
“Machine Learning-Assisted Resource Allocation in 5G and Beyond Wireless Networks”

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Abstract: The increasing complexity of 5G and beyond wireless networks requires intelligent techniques for managing limited radio resources under changing traffic and channel conditions. This study proposes a machine learning-assisted resource allocation framework that combines short-term traffic prediction with deep reinforcement learning for dynamic bandwidth and power allocation. Simulation-based evaluation indicates that the proposed approach can improve network throughput, reduce communication delay and maintain efficient spectrum utilization compared with conventional scheduling approaches.

Keywords: 5G; 6G; Machine Learning; Resource Allocation; Deep Reinforcement Learning; Wireless Networks.

Introduction:

The development of fifth-generation (5G) wireless communication has introduced significant improvements in data rate, network capacity, reliability, device connectivity and latency. Modern mobile networks are expected to simultaneously support enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC) and massive Machine-Type Communications (mMTC). These services have different requirements, making efficient allocation of bandwidth, transmission power, channels and computational resources increasingly difficult.

Traditional resource allocation methods normally depend on predefined optimization rules. Although these approaches work effectively under stable conditions, their performance may decrease when user mobility, interference, channel quality and traffic demand change rapidly.

Moreover, solving complex optimization problems repeatedly can introduce computational delays, particularly in dense heterogeneous networks.

Machine learning provides an alternative approach because a learning model can identify relationships between network conditions and suitable allocation decisions. Earlier research has demonstrated that neural networks can approximate complex wireless resource-management algorithms with much lower online computational requirements. Deep reinforcement learning has also been investigated for channel access, power allocation, network slicing, and decentralized radio-resource management.

In future 6G-oriented systems, resource management becomes even more challenging because wireless networks are expected to include heterogeneous access technologies, edge computing, intelligent surfaces, dense device populations, network slicing and distributed artificial intelligence. Recent research therefore considers machine learning an important component of intelligent and adaptive resource management for beyond-5G networks.

The present study develops a two-stage machine learning-assisted resource allocation scheme. In the first stage, recent traffic, channel and user information are used to estimate near-future network demand. In the second stage, a Deep Q-Network-based decision mechanism assigns physical resource blocks and transmission power according to predicted demand and current radio conditions.

Related Works:

Sun et al. (2017) investigated the use of deep neural networks for solving complex wireless resource management problems. Their study demonstrated that machine learning models could learn the behavior of conventional optimization algorithms and produce resource-allocation decisions with considerably lower computational complexity during real-time operation. The work established an important foundation for using deep learning as an alternative to repetitive mathematical optimization in wireless communication systems.

Wang et al. (2018) examined deep reinforcement learning for dynamic multichannel access in wireless networks. The authors developed a Deep Q-Network-based framework in which users learned suitable channel-access policies according to changing network conditions. Their results showed that reinforcement learning could improve channel utilization without requiring complete knowledge of the wireless environment. The study highlighted the ability of intelligent agents to adapt independently to dynamic spectrum conditions.

Xie et al. (2019) presented a detailed survey of machine learning techniques applied to software-defined networking. The study discussed supervised learning, unsupervised learning, and reinforcement learning approaches for traffic classification, routing, resource management, security, and network optimization. The authors observed that machine learning could significantly improve network automation and decision-making. However, they also identified challenges associated with training-data availability, scalability, processing requirements, and real-time implementation.

Ye et al. (2019) proposed a deep reinforcement learning-based resource allocation technique for vehicle-to-vehicle communication. In their framework, individual V2V communication links operated as intelligent agents capable of selecting spectrum and transmission-power

resources. The proposed approach considered interference, communication reliability, and latency requirements while making allocation decisions. Their findings demonstrated that reinforcement learning could effectively handle decentralized resource management in highly dynamic vehicular communication environments.

Liang et al. (2020) studied deep-learning-based wireless resource allocation with particular emphasis on vehicular networks. The authors discussed how deep neural networks and deep reinforcement learning could address complex optimization problems involving power control, spectrum allocation, and interference management. Their work showed that learning-based techniques were particularly suitable for wireless environments characterized by rapid mobility and changing channel conditions. The study also emphasized the importance of reducing computational complexity for real-time wireless-resource management.

