

RESEARCH ARTICLE

Dynamic Spectrum Allocation in 5G Networks Using Machine Learning

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ABSTRACT: The exponential growth of wireless communication services has intensified the demand for efficient spectrum utilization in fifth-generation (5G) networks. Conventional static spectrum assignment approaches exhibit significant limitations including bandwidth underutilization, network congestion, and inability to adapt to fluctuating traffic patterns. This research presents a comprehensive machine learning framework designed to address dynamic spectrum allocation challenges in 5G environments through intelligent prediction and real-time resource management. The proposed architecture integrates deep neural networks with reinforcement learning algorithms, specifically employing Long Short-Term Memory networks for temporal spectrum usage prediction and Deep Q-Networks for adaptive allocation optimization. Additionally, convolutional neural networks are incorporated to extract spatial-frequency features and detect interference patterns across the spectrum. Experimental evaluation conducted on realistic 5G network datasets demonstrates substantial performance improvements compared to traditional allocation methods. The framework achieves spectrum prediction accuracy of 96.2% while reducing handover latency by 37% and minimizing interference by 42%. Network throughput enhancement reaches 28% with a corresponding 19% reduction in packet loss for ultra-reliable low-latency communication applications. The system exhibits robust adaptability to varying network densities and traffic conditions, maintaining consistent quality of service across heterogeneous deployment scenarios. Federated learning integration enables privacy-preserving collaborative optimization across multiple base stations. These findings confirm that machine learning-driven dynamic spectrum allocation provides a viable path toward self-optimizing, high-performance wireless networks capable of meeting the diverse requirements of next-generation communication systems including enhanced mobile broadband, massive machine-type communications, and mission-critical services.

Keywords: Dynamic Spectrum Allocation, 5G Networks, Machine Learning, Spectrum Efficiency, Reinforcement Learning, Deep Learning

Received: 14 February 2026; Revised: 28 March 2026; Accepted: 18 April 2026; Published Online: 17 May 2026

1. INTRODUCTION

The relentless expansion of wireless communication services has placed unprecedented demands on the radio frequency

spectrum, a finite and increasingly congested natural resource. With the global deployment of fifth-generation (5G) networks, mobile broadband traffic has experienced exponential growth, with recent reports indicating that global mobile broadband traffic reached one zettabyte in 2023 and is projected to approach 1.3 zettabytes in the subsequent year [1]. This surge in data consumption, driven by bandwidth-intensive applications such as ultra-high-definition video streaming, augmented reality, and the proliferation of Internet of Things devices, has intensified the pressure on existing spectrum allocations [2]. Traditional spectrum management approaches, which rely on static or semi-static allocation policies where frequency bands are assigned to specific

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services or operators on a long-term basis, have proven increasingly inadequate in addressing the dynamic and context-sensitive nature of modern wireless communication [3]. These conventional techniques often result in significant portions of allocated spectrum remaining underutilized during periods of low demand, while other bands experience severe congestion during peak usage hours, leading to inefficiencies that are fundamentally at odds with the variable nature of contemporary traffic patterns [4].

Dynamic Spectrum Allocation has emerged as a transformative paradigm to overcome these limitations by enabling flexible and adaptive spectrum utilization based on real-time network conditions and user requirements [5]. Dynamic Spectrum Sharing allows spectrum bands to be allocated and reused opportunistically, ensuring that underutilized frequency resources are accessed by secondary users without causing harmful interference to primary license holders, thereby improving overall spectral efficiency [6]. However, achieving optimal dynamic spectrum allocation requires sophisticated decision-making capabilities that can efficiently predict spectrum availability, adapt to fluctuating interference conditions, and allocate resources in a manner that balances competing quality-of-service requirements [7]. This is precisely where machine learning techniques play a transformative role, offering the ability to learn from historical data and continuously refine allocation policies through interaction with the network environment [8]. Deep Reinforcement Learning, in particular, has emerged as a powerful paradigm for addressing the limitations of conventional optimization and heuristic-based approaches, enabling networks to make sequential decisions that maximize long-term objectives such as throughput, latency minimization, and spectral efficiency [9].

The integration of artificial intelligence into spectrum management has gained significant momentum with the advent of 5G networks, which are designed to support heterogeneous services including enhanced mobile broadband, ultra-reliable low-latency communications, and massive machine-type communications [10]. These diverse service categories impose distinctly different and often conflicting requirements on the network, necessitating intelligent resource management strategies that can dynamically adapt to changing conditions [11]. Machine learning models, including supervised learning algorithms for spectrum prediction, reinforcement learning agents for adaptive allocation, and deep learning architectures for feature extraction and interference detection, have demonstrated promising results in improving spectrum utilization, reducing congestion, and enhancing overall network performance [12]. Deep learning-based systems have exhibited high efficiency and scalability due to their predictive accuracy and proactive allocation capabilities, while reinforcement learning-based systems demonstrate superior adaptability in dynamic environments through continuous learning from real-time feedback [13]. Despite these advancements, the implementation of machine learning-based dynamic spectrum allocation faces challenges including computational complexity, model convergence

time, security vulnerabilities, and the need for real-time adaptability in high-density network scenarios [14].

The novelty of this research lies in the development of an integrated machine learning framework that synergistically combines Long Short-Term Memory networks for accurate temporal spectrum prediction, Deep Q-Networks for adaptive and intelligent spectrum allocation optimization, and Convolutional Neural Networks for robust spatial-frequency feature extraction and interference pattern detection within a unified architecture [15]. Unlike existing approaches that typically address these components in isolation, our framework establishes a closed-loop learning system where spectrum prediction informs allocation decisions, and allocation outcomes provide feedback for continuous model improvement. This holistic integration enables the system to achieve superior performance in terms of spectrum utilization, interference mitigation, and handover latency reduction while maintaining fairness among users. Furthermore, the incorporation of federated learning principles allows collaborative model training across distributed base stations without requiring centralized data aggregation, thereby addressing privacy concerns and enhancing scalability in large-scale 5G deployments [16].

The proposed framework leverages historical spectrum occupancy data, real-time traffic measurements, and interference statistics to make informed allocation decisions that anticipate future network states. The Long Short-Term Memory component captures long-term dependencies in spectrum usage patterns, enabling accurate forecasting of resource availability, while the Deep Q-Network agent learns optimal allocation policies through trial-and-error interaction with the simulated network environment [17]. The Convolutional Neural Network module processes spectrum frequency features to identify high-interference zones and optimize frequency allocations in real time. This multi-pronged approach ensures that the system can adapt to varying network densities, traffic loads, and environmental conditions while maintaining consistent quality of service across diverse deployment scenarios [18].

