AI-driven 5G network optimization: Resource allocation, traffic management, and dynamic slicing. *American Journal of Artificial Intelligence*. https://sciencepublishinggroup.com/article/10.11648/j.ajai.20240802.14

Bronson, A. (2025). AI-driven demand forecasting for 5G rollouts. *Bronson.AI Technical Reports*. https://bronson.ai/resources/ai-driven-demand-forecasting-5g/

Cullen, A. C., Rubinstein, B. I. P., Kandeepan, S., Flower, B., & Leong, P. H. W. (2023). Predicting dynamic spectrum allocation: A review. *Artificial Intelligence Review*. https://link.springer.com/article/10.1007/s10462-023-10449-9

Elmorsy, S. M. A., Osman, S. M., & Gamel, S. A. (2025). Enhanced spectrum sensing for 5G and LTE signals using deep learning. *Scientific Reports*. https://www.nature.com/articles/s41598-025-07837-2.pdf

Eldeeb, E., & Alves, H. (2025). Offline and distributional reinforcement learning for wireless communications. *arXiv*. https://arxiv.org/abs/2504.03804

Giwa, O., Awodunmila, T., Mohsin, M. A., Bilal, A., & Jamshed, M. A. (2025). Meta-reinforcement learning for fast and data-efficient spectrum allocation. *arXiv*. https://arxiv.org/pdf/2507.10619

Gowda, S. G. K., &Panchaxari. (2023). Artificial intelligence in enhancing QoS in 5G networks. *IJRITCC*. https://ijritcc.org/index.php/ijritcc/article/view/10993

Guel, D., Kabore, A., & Bassole, D. (2024). 5G NR PRACH detection with CNN: Overcoming cell interference challenges. *arXiv*. https://arxiv.org/abs/2408.11659

Havolli, A., &Fetaji, M. (2025). AI-driven resource allocation strategies for enhanced QoS in 5G networks. *IJITS*. https://ijits-bg.com/sites/default/files/archive/2025%28vol.17%29/No2/contents/2025-N2-08.pdf

Hussien, A. A., Nashaat, H., & Abdel-Kader, R. F. (2025). Machine learning techniques for spatiotemporal traffic prediction in 5G cellular networks. *Discover Applied Sciences*. https://link.springer.com/article/10.1007/s42452-025-06746-3

Islam Rony, R., Lopez-Aguilera, E., & Garcia-Villegas, E. (2021). Dynamic spectrum allocation following ML-based traffic predictions in 5G. *IEEE Access*. https://ieeexplore.ieee.org/document/9584903

Mao, J., Sun, R., Poletti, M., Gandotra, R., Guo, H., & Yener, A. (2026). AI-driven spectrum occupancy prediction using real-world spectrum measurements. *arXiv*. https://arxiv.org/html/2601.11742v1

Patil, V. D., Kori, V. B., &Padmannavar, S. S. (2025). Intelligent spectrum allocation in 5G/6G networks: A machine learning approach. *IJSRED*. https://www.ijsred.com/volume8/issue4/IJSRED-V8I4P109.pdf

Verma, P., Saxena, S., Arora, D., & Ramola, J. (2025). Role of cognitive radio in 5G-enabled IoT networks. In *Next-Generation Wireless Technologies*. Springer. https://link.springer.com/chapter/10.1007/978-3-031-82733-4_6

Zhang, Y., & Li, J. (2021). Study on spectrum allocation and optimization of wireless communication networks based on SFOA. Wireless Communications and Mobile Computing, 2021, Article ID 2262963, 11 pages. https://doi.org/10.1155/2021/2262963