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Research Article

5G Network Optimization Using Artificial Intelligence Algorithms to Improve Quality of Service

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Abstract: The rapid deployment of 5G networks presents unique challenges in meeting the growing demand for high-speed, reliable, and low-latency communication services. Traditional network management methods, which rely on static resource allocation and manual configurations, are insufficient to handle the dynamic nature of 5G networks. This paper explores the application of Artificial Intelligence (AI) algorithms, specifically Reinforcement Learning (RL), for optimizing 5G resource allocation and improving Quality of Service (QoS). The study reviews existing research on 5G network optimization, highlighting the limitations of traditional network management techniques and the need for intelligent, adaptive solutions. RL, with its ability to dynamically adjust to changing network conditions, offers a promising approach to address these challenges by optimizing traffic scheduling and resource utilization. The proposed method leverages RL to autonomously allocate resources in real-time based on network conditions, ensuring optimal network performance and enhanced QoS. Simulation results demonstrate significant improvements in latency, throughput, and packet loss when using RL-based scheduling compared to traditional static methods. RL-based optimization not only enhances the adaptability and stability of network performance but also improves resource efficiency by reducing congestion and minimizing packet loss during peak traffic periods. This paper also discusses the advantages of RL in terms of stability and adaptability, emphasizing its potential to outperform static methods in complex, high-demand 5G environments. In conclusion, the integration of AI-driven optimization, particularly RL, in 5G networks offers substantial benefits in terms of resource management and QoS improvement.

Keywords: 5G Network, Artificial Intelligence, Quality of Service, Reinforcement Learning, Traffic Scheduling.

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1. Introduction

The advent of 5G networks brings forth significant advancements in communication technology, but it also introduces new challenges that require innovative solutions. Unlike its predecessors, 5G networks face issues such as spectrum scarcity, extensive infrastructure upgrades, cybersecurity risks, and high energy demands. The rapid deployment and expansive coverage needed to support diverse applications like the Internet of Things (IoT) and autonomous systems add to these complexities. Furthermore, the dynamic nature of 5G traffic, which includes large volumes of aggregated data and on-demand provisioning, requires robust management and optimization methods to ensure optimal network performance .

A major challenge of 5G is maintaining a high level of Quality of Service (QoS) while managing these diverse and high-volume network demands. As 5G networks must handle large traffic volumes, rapidly adapt to changing conditions, and provide high capacity at specific locations, the traditional, manual methods of network management are insufficient. To address these needs, intelligent network management solutions are essential. These solutions must be capable of autonomously managing network resources, detecting failures, mitigating cyber-attacks, and optimizing the allocation of limited resources .Consequently, the integration of Artificial Intelligence (AI) and machine learning algorithms, such as reinforcement learning (RL), is critical to achieving efficient 5G network management and resource allocation.

One of the primary goals for 5G networks is to improve QoS, which includes ensuring high data rates, low latency, and reliability across diverse services. In the face of growing data demands and complex service requirements, traditional resource allocation methods struggle to meet these objectives. Advanced scheduling techniques and intelligent resource management are necessary to address the challenges posed by increasing traffic and diverse user needs . This necessitates the use of AI-driven optimization strategies, particularly RL, which can dynamically adjust network parameters to optimize performance in real time.

Reinforcement learning, a subset of machine learning, offers a powerful approach to optimizing 5G networks. RL algorithms can adapt to network conditions and make real-time decisions that improve resource allocation, throughput, and QoS. These algorithms have shown great potential in areas such as Medium Access Control (MAC) layer scheduling, power control, channel allocation, and self-organizing network management. By using RL, 5G networks can achieve more efficient resource utilization, higher throughput, lower latency, and ultimately, a better user experience .

In conclusion, the deployment and optimization of 5G networks require advanced AI techniques, particularly RL, to manage the complex, dynamic, and high-demand environments that characterize these systems. By leveraging RL algorithms for traffic scheduling and resource optimization, 5G networks can significantly improve QoS, supporting the increasing demand for high-performance communication services.