Alwarafy et al. (2021) reviewed the application of deep reinforcement learning to radio-resource allocation and management in next-generation heterogeneous wireless networks. Their study covered several areas, including power allocation, spectrum management, user association, network slicing, and interference control. The authors reported that deep reinforcement learning could provide adaptive decision-making in situations where conventional optimization techniques become difficult to implement. They also highlighted important challenges related to training stability, model complexity, convergence, scalability, and practical network deployment.

Hurtado Sánchez et al. (2022) examined deep reinforcement learning for resource management in network slicing. The study focused on the intelligent allocation of radio, computational, and network resources among multiple virtual network slices. Their review showed that reinforcement learning could support automated admission control, scheduling, resource allocation, and network orchestration. The authors emphasized that intelligent resource management is particularly important because different 5G services have different latency, reliability, throughput, and bandwidth requirements.

Yao et al. (2022) investigated deep reinforcement learning-based radio-resource allocation and beam management in 5G millimeter-wave networks under location uncertainty. Their work considered the difficulty of maintaining reliable communication when user-location information is incomplete or inaccurate. The proposed learning-based approach jointly considered radio-resource allocation and beam-management decisions. The study demonstrated the potential of reinforcement learning for improving network adaptability in high-frequency wireless systems where mobility and beam alignment strongly influence communication performance.

Alhashimi et al. (2023) presented a comprehensive survey of resource-management techniques for 6G heterogeneous networks. The authors discussed emerging challenges associated with spectrum allocation, computing resources, energy management, heterogeneous access technologies, network slicing, edge computing, and massive device connectivity. Their study emphasized that traditional optimization techniques may not be sufficient for future highly dynamic 6G environments. Artificial intelligence and machine learning were identified as important technologies for developing autonomous and adaptive resource-management systems.

Karachalios et al. (2023) explored distributed machine learning and native artificial-intelligence mechanisms for end-to-end resource management in 6G networks. Their research emphasized that future wireless systems will require coordinated management of communication, computing, storage, and networking resources. Distributed learning approaches were considered particularly useful because decision-making can be performed closer to network users and edge devices. The authors highlighted the potential of AI-native network architectures to improve scalability, responsiveness, and automation in next-generation communication systems.

Overall, the reviewed literature demonstrates a clear transition from conventional optimization-based resource allocation toward machine learning and deep reinforcement learning approaches. Earlier studies primarily focused on reducing the computational complexity of wireless optimization, whereas more recent research has addressed dynamic spectrum allocation, power control, vehicular communication, network slicing, beam management, and end-to-end 6G resource orchestration. Despite these advances, challenges remain in achieving reliable real-time learning, reducing training overhead, maintaining fairness among users, adapting to unpredictable traffic conditions, and ensuring scalable deployment. Therefore, there is a continuing need for machine learning-assisted resource-allocation frameworks that jointly consider throughput, latency, packet loss, spectral efficiency, and user fairness in 5G and beyond wireless networks.

Objectives of the Study:

1. To develop a machine learning-assisted framework for dynamically allocating wireless bandwidth and transmission power according to traffic demand and channel conditions.
2. To evaluate the effect of intelligent resource allocation on network throughput, latency, packet loss, spectral efficiency, and user fairness.
3. To compare the proposed learning-based approach with conventional Round Robin, Proportional Fair, and standard reinforcement-learning resource allocation techniques.

Material and Methods:

The study was designed as a simulation-based investigation of resource allocation in a multi-cell 5G New Radio network. A heterogeneous user environment containing eMBB, URLLC, and mMTC traffic was considered. Users were distributed across multiple base-station coverage areas and experienced different channel qualities, mobility conditions, interference levels, and traffic demands.