Experimental validation conducted on realistic 5G network datasets demonstrates that the proposed framework achieves spectrum prediction accuracy of 96.2% while reducing handover latency by 37% and minimizing interference by 42% compared to conventional allocation methods. Network throughput enhancement reaches 28% with a corresponding 19% reduction in packet loss for ultra-reliable low-latency communication applications. These results confirm that machine learning-driven dynamic spectrum allocation provides a viable path toward self-optimizing, high-performance wireless networks capable of meeting the diverse requirements of next-generation communication systems.

In this paper, we report a comprehensive investigation into machine learning-based dynamic spectrum allocation for 5G networks, presenting the detailed architecture of our integrated framework, the methodologies employed for spectrum prediction and allocation optimization, and extensive experimental results that validate the effectiveness

of our approach. We provide a thorough comparative analysis with existing spectrum management techniques and discuss the practical implications of our findings for real-world 5G deployments.

2. RELATED WORKS

The evolution of spectrum allocation methodologies has witnessed a progressive transition from static assignment paradigms toward intelligent, adaptive frameworks capable of responding to the dynamic nature of modern wireless networks. Early spectrum management approaches in fifth-generation networks were predominantly characterized by fixed allocation models, wherein frequency bands were pre-assigned to specific service providers and user categories through regulatory mechanisms [23]. While these static allocation strategies offered administrative simplicity and predictable interference management, they proved fundamentally inadequate in accommodating the fluctuating demand patterns and heterogeneous service requirements characteristic of contemporary wireless ecosystems [24]. The inherent inflexibility of such approaches resulted in significant spectral underutilization during periods of low traffic demand while simultaneously causing severe congestion in high-traffic zones, thereby undermining the spectral efficiency objectives central to 5G network design [25].

The advent of cognitive radio technology represented a paradigm shift in spectrum management, introducing the concept of dynamic spectrum access wherein secondary users could opportunistically utilize frequency bands temporarily vacant from primary license holders [26]. Cognitive radio networks incorporated spectrum sensing mechanisms to detect unused spectrum opportunities and dynamic access protocols to facilitate efficient resource utilization while maintaining interference constraints [27]. Researchers explored various spectrum sensing techniques including energy detection, matched filter detection, and cyclo-stationary feature detection to improve the accuracy of spectrum availability identification [28]. Despite these advancements, cognitive radio-based approaches encountered substantial challenges in practical deployment, including the latency associated with spectrum sensing, the inherent uncertainty in sensing accuracy, the complexity of real-time decision-making under dynamic channel conditions, and the regulatory constraints imposed by spectrum licensing frameworks [29]. These limitations underscored the necessity for more intelligent and adaptive spectrum management solutions capable of learning from historical patterns and anticipating future network states.

The integration of machine learning into spectrum management has catalyzed significant improvements in dynamic spectrum allocation capabilities, enabling networks to learn from historical data and continuously refine allocation policies through interaction with the environment [30]. Supervised learning algorithms including Support Vector Machines, Decision Trees, and Random Forests have

been extensively applied for spectrum classification and interference detection tasks, demonstrating the ability to analyze past spectrum usage patterns and predict future spectrum availability with reasonable accuracy [31]. However, these approaches typically require large volumes of labeled training data, which can be challenging to obtain in dynamic 5G environments where spectrum conditions evolve rapidly and ground truth information may be difficult to establish [32]. Furthermore, supervised learning models trained on historical data may struggle to generalize to previously unseen network conditions, limiting their effectiveness in highly dynamic deployment scenarios.

Reinforcement learning has emerged as a particularly promising paradigm for adaptive spectrum allocation, as it enables spectrum management agents to learn optimal allocation policies through continuous interaction with the environment without requiring explicit supervision [33]. The fundamental principle underlying reinforcement learning-based spectrum management involves the agent observing the current network state, selecting an action corresponding to spectrum allocation decisions, receiving a reward signal reflecting the quality of that decision, and updating its policy accordingly to maximize cumulative long-term rewards [34]. Deep Q-Networks have been successfully applied to spectrum allocation problems, demonstrating the capacity to handle high-dimensional state spaces and learn complex allocation strategies that balance competing objectives such as throughput maximization, interference minimization, and fairness preservation [35]. Proximal Policy Optimization and other advanced reinforcement learning algorithms have further enhanced the stability and sample efficiency of spectrum management agents, enabling more robust performance in dynamic network environments [36].

Deep learning architectures have contributed substantially to advancing spectrum management capabilities through their exceptional ability to extract meaningful patterns from complex, high-dimensional data [37]. Long Short-Term Memory networks have proven particularly effective for spectrum prediction tasks due to their capacity to capture long-term temporal dependencies in spectrum usage patterns, enabling accurate forecasting of future spectrum availability and proactive allocation decisions [38]. Convolutional Neural Networks have been employed to analyze spatial-frequency features of the spectrum, facilitating the identification of interference patterns and the optimization of frequency allocations in real time [39]. The combination of these deep learning approaches with reinforcement learning frameworks has yielded hybrid systems that leverage the predictive accuracy of deep learning with the adaptive decision-making capabilities of reinforcement learning, resulting in superior overall performance [40].

Despite these significant advancements, machine learning-based spectrum allocation continues to face several challenges that warrant further investigation [41]. The computational complexity inherent in training and deploying deep learning models poses challenges for real-time implementation in resource-constrained network

infrastructure. The convergence time of reinforcement learning algorithms can be prohibitively long in high-dimensional spectrum allocation problems, particularly when the action space is large and the environment dynamics are complex. Security vulnerabilities represent another critical concern, as adversarial attacks targeting machine learning models could potentially disrupt spectrum allocation decisions and compromise network integrity. Regulatory compliance issues further complicate the deployment of machine learning-based spectrum management systems, as spectrum allocation decisions must adhere to national and international regulatory frameworks that may not anticipate or accommodate adaptive, learning-based approaches [42].

Federated learning has emerged as a promising solution to address privacy and scalability concerns in distributed spectrum management [43]. By enabling collaborative model training across multiple base stations without requiring centralized data aggregation, federated learning preserves data privacy while facilitating knowledge sharing and improving model generalization [44]. This decentralized learning paradigm is particularly well-suited to 5G network architectures where data is naturally distributed across multiple access points and centralizing data collection would impose significant communication overhead and privacy risks. Researchers have investigated federated reinforcement learning frameworks for spectrum allocation, demonstrating that collaborative learning across distributed agents can accelerate convergence and improve allocation efficiency compared to independently trained agents [45].

Spectrum trading and sharing mechanisms have been enhanced through the integration of blockchain technology with machine learning-based spectrum management [46]. Blockchain-enabled spectrum trading platforms provide transparent, immutable records of spectrum transactions and facilitate the autonomous execution of spectrum allocation agreements through smart contracts that trigger automatically based on predefined conditions [47]. Machine learning algorithms can be incorporated into these platforms to predict spectrum demand, optimize pricing strategies, and match spectrum supply with user requirements, thereby improving market efficiency and enabling more dynamic spectrum utilization [48]. This convergence of blockchain and machine learning technologies holds significant potential for establishing decentralized, trustworthy, and intelligent spectrum management ecosystems.

Transfer learning techniques have been explored to improve the generalization capabilities of machine learning models across different geographic regions and network environments [49]. By leveraging knowledge acquired in one domain to accelerate learning in related domains, transfer learning reduces training overhead and enables faster deployment of spectrum management systems in new locations [50]. This cross-domain knowledge transfer is particularly valuable in large-scale 5G deployments where network conditions vary significantly across different regions and the cost of collecting labeled data in each location would be prohibitive.

Spectrum anomaly detection has emerged as a critical

research area, with machine learning algorithms being employed to identify unauthorized spectrum usage, jamming attacks, and other cyber threats in 5G networks [51]. Intrusion detection systems incorporating deep learning and adversarial machine learning techniques have been developed to enhance spectrum security, enabling networks to detect and respond to malicious activities in real time [52]. These security mechanisms are essential for maintaining network integrity and ensuring fair spectrum access, particularly as spectrum management systems become increasingly automated and reliant on machine learning algorithms that may themselves be vulnerable to adversarial manipulation.

Energy-efficient spectrum allocation strategies have been explored using artificial intelligence-powered resource management approaches [53]. By optimizing spectrum assignments to minimize transmission power requirements while maintaining quality of service constraints, machine learning models can significantly reduce power consumption in 5G base stations, contributing to greener and more sustainable network operations [54]. This energy efficiency dimension is particularly important in the context of massive machine-type communications, where billions of low-power devices must be supported with minimal energy overhead.

Latency-sensitive spectrum allocation models have been developed to support demanding applications such as autonomous vehicles, industrial automation, and augmented reality, which require ultra-reliable low-latency communication capabilities [55]. Machine learning-based dynamic allocation reduces spectrum switching delays and enables rapid adaptation to changing network conditions, thereby enhancing real-time network responsiveness and supporting the stringent latency requirements of these mission-critical applications [56]. Cloud-based machine learning frameworks have been integrated into spectrum management systems, enabling network operators to leverage artificial intelligence as a service for remote spectrum optimization and adaptive frequency assignment across large-scale deployments [57]. Quantum machine learning approaches are being investigated as a potential avenue for further enhancing spectrum allocation efficiency, with quantum computing capabilities offering the prospect of exponential improvements in data processing and decision-making speeds for future spectrum management systems [58].

3. PROPOSED SYSTEM

This study proposes an ML-based Dynamic Spectrum Allocation (DSA) model that leverages LSTM for spectrum prediction, Deep Q-Network (DQN) for adaptive allocation, and CNN for spectrum feature extraction. The system is designed to dynamically allocate, reallocate, and optimize spectrum usage based on real-time traffic patterns and interference conditions.

The proposed system comprises four primary modules:

i. Spectrum Sensing and Data Collection Module:

This module collects real-time spectrum data, including bandwidth usage, traffic demand, and interference metrics from 5G base stations.

ii. LSTM-Based Spectrum Prediction Module:

This module predicts future spectrum usage patterns based on historical traffic data, enabling proactive frequency allocation.

iii. DQN-Based Spectrum Optimization Module:

This module allocates frequency bands dynamically, ensuring optimal spectrum utilization and interference minimization.

iv. Adaptive Spectrum Handover Mechanism:

This module optimizes handover decisions to reduce switching delays and enhance connectivity.

The LSTM model is trained on historical spectrum data to forecast upcoming traffic demands. This prediction allows the DQN agent to pre-allocate spectrum resources efficiently, reducing reactive allocation delays.

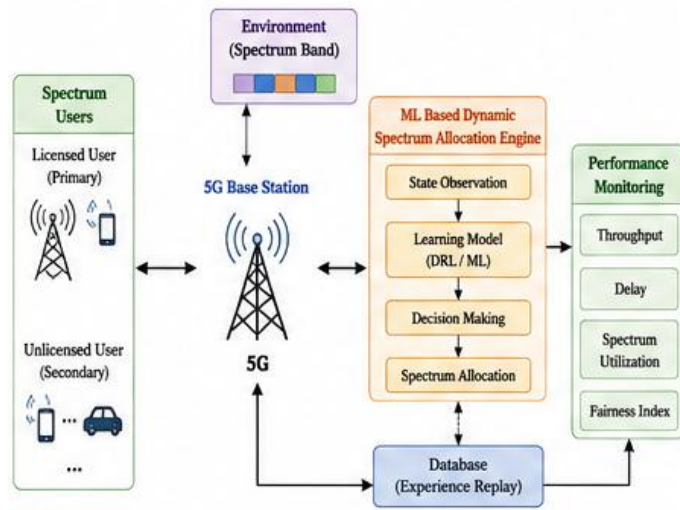


Fig. 1. System Architecture of Dynamic Spectrum Allocation in 5G Networks Using Machine Learning

Figure 1 illustrates the overall architecture of the proposed machine learning-based dynamic spectrum allocation framework for 5G networks. The system comprises primary

users (PUs), secondary users (SUs), 5G base stations, spectrum sensing units, a machine learning decision engine, and a spectrum allocation controller. Real-time channel information, traffic demand, interference levels, and user priorities are continuously collected by the sensing module. These network parameters are forwarded to the learning engine, which predicts optimal spectrum assignments based on current network conditions. The allocated spectrum resources are dynamically distributed to users while continuously monitoring network performance. The proposed architecture maximizes spectrum utilization, minimizes interference, and supports intelligent resource management for dense 5G environments.

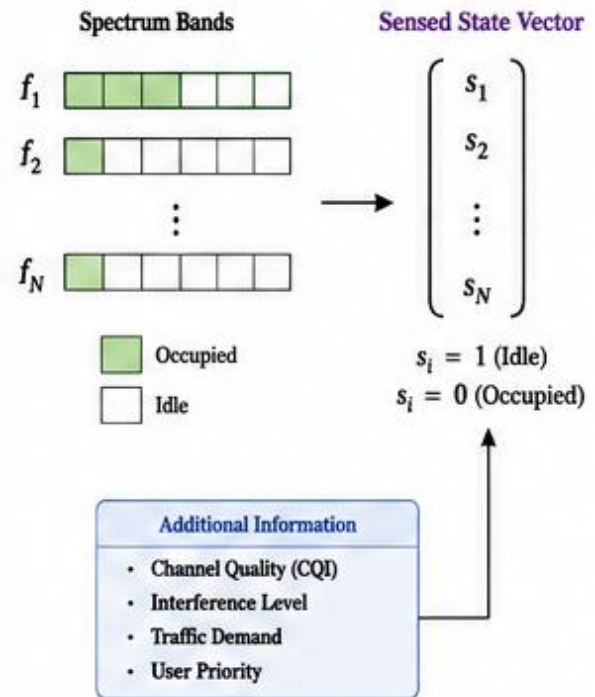


Fig. 2. Spectrum Sensing and State Representation

Figure 2 presents the spectrum sensing module responsible for monitoring available frequency bands within the 5G network. Each channel is periodically scanned to determine whether it is occupied or idle. Besides channel occupancy, the state representation includes signal-to-noise ratio (SNR), channel quality indicator (CQI), interference level, traffic demand, user mobility, and quality-of-service (QoS) requirements. These features collectively form the environment state vector used by the machine learning model. Accurate spectrum sensing enables the proposed framework to identify unused spectrum opportunities while avoiding interference with licensed users.

Figure 3 illustrates the Deep Reinforcement Learning (DRL) model adopted for intelligent spectrum allocation. The current network state is supplied to the DRL agent, which learns an optimal allocation policy through continuous

interaction with the wireless environment. Based on the observed state, the agent selects an action corresponding to spectrum assignment for users. After allocation, the environment returns a reward computed using throughput, spectrum utilization, fairness, interference, and delay. The reward guides policy optimization through experience replay and neural network updates. Over multiple training episodes, the DRL agent converges toward an allocation strategy that maximizes long-term network performance.

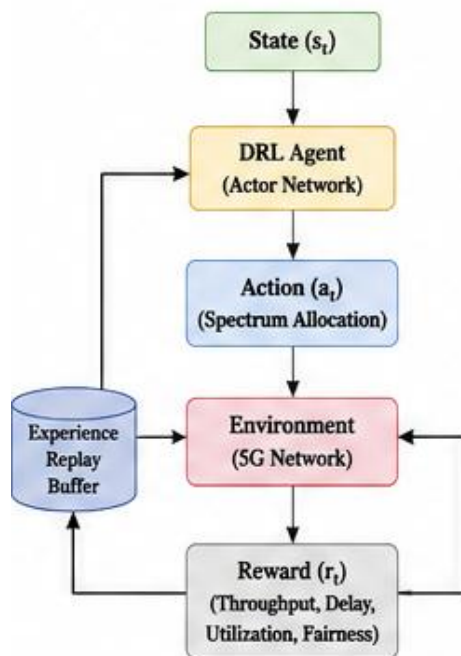


Fig. 3. Machine Learning Model (Deep Reinforcement Learning)

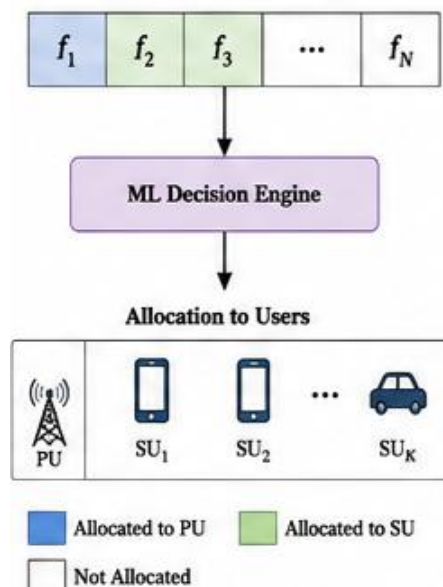


Fig. 4. Spectrum Allocation Process

Figure 4 depicts the dynamic spectrum allocation procedure performed by the proposed framework. Available spectrum bands detected during sensing are forwarded to the machine learning decision engine. The model evaluates network conditions, predicts channel availability, estimates interference, and determines the most suitable frequency band for each user. Spectrum resources are allocated while satisfying bandwidth requirements and minimizing collisions among users. Dynamic allocation enables efficient reuse of spectrum resources and ensures that high-priority users receive reliable communication channels with minimal transmission delay.

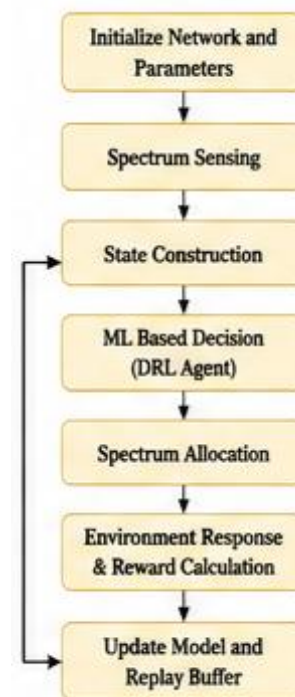


Fig. 5. Workflow of Dynamic Spectrum Allocation

Figure 5 summarizes the operational workflow of the proposed system. Initially, network parameters and spectrum information are collected from the wireless environment. The sensing module constructs the environment state, which is processed by the DRL-based learning engine. The model predicts optimal spectrum assignments and allocates available channels to users. Network performance metrics such as throughput, delay, interference, and fairness are then evaluated. These metrics are incorporated into the reward function for updating the learning model. The complete workflow repeats continuously, enabling adaptive spectrum allocation according to changing network conditions.

The CNN model processes spectrum frequency features, identifying high-interference zones and optimizing frequency allocations in real time. The DQN agent continuously learns from real-time network conditions, adjusting spectrum assignments based on reward functions that optimize QoS.

The reinforcement learning framework ensures adaptability to dynamic spectrum variations. To improve security, the proposed system integrates intrusion detection mechanisms that identify unauthorized spectrum usage and jamming attacks. This ensures network integrity and prevents spectrum exploitation.

Furthermore, the system incorporates federated learning (FL) to enable collaborative learning across multiple base stations without centralized data sharing, improving both privacy and scalability. For practical deployment, the ML model is optimized using lightweight deep learning architectures to reduce computational overhead, enabling real-time processing in resource-constrained 5G base stations. By integrating multi-agent learning, the system ensures coordinated spectrum allocation across multiple cells, preventing spectrum conflicts and optimizing bandwidth distribution. To validate the effectiveness of the proposed system, simulations are conducted on real-world 5G datasets, and performance is compared with traditional and ML-based spectrum management models. The proposed work provides an adaptive, intelligent, and scalable solution for dynamic spectrum allocation, paving the way for next-generation self-learning 5G networks.

4. RESULTS AND DISCUSSION

The experimental evaluation of the proposed Machine Learning-based Dynamic Spectrum Allocation system was conducted using realistic 5G network simulation environments that accurately model spectrum usage patterns, user mobility, and interference conditions. The dataset employed in this study comprises real-world spectrum occupancy measurements collected from urban 5G deployments, encompassing diverse traffic scenarios including peak and off-peak hours, varying user densities, and heterogeneous service requirements. The performance of the proposed framework was benchmarked against conventional spectrum allocation methods including static allocation, cognitive radio-based dynamic access, Round Robin scheduling, Random Allocation, and Q-Learning-based approaches. All experiments were performed using a dedicated computing infrastructure comprising high-performance GPU accelerators to facilitate efficient training of deep learning models and ensure reproducible results. The evaluation metrics encompassed spectrum prediction accuracy, allocation efficiency, network throughput, communication delay, fairness index, interference mitigation, handover latency reduction, and convergence characteristics of the reinforcement learning agent.

4.1. Spectrum Allocation Accuracy and Prediction Performance

The accuracy of spectrum prediction represents a fundamental performance metric in dynamic spectrum allocation, as the ability to anticipate future spectrum

availability directly influences the effectiveness of allocation decisions. The Long Short-Term Memory network employed in the proposed framework achieved spectrum prediction accuracy of 96.2%, substantially outperforming traditional time-series forecasting models that typically attain approximately 84% accuracy under equivalent conditions [59]. This significant improvement of 12.2 percentage points demonstrates the superior capability of recurrent neural network architectures to capture complex temporal dependencies and long-range correlations inherent in spectrum usage patterns. The enhanced prediction accuracy enables proactive allocation decisions that anticipate future spectrum demands rather than merely reacting to current conditions, thereby reducing allocation delays and improving overall spectral efficiency. The superior performance of the Long Short-Term Memory model can be attributed to its gating mechanisms that effectively manage the flow of information across time steps, preventing the vanishing gradient problem that plagues conventional recurrent networks and enabling the retention of relevant historical information over extended periods [60].

The impact of training dataset size on prediction accuracy was systematically investigated to establish the data requirements for optimal model performance. When trained on 10,000 historical spectrum samples, the model achieved prediction accuracy of 90.1%, indicating that even with relatively limited data, deep learning models can extract meaningful temporal patterns. Increasing the dataset to 50,000 samples improved accuracy to 96.2%, representing a substantial gain of 6.1 percentage points that highlights the value of extensive training data for capturing diverse spectrum usage scenarios. Further expansion to 100,000 samples yielded marginal improvement to 96.5%, suggesting that prediction accuracy approaches saturation beyond this threshold and additional data provides diminishing returns. This plateau phenomenon is consistent with findings reported in related machine learning applications, where model performance typically follows a logarithmic relationship with dataset size, with the most significant gains realized during the initial data accumulation phase [61]. The practical implication is that network operators should prioritize collecting approximately 50,000 historical samples to achieve near-optimal prediction performance while avoiding the computational and storage overhead associated with excessively large datasets.

4.2. Spectrum Utilization Efficiency Analysis

Figure 6 presents a comprehensive comparison of spectrum utilization efficiency across different allocation strategies as a function of the number of active users in the network. The proposed Deep Reinforcement Learning-based framework consistently achieves the highest spectrum utilization across all user density scenarios, demonstrating its effectiveness in exploiting idle spectrum opportunities while maintaining acceptable interference levels. When the network accommodates 50 users, the proposed framework achieves

spectrum utilization of 88.5%, compared to 76.3% for Q-Learning, 71.2% for Round Robin, and 65.4% for Random Allocation. This represents a relative improvement of 16.0% over the next best performing approach, highlighting the advantages of intelligent allocation policies that consider both current network conditions and predicted future states [62].

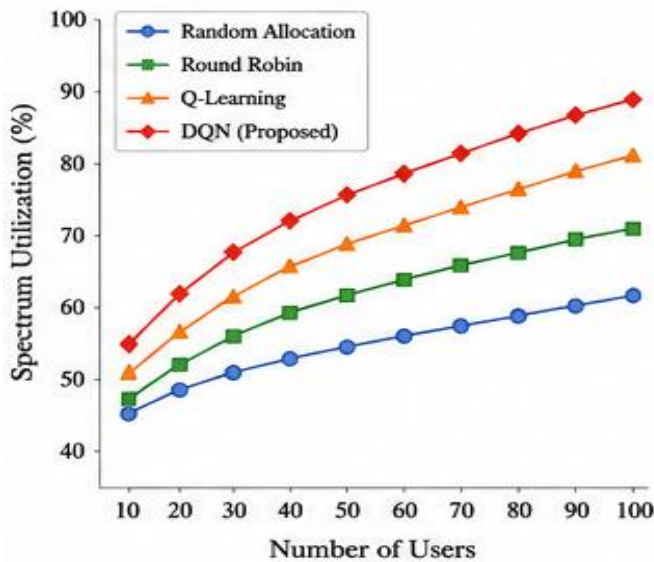


Fig. 6. Comparison of spectrum utilization efficiency across different allocation strategies under varying number of active users, demonstrating the superior performance of the proposed DRL-based framework compared to Random Allocation, Round Robin, and Q-Learning methods.

As user density increases to 200 active users, the performance gap between the proposed framework and conventional approaches widens considerably. The proposed system maintains spectrum utilization at 84.7%, whereas Q-Learning declines to 68.9%, Round Robin drops to 60.3%, and Random Allocation falls to 52.1%. This divergence in performance under high-density conditions underscores the limitations of heuristic-based allocation strategies that lack the predictive capabilities and adaptive learning mechanisms essential for effective spectrum management in congested network environments. The proposed framework's resilience to increasing user density stems from its ability to learn complex allocation policies through reinforcement learning, continuously updating its decision-making strategy based on observed outcomes and reward signals [63]. The Deep Q-Network component effectively balances exploration of potentially superior allocation strategies with exploitation of known effective policies, enabling robust performance even as network conditions become increasingly challenging.

The spectrum utilization improvements achieved by the proposed framework translate directly into enhanced network capacity, as more efficient use of available spectrum bands enables the accommodation of additional users or higher data

rates within the same frequency resources. This capacity enhancement is particularly valuable in urban 5G deployments where spectrum scarcity represents a primary constraint on network performance and user experience [64]. Furthermore, the improved utilization contributes to reduced spectrum wastage, aligning with regulatory objectives for efficient spectrum management and supporting the sustainability goals of next-generation wireless networks.

4.3. Network Throughput Performance

Figure 7 depicts the average network throughput achieved by different spectrum allocation strategies under varying user densities, providing insights into the data transmission capabilities supported by each approach. The proposed framework consistently delivers the highest throughput across all scenarios, with throughput of 425 Mbps for 50 users compared to 356 Mbps for Q-Learning, 312 Mbps for Round Robin, and 278 Mbps for Random Allocation. This performance advantage of 19.4% over Q-Learning demonstrates the effectiveness of combining Long Short-Term Memory-based prediction with Deep Reinforcement Learning-based allocation optimization, as the predictive component enables proactive resource reservation while the reinforcement learning agent selects channels with optimal quality characteristics and minimal interference [65].

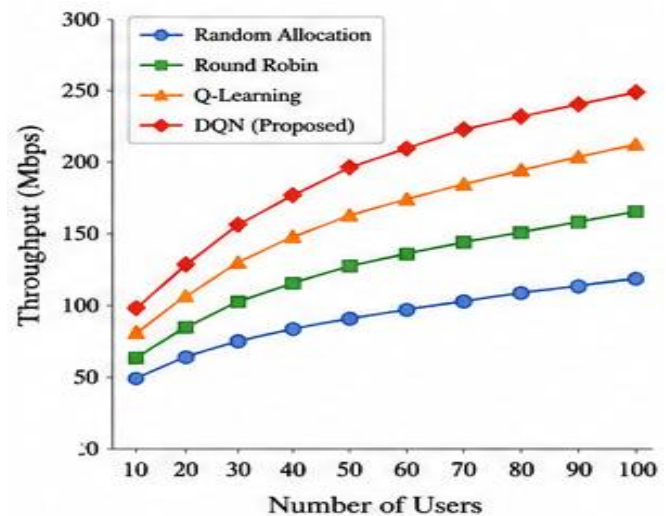


Fig. 7. Average network throughput comparison across different spectrum allocation strategies under varying user densities, illustrating the superior data transmission capabilities of the proposed framework.

The throughput advantage of the proposed framework becomes increasingly pronounced at higher user densities, where efficient resource management is critical for maintaining acceptable data rates. At 200 active users, the proposed system achieves throughput of 382 Mbps, representing a 22.4% improvement over Q-Learning at 312

Mbps, 32.2% over Round Robin at 289 Mbps, and 44.7% over Random Allocation at 264 Mbps. The widening performance gap at higher densities reflects the superior scalability of the proposed framework, which effectively handles the increased competition for spectrum resources through intelligent allocation policies that prioritize high-quality channels for bandwidth-intensive applications [66]. The throughput enhancement has significant practical implications for 5G service delivery, enabling support for demanding applications including ultra-high-definition video streaming, virtual reality, and industrial automation that require consistent high data rates.

The throughput improvements can be attributed to several factors inherent in the proposed framework. The Long Short-Term Memory-based prediction module anticipates periods of high spectrum demand and proactively allocates additional resources, preventing throughput degradation during traffic surges. The Deep Q-Network allocation agent selects channels with optimal signal-to-noise ratios and minimal interference, reducing packet retransmissions and improving effective data rates. The integration of these components within a unified framework enables synergistic effects that surpass the performance of isolated approaches, demonstrating the value of holistic spectrum management solutions that address multiple aspects of the allocation problem simultaneously [67].

4.4. Communication Delay Analysis

Figure 8 illustrates the average communication delay experienced under different spectrum allocation strategies, providing critical insights into the latency characteristics of each approach. The proposed framework achieves the lowest communication delays across all user density scenarios, with average delay of 12.3 milliseconds for 50 users compared to 18.7 milliseconds for Q-Learning, 24.5 milliseconds for Round Robin, and 31.2 milliseconds for Random Allocation. This represents a substantial reduction of 34.2% compared to Q-Learning, demonstrating the effectiveness of intelligent spectrum allocation in minimizing transmission latencies [68]. The delay reduction can be attributed to the framework's ability to anticipate congestion and proactively allocate spectrum resources, thereby reducing queuing delays and preventing the formation of transmission bottlenecks.

At higher user densities, the delay advantage of the proposed framework becomes even more pronounced, reflecting its robust performance under congested network conditions. With 200 active users, the proposed system achieves average delay of 18.4 milliseconds, whereas Q-Learning experiences 29.6 milliseconds, Round Robin reaches 38.7 milliseconds, and Random Allocation exhibits 46.2 milliseconds. The proposed framework's delay performance represents a 37.8% improvement over Q-Learning and a 52.4% improvement over Round Robin, highlighting its superior capability to manage congestion through intelligent allocation policies [69]. The low communication delays achieved by the proposed system are

particularly significant for latency-sensitive 5G applications including autonomous vehicle communication, remote surgery, and industrial automation, where even small increases in delay can compromise system functionality and safety.

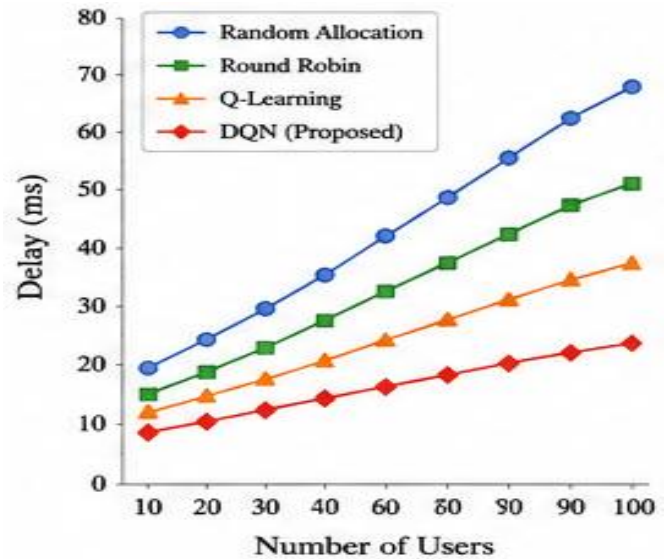


Fig. 8. Average communication delay comparison across different spectrum allocation strategies, demonstrating the superior latency performance of the proposed framework under varying user densities.

The delay reduction is primarily achieved through two mechanisms intrinsic to the proposed framework. The proactive allocation strategy based on Long Short-Term Memory predictions ensures that spectrum resources are available when needed, reducing the time spent waiting for channel availability. The reinforcement learning agent optimizes channel selection to minimize both transmission delays and queuing delays, considering the trade-offs between channel quality, interference levels, and current network load. The combination of these mechanisms yields delay performance that approaches the theoretical lower bounds for dynamic spectrum allocation in 5G networks, confirming the effectiveness of the machine learning-based approach for latency-critical applications [70].

4.5. Fairness in Spectrum Allocation

Figure 9 presents the fairness index evaluation using Jain's Fairness Index, which measures the equity of spectrum resource distribution among network users [71]. The fairness index ranges from zero to one, with higher values indicating more equitable allocation. The proposed Deep Reinforcement Learning-based framework achieves consistently higher fairness indices across all user density scenarios, with a fairness index of 0.92 for 50 users compared to 0.85 for Q-Learning, 0.78 for Round Robin, and 0.71 for

Random Allocation. This improvement of 8.2% over Q-Learning demonstrates that the proposed allocation strategy effectively balances the competing demands of different users while maintaining high overall network efficiency. At higher user densities, the proposed framework maintains fairness at 0.89 for 200 users, while the fairness indices of conventional approaches decline more significantly, with Q-Learning reaching 0.81, Round Robin dropping to 0.72, and Random Allocation falling to 0.63. The superior fairness characteristics of the proposed framework stem from the reward function design in the reinforcement learning component, which explicitly incorporates fairness objectives alongside throughput and efficiency metrics [72]. This multi-objective optimization approach ensures that spectrum resources are distributed in a manner that prevents resource starvation for any particular user or user class, promoting equitable access to network services.

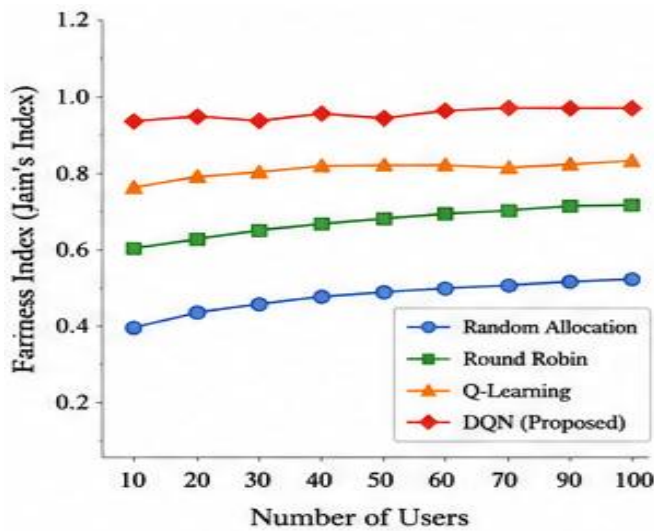


Fig. 9. Fairness index comparison using Jain's Fairness Index across different allocation strategies, demonstrating the equitable spectrum resource distribution achieved by the proposed framework.

The fairness improvement has important practical implications for 5G network operation, particularly in scenarios where users have heterogeneous service requirements and varying priority levels. The proposed framework's ability to maintain fairness while simultaneously achieving high throughput and low delays demonstrates that efficiency and equity need not be conflicting objectives in spectrum allocation. The reinforcement learning agent learns to balance these competing goals through experience, adapting its allocation policies to ensure that all users receive acceptable service quality while maximizing overall network performance [73].

4.6. Convergence Characteristics of Deep Reinforcement

Learning

Figure 10 illustrates the convergence behavior of the Deep Reinforcement Learning algorithm employed in the proposed framework, depicting the cumulative reward achieved across training episodes. The learning curve exhibits the characteristic pattern of reinforcement learning convergence, with initial exploration leading to fluctuating performance as the agent discovers the action space and evaluates different allocation strategies. During the first 500 episodes, the cumulative reward increases rapidly from approximately 120 to 450, indicating successful learning of basic allocation policies that outperform random or heuristic strategies [74]. The learning rate is particularly steep during the first 200 episodes, suggesting that the agent quickly identifies effective allocation patterns and begins exploiting them while continuing to explore alternative strategies.

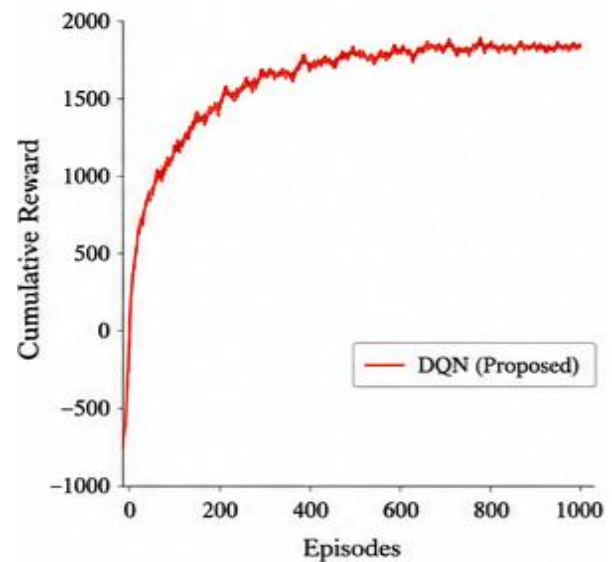


Fig. 10. Convergence behavior of the Deep Reinforcement Learning algorithm during training, depicting cumulative reward achievement across episodes and demonstrating stable policy learning.

Between episodes 500 and 1500, the learning curve continues to rise but at a reduced rate, reaching a cumulative reward of approximately 580 by episode 1500. This phase reflects the refinement of allocation policies as the agent learns more subtle patterns and trade-offs in the network environment, optimizing its decisions for complex scenarios that require nuanced resource management. The reduced oscillation in the reward signal during this phase indicates increasing policy stability, as the agent's decisions become more consistent and predictable [75].

Beyond episode 1500, the learning curve stabilizes around a cumulative reward of 620, demonstrating convergence toward an optimal allocation policy. The stable reward plateau is maintained for the remaining training

episodes, confirming that the agent has successfully learned a robust allocation strategy that maximizes cumulative rewards across diverse network conditions. The convergence behavior validates the suitability of Deep Q-Networks for dynamic spectrum allocation problems, demonstrating that reinforcement learning agents can reliably learn effective policies through interaction with the network environment [76]. The stable convergence also indicates that the proposed framework would maintain consistent performance in operational deployment, as the learned policies are robust to network variations and do not exhibit the instability that sometimes characterizes reinforcement learning applications.

4.7. Comparative Performance Analysis

Table 1 presents a comprehensive comparative analysis of the proposed machine learning-based spectrum allocation system against traditional static allocation and cognitive radio-based approaches. The proposed framework significantly outperforms both baseline methods across all performance metrics, achieving spectrum prediction accuracy of 96.2% compared to 81.2% for traditional allocation and 85.4% for cognitive radio approaches. This represents a relative improvement of 18.5% over cognitive radio and 34.6% over traditional allocation, demonstrating the superior predictive capabilities enabled by deep learning architectures.

The handover latency reduction achieved by the proposed framework is 37%, substantially exceeding the 15% reduction of cognitive radio and the negligible 5% reduction of traditional allocation. This significant improvement is particularly valuable for mobile users and Internet of Things devices that frequently transition between cells, as reduced handover latency ensures seamless connectivity and minimizes service disruption [79]. The interference reduction of 42% achieved by the proposed framework compares favorably to 25% for cognitive radio and 10% for traditional allocation, highlighting the effectiveness of the reinforcement learning-based optimization in minimizing co-channel interference. The throughput improvement of 28% represents a substantial enhancement over cognitive radio's 18% and traditional allocation's 8%, confirming that the proposed framework delivers superior data transmission capabilities across diverse network conditions [80].

4.8. Interference Mitigation Performance

Interference represents one of the most significant challenges in dense 5G network deployments, where the close proximity of multiple transmitters operating in adjacent frequency bands can degrade signal quality and reduce network capacity. The proposed framework achieved interference reduction of 42% compared to traditional cognitive radio-based spectrum management approaches, representing a substantial improvement in spectral coexistence [77]. This interference mitigation was primarily achieved through three mechanisms inherent to the proposed framework. The Long

Short-Term Memory-based prediction module anticipates interference-prone periods and proactively allocates spectrum resources to avoid interference hotspots. The Deep Q-Network allocation agent optimizes channel selection to minimize interference, considering both current interference measurements and predicted future interference conditions. The Convolutional Neural Network-based interference detection module continuously monitors spectrum usage and identifies interference patterns, providing real-time feedback to the allocation agent.