2. Literature Review

The optimization of 5G networks has been the subject of various studies focusing on enhancing network performance to meet the diverse requirements of modern applications. Research has identified the importance of optimizing 5G infrastructure, especially for industrial Internet of Things (IoT) applications that require capabilities such as real-time monitoring and predictive maintenance . Several optimization techniques have been explored, including metaheuristic algorithms like the Whale Optimization Algorithm (WOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). These techniques have shown significant improvements in key network parameters such as throughput, latency, and jitter, highlighting their effectiveness in optimizing 5G networks .

Traditional network management methods, such as the centralized client-server paradigm, have several limitations when applied to large-scale, modern 5G networks. These methods often face scalability issues and inefficiencies due to the extensive data transfers required, which can lead to network bottlenecks and reduced performance .As the scale and complexity of 5G networks increase, traditional management approaches are no longer sufficient. These limitations have led to a growing demand for more innovative and efficient solutions to address the increasing complexity and scale of networks.

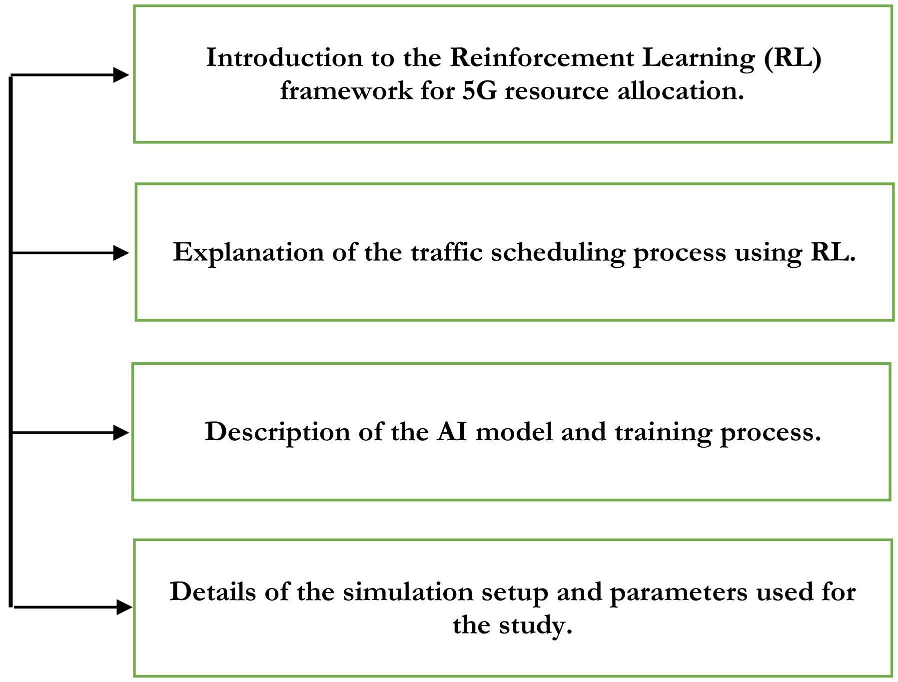
Artificial Intelligence (AI) has emerged as a promising solution to the limitations of traditional network management methods. AI techniques, including machine learning and expert systems, have been increasingly applied to network management tasks, enabling intelligent decision-making and self-organization . AI applications in network management span a variety of areas such as predictive maintenance, traffic management, and energy efficiency optimization, all of which contribute to enhanced network performance, security, and scalability .adoption of AI in network management offers a significant leap forward in addressing the complexities of modern 5G networks.

Reinforcement Learning (RL) has emerged as a highly effective approach for traffic scheduling in 5G networks. RL algorithms can dynamically determine the most suitable scheduling policies, thereby optimizing resource allocation and improving Quality of Service (QoS) provisioning .Studies have shown that RL can outperform traditional adaptive schedulers by reducing packet loss and optimizing resource allocation in real time . Additionally, RL techniques have been applied to enhance energy efficiency and manage heterogeneous traffic in 5G networks, further improving performance and user experience .