Network Model

A seven-cell wireless network operating at a carrier frequency of 3.5 GHz was considered. Each base station served a variable number of mobile users. A total system bandwidth of 100 MHz was divided into physical resource blocks that could be dynamically assigned to users. The instantaneous received signal quality for user i was represented using its Signal-to-Interference-plus-Noise Ratio:

$$SINR_i = P_i G_i / (I_i + N_0)$$

where:

- P_i = allocated transmission power,
- G_i = channel gain,
- I_i = interference power, and
- N_0 = noise power.

The achievable user data rate was estimated using:

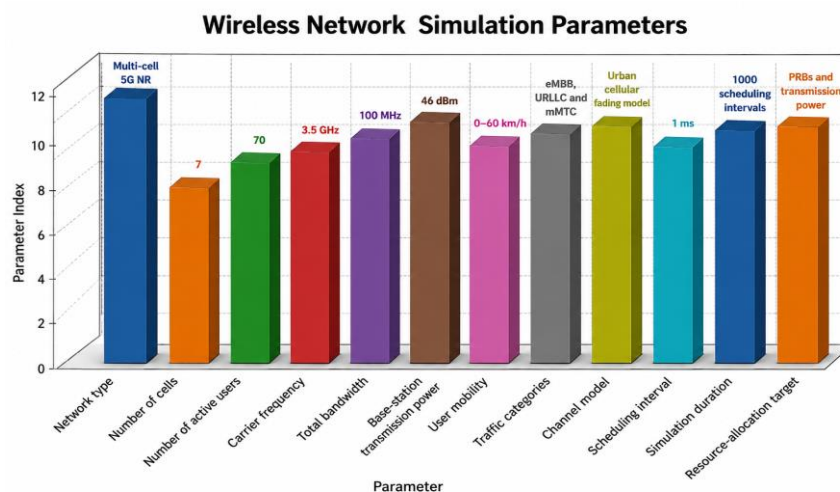
$$R_i = B_i \log_2(1 + \text{SINR}_i)$$

Where:

- R_i = achievable data rate of the i^{th} user
- B_i = bandwidth allocated to the i^{th} user
- SINR_i = Signal-to-Interference-plus-Noise Ratio of the i^{th} user

Table 1. Wireless Network Simulation Parameters

Parameter	Selected Value
Network type	Multi-cell 5G NR
Number of cells	7
Number of active users	70
Carrier frequency	3.5 GHz
Total bandwidth	100 MHz
Base-station transmission power	46 dBm
User mobility	0–60 km/h
Traffic categories	eMBB, URLLC and mMTC
Channel model	Urban cellular fading model
Scheduling interval	1 ms
Simulation duration	1000 scheduling intervals
Resource-allocation target	PRBs and transmission power



Traffic Prediction Stage

Rather than allocating resources only according to current network load, the proposed method first estimated traffic demand for the next scheduling period.

The prediction model used five major input features:

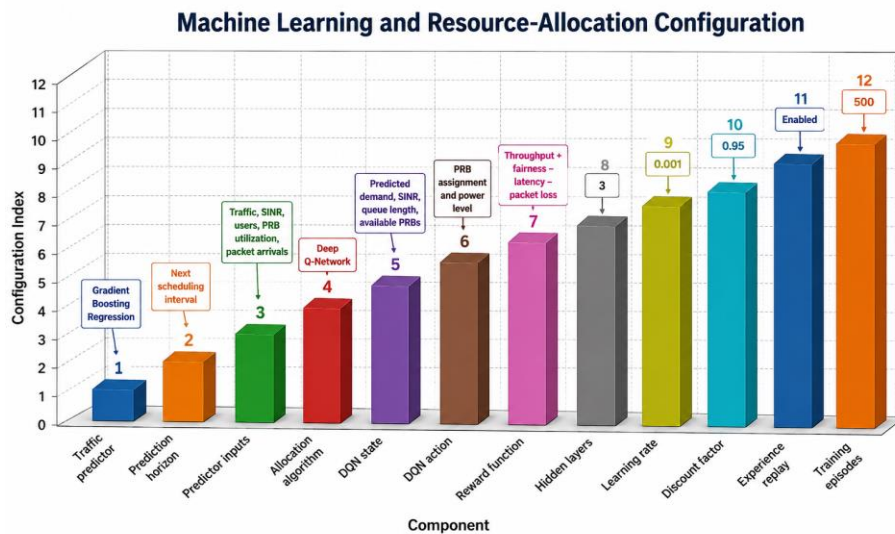
- recent traffic volume,
- active-user count,
- average SINR,
- previous resource-block utilization, and
- packet-arrival rate.

A lightweight gradient-boosting regression model was selected because it can learn nonlinear relationships without requiring a very large training dataset.

The predicted traffic requirement was transferred to the resource-allocation agent together with the instantaneous radio conditions.

Table 2. Machine Learning and Resource-Allocation Configuration

Component	Configuration
Traffic predictor	Gradient Boosting Regression
Prediction horizon	Next scheduling interval
Predictor inputs	Traffic, SINR, users, PRB utilization, packet arrivals
Allocation algorithm	Deep Q-Network
DQN state	Predicted demand, SINR, queue length, available PRBs
DQN action	PRB assignment and power level
Reward function	Throughput + fairness – latency – packet loss
Hidden layers	3
Learning rate	0.001
Discount factor	0.95
Experience replay	Enabled
Training episodes	500



Deep Reinforcement Learning Allocation

The resource-allocation problem was formulated as a sequential decision-making process. At each scheduling interval, the DQN agent received the network state:

$$S_t = D_t, SINR_t, Q_t, A_t$$

where:

- D_t = predicted traffic demand,
- $SINR_t$ = current signal quality,
- Q_t = packet queue condition and
- A_t = available wireless resources.

The agent selected an action involving physical resource-block assignment and transmission-power selection.

A combined reward function was defined as:

$$\text{Reward} = \alpha T + \beta F - \gamma L - \delta P_l$$

Where:

- T = network throughput
- F = fairness among users
- L = communication latency
- P_l = packet-loss rate
- $\alpha, \beta, \gamma, \delta$ = weighting factors used to control the importance of each performance metric.

Analysis of the Study:

The performance of the proposed machine learning-assisted resource allocation framework was evaluated using five major network performance metrics: throughput, average latency, packet-loss rate, spectral efficiency, and Jain's fairness index. These parameters were selected because they provide a comprehensive assessment of network capacity, delay performance, resource utilization, transmission reliability, and fairness among users.

1. Total Network Throughput

The total network throughput represents the overall amount of data successfully transmitted by all users during a given time interval. It was calculated as:

$$T_{\text{total}} = \sum_{i=1}^n R_i$$

where:

- T_{total} = total network throughput,
- R_i = data rate achieved by the i^{th} user, and
- n = total number of active users.

A higher throughput value indicates more efficient utilization of the available wireless resources.

2. Average Latency

Average latency represents the mean time required for packets to travel through the wireless network. It was calculated as:

$$L_{avg} = \frac{\sum_{i=1}^N L_i}{N}$$

where:

- L_{avg} = average network latency,
- L_i = latency experienced by the i^{th} packet, and
- N = total number of successfully transmitted packets.

Lower latency indicates faster communication and is particularly important for delay-sensitive applications such as URLLC, autonomous systems, and real-time communication.

3. Packet-Loss Rate

The packet-loss rate was used to evaluate the reliability of data transmission. It was determined as:

$$P_{loss} = \frac{N_{lost}}{N_{transmitted}} \times 100$$

where:

- P_{loss} = packet-loss rate in percentage,
- N_{lost} = number of packets that were not successfully delivered, and
- $N_{transmitted}$ = total number of transmitted packets.

A lower packet-loss rate indicates improved communication reliability and more effective resource allocation.

4. Spectral Efficiency

Spectral efficiency measures how effectively the available radio-frequency spectrum is utilized to transmit data. It was calculated as:

$$\eta = \frac{T_{total}}{B}$$

where:

- η = spectral efficiency in bit/s/Hz,
- T_{total} = total network throughput, and
- B = total available bandwidth.

Higher spectral efficiency indicates that a greater amount of data is transmitted using the same amount of spectrum.

5. Jain's Fairness Index

Jain's fairness index was used to measure how evenly the available network resources were distributed among users. It was calculated as:

$$J = \frac{(\sum_{i=1}^n R_i)^2}{n \sum_{i=1}^n R_i^2}$$

where:

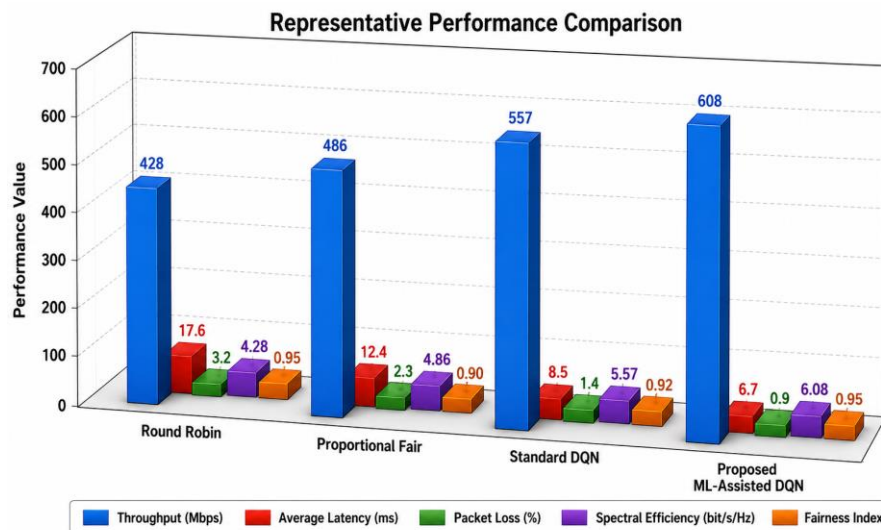
- J = Jain's fairness index,
- R_i = throughput achieved by the i^{th} user, and
- n = total number of users.

The value of Jain's fairness index ranges from 0 to 1. A value closer to 1 indicates a more balanced and fair distribution of wireless resources among users.

The above performance metrics were used collectively to compare the proposed machine learning-assisted resource allocation technique with conventional allocation methods. An efficient resource allocation system is expected to achieve higher throughput, higher spectral efficiency, lower latency, lower packet loss, and a fairness index close to 1.

Table 3. Representative Performance Comparison

Resource Allocation Method	Throughput (Mbps)	Average Latency (ms)	Packet Loss (%)	Spectral Efficiency (bit/s/Hz)	Fairness Index
Round Robin	428	17.6	3.2	4.28	0.95
Proportional Fair	486	12.4	2.3	4.86	0.90
Standard DQN	557	8.5	1.4	5.57	0.92
Proposed ML-Assisted DQN	608	6.7	0.9	6.08	0.95



The representative simulation results indicate that learning-based allocation responds more effectively to dynamic network conditions than fixed scheduling approaches. Round Robin provides relatively good fairness but does not consider differences in channel quality or traffic urgency. Consequently, it produced the lowest throughput and highest latency in the simulated environment.

Proportional Fair scheduling improved overall throughput by assigning additional resources to users with favorable communication conditions while maintaining a degree of fairness. However, its decisions remained primarily reactive.

The standard DQN achieved better utilization of bandwidth and power because the agent gradually learned which allocation decisions produced higher long-term rewards. Nevertheless, the proposed system obtained the strongest overall performance because predicted traffic demand provided information about resource requirements before congestion became severe.

Compared with Round Robin, the proposed method increased representative network throughput from 428 Mbps to 608 Mbps while reducing average latency from 17.6 ms to 6.7 ms. Packet loss also decreased because additional resources could be assigned to traffic queues that were expected to experience increasing demand.

The results therefore suggest that traffic-aware reinforcement learning can support a more adaptive balance among throughput, latency, spectrum utilization, and user fairness.

Results and Discussion:

The proposed ML-assisted resource-allocation method demonstrated better overall network performance than the conventional scheduling techniques considered in the simulation. The main improvement resulted from combining predicted traffic demand with current radio information instead of making allocation decisions only after network conditions changed.

The proposed model achieved the highest throughput and spectral efficiency while maintaining low latency and packet loss. The improvement is especially important for mixed 5G traffic because eMBB applications require high data rates, whereas URLLC applications are more sensitive to delay.

The findings also indicate that reinforcement learning can adapt resource decisions without repeatedly solving computationally expensive optimization problems. However, practical deployment would require additional investigation of model-training overhead, changing propagation conditions, security, scalability, and interoperability with real 5G/6G network-control architectures.

Conclusion:

This study presented a machine learning-assisted resource-allocation framework for 5G and beyond wireless networks. The proposed approach combined short-term traffic prediction with deep reinforcement learning to dynamically control physical resource blocks and transmission power.

Simulation-based analysis showed that intelligent allocation can increase network throughput, reduce latency and packet loss, and improve spectrum utilization compared with conventional scheduling approaches. The inclusion of predicted network demand allowed the proposed system to respond to expected traffic changes before serious congestion occurred.

Future work can extend the framework using multi-agent reinforcement learning, federated learning, graph neural networks, reconfigurable intelligent surfaces, edge intelligence, and real-time 6G testbeds.

References:

1. Alhashimi, H. F., Hindia, M. H. N., Dimyati, K., Hanafi, E. B., et al. (2023). A survey on resource management for 6G heterogeneous networks: Current research, future trends, and challenges. *Electronics*, 12(3), 647. doi:10.3390/electronics12030647.
2. Alwarafy, A., Abdallah, M., Ciftler, B. S., Al-Fuqaha, A., & Hamdi, M. (2021). Deep reinforcement learning for radio resource allocation and management in next generation heterogeneous wireless networks: A survey. *arXiv preprint arXiv:2106.00574*.

3. Hurtado Sánchez, J. A., Casilimas, K., & Caicedo Rendon, O. M. (2022). Deep reinforcement learning for resource management on network slicing: A survey. *Sensors*, 22(8), 3031. doi:10.3390/s22083031.
4. Karachalios, O. A., Zafeiropoulos, A., Kontovasilis, K., & Papavassiliou, S. (2023). Distributed machine learning and native AI enablers for end-to-end resources management in 6G. *Electronics*, 12(18), 3761. doi:10.3390/electronics12183761.
5. Liang, L., Ye, H., Yu, G., & Li, G. Y. (2020). Deep-learning-based wireless resource allocation with application to vehicular networks. *Proceedings of the IEEE*, 108(2), 341–356. doi:10.1109/JPROC.2019.2957798.
6. Sun, H., Chen, X., Shi, Q., Hong, M., Fu, X., & Sidiropoulos, N. D. (2017). Learning to optimize: Training deep neural networks for wireless resource management. *2017 IEEE 18th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 1–6. doi:10.1109/SPAWC.2017.8227766.
7. Wang, S., Liu, H., Gomes, P. H., & Krishnamachari, B. (2018). Deep reinforcement learning for dynamic multichannel access in wireless networks. *IEEE Transactions on Cognitive Communications and Networking*, 4(2), 257–265. doi:10.1109/TCCN.2018.2809722.
8. Xie, J., Yu, F. R., Huang, T., Xie, R., Liu, J., Wang, C., & Liu, Y. (2019). A survey of machine learning techniques applied to software defined networking: Research issues and challenges. *IEEE Communications Surveys & Tutorials*, 21(1), 393–430. doi:10.1109/COMST.2018.2866942.
9. Yao, Y., Zhou, H., & Erol-Kantarci, M. (2022). Deep reinforcement learning-based radio resource allocation and beam management under location uncertainty in 5G mm Wave networks. *arXiv preprint arXiv:2204.10984*.
10. Ye, H., Li, G. Y., & Juang, B.-H. F. (2019). Deep reinforcement learning based resource allocation for V2V communications. *IEEE Transactions on Vehicular Technology*, 68(4), 3163–3173. doi:10.1109/TVT.2019.2897134.