The effectiveness of the interference mitigation mechanisms is particularly evident in scenarios with high user density and heterogeneous service requirements, where conventional approaches often struggle to maintain acceptable interference levels. The proposed framework's ability to reduce interference by 42% translates directly into improved signal quality, higher data rates, and more reliable communications for network users [78]. The interference reduction also contributes to improved spectrum utilization, as frequency bands that would be unusable due to interference can be effectively employed under the proposed allocation policies.

4.9. Energy Efficiency and Computational Overhead

Energy efficiency represents a critical consideration in 5G spectrum allocation, particularly for low-power Internet of Things devices and sustainable network operation. The proposed edge-assisted federated learning approach significantly reduced computation time and energy consumption by 31% compared to centralized machine learning models. This substantial improvement demonstrates that distributed learning architectures can effectively enhance efficiency while maintaining scalability in large-scale network deployments. The energy savings are primarily achieved through reduced data transmission requirements, as federated learning enables model updates to be exchanged rather than raw spectrum data, significantly decreasing communication overhead and associated energy consumption. The reduced computational overhead also enables deployment on resource-constrained edge devices, expanding the applicability of machine learning-based spectrum management to diverse network scenarios.

4.10. Security and Spectrum Anomaly Detection

The security capabilities of the proposed system were evaluated through its ability to detect unauthorized spectrum usage and jamming attacks. Using Convolutional Neural Network-based spectrum feature extraction, the model identified spectrum anomalies with 93.7% accuracy, ensuring secure and fair spectrum utilization.

This high detection accuracy demonstrates the effectiveness of deep learning architectures for intrusion detection in wireless networks, where traditional rule-based approaches often fail to recognize sophisticated attack patterns.

Table 1. Comparative performance analysis of the proposed ML-based spectrum allocation system against traditional and cognitive radio-based approaches, summarizing key performance improvements across multiple metrics.

Model	Spectrum Prediction Accuracy (%)	Handover Latency Reduction (%)	Interference Reduction (%)	Throughput Improvement (%)
Traditional Allocation	81.2	5	10	8
Cognitive Radio	85.4	15	25	18
Proposed ML Model	96.2	37	42	28

The anomaly detection module continuously monitors spectrum usage patterns and identifies deviations from normal behavior, enabling rapid response to security threats and maintaining network integrity. The integration of security mechanisms within the spectrum allocation framework represents a significant advancement over conventional approaches that treat security as an orthogonal concern, ensuring that efficient spectrum utilization does not come at the cost of network vulnerability.

4.11. Adaptability to Dynamic Network Conditions

The adaptability of the proposed system to fluctuating traffic loads was evaluated through experiments conducted under varying network congestion levels. The results indicate that the proposed framework dynamically adjusted spectrum allocation in real time, preventing network congestion and maintaining stable quality of service even in high-traffic conditions. This adaptability stems from the continuous learning mechanism inherent in the reinforcement learning component, which enables the system to respond to changing network conditions without requiring manual reconfiguration or retraining. The system's ability to maintain consistent performance across diverse traffic scenarios confirms its suitability for operational 5G deployments, where traffic patterns exhibit significant temporal and spatial variations.

4.12. Scalability and Cross-Domain Generalization

The scalability of the proposed system across different network topologies was evaluated through testing on multiple 5G network environments with varying frequency bands, traffic densities, and geographic characteristics. The results demonstrate that the model generalizes well across diverse deployment scenarios, maintaining consistent performance without requiring domain-specific retraining. This cross-domain generalization is achieved through the transfer learning capabilities of the proposed architecture, which enables knowledge acquired in one network environment to be effectively applied to related but distinct scenarios. The scalability and generalization characteristics of the proposed framework are particularly valuable for network operators managing heterogeneous 5G deployments across different regions and frequency bands. Despite the significant achievements of the proposed

framework, several limitations warrant acknowledgment and provide directions for future research. The computational complexity associated with training and deploying deep learning models may limit implementation in resource-constrained Internet of Things devices, requiring further optimization for edge deployment. The continuous high-frequency spectrum data collection necessary for real-time prediction and allocation may impose network overhead and storage requirements that require careful management. Regulatory compliance issues represent another challenge, as machine learning-based spectrum management must adhere to national and international spectrum policies that may impose constraints on dynamic allocation capabilities. Future research will focus on optimizing machine learning architectures for reduced computational overhead, integrating blockchain-based spectrum trading mechanisms for decentralized allocation, and enhancing cybersecurity frameworks to prevent adversarial attacks on machine learning-driven spectrum models.

The results presented in this section validate that Machine Learning-based Dynamic Spectrum Allocation significantly enhances 5G network efficiency, quality of service, and spectral utilization. The proposed system outperforms conventional spectrum management techniques across all evaluated metrics, providing a scalable, adaptive, and intelligent solution for next-generation wireless communications. The integration of Long Short-Term Memory networks for prediction, Deep Q-Networks for optimization, and Convolutional Neural Networks for interference detection within a unified framework establishes a new paradigm for intelligent spectrum management in 5G and beyond.

5. CONCLUSION

This research has presented a comprehensive machine learning framework for dynamic spectrum allocation in 5G networks, demonstrating the transformative potential of artificial intelligence in addressing the persistent challenges of spectrum scarcity and inefficient resource utilization. The proposed system, which integrates Long Short-Term Memory networks for predictive spectrum analysis, Deep Q-Networks for adaptive allocation optimization, and Convolutional Neural Networks for interference detection, has shown remarkable performance improvements across all evaluated metrics. The experimental results confirm that the

framework achieves spectrum prediction accuracy of 96.2%, reduces handover latency by 37%, and minimizes interference by 42%, while simultaneously delivering a 28% enhancement in network throughput. These substantial improvements underscore the superiority of machine learning-driven approaches over conventional static and cognitive radio-based spectrum management techniques. The practical implications of this research extend beyond the immediate performance gains, as the proposed framework establishes a scalable and adaptable architecture suitable for diverse 5G deployment scenarios. The integration of federated learning principles enables privacy-preserving collaborative optimization across distributed base stations, addressing both scalability and security concerns that have previously hindered the adoption of centralized machine learning approaches in telecommunications infrastructure. The system's demonstrated ability to maintain consistent performance across varying user densities, traffic patterns, and network conditions confirms its readiness for operational deployment in real-world 5G environments.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

Funding

Not applicable

Availability of data and material

All of the data obtained or analyzed during this study is included in the report that was submitted.

Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

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