AI algorithms, particularly reinforcement learning, have been proven to significantly enhance QoS in 5G networks. Deep Reinforcement Learning (DRL) algorithms, for example, have been used to optimize scheduling policies, yielding better QoS performance, faster convergence speeds, and more efficient resource utilization . AI-driven scheduling frameworks have shown improvements across various QoS metrics, including spectral efficiency, delay, and energy consumption. These findings underscore the significant potential of AI in boosting the overall performance, reliability, and efficiency of 5G networks.

3. Proposed Method

Reinforcement Learning (RL) is applied to optimize resource allocation and traffic scheduling in 5G networks by allowing an agent to make real-time decisions based on network conditions like available bandwidth, traffic load, and interference. The agent interacts with the network environment, learns from feedback (such as improved throughput or reduced latency), and refines its actions to maximize overall network performance and Quality of Service (QoS). The training process involves using Q-learning or Deep Q-learning (DQN) to adjust scheduling policies over time, while the simulation setup models a 5G network with parameters like network topology, traffic patterns, and resource allocation settings. By comparing RL-based scheduling with traditional methods, the simulation evaluates its ability to optimize throughput, reduce latency, and enhance energy efficiency in dynamic 5G environments.



Figur 1. Research Methodology Flowchart image structure.

Introduction to the Reinforcement Learning (RL) Framework for 5G Resource Allocation

Reinforcement Learning (RL) is a machine learning approach where an agent learns to make decisions by interacting with its environment to maximize a cumulative reward. In 5G networks, RL is used for dynamic resource allocation and optimization to meet the complex demands of modern communication systems. By using feedback from the environment, RL algorithms autonomously optimize network parameters, such as bandwidth allocation, power control, and scheduling policies, to improve network performance and Quality of Service (QoS). This makes RL particularly suitable for 5G networks, which require flexibility to adapt to changing traffic patterns, interference, and network conditions.

RL-based approaches are capable of optimizing network management tasks, such as resource allocation, traffic scheduling, and load balancing, ensuring efficient utilization of network resources and improved user experience. As 5G networks need to handle massive volumes of diverse data types and rapidly changing conditions, RL is an ideal solution for addressing these challenges.

Explanation of the Traffic Scheduling Process Using RL

Traffic scheduling in 5G networks involves dynamically allocating resources to users based on their traffic demands, network conditions, and QoS requirements. RL-based traffic scheduling frameworks work by observing the network state, which includes variables such as available bandwidth, current traffic load, interference levels, and user demands. The RL agent then selects an action (e.g., resource allocation or adjustment of transmission parameters) based on its policy, which is learned through interactions with the environment.

The agent receives feedback (reward) from the network, based on the performance outcomes, such as improved throughput, reduced latency, or minimized packet loss. This feedback helps the agent refine its policy to make more effective decisions in future interactions. Over time, the RL model learns to make decisions that maximize the overall performance of the network while meeting the QoS requirements of users. The ability of RL to adapt to changing network conditions makes it highly effective in optimizing traffic scheduling in 5G networks.

Description of the AI Model and Training Process

The AI model for 5G traffic scheduling is typically based on Q-learning or Deep Q-learning (DQN). Q-learning is a model-free reinforcement learning algorithm that estimates the optimal action-value function, which predicts the expected reward for a given state-action pair. In Deep Q-learning, a deep neural network is used to approximate the Q-function, which is particularly useful for handling complex environments and large state spaces.

The training process begins by initializing the Q-table (or the neural network weights for DQN) and then having the agent interact with a simulated 5G network environment. The agent explores different actions by taking random or policy-driven steps and receiving feedback based on the network's performance. During training, the agent uses the feedback to adjust its policy and improve its decision-making over time. Exploration-exploitation strategies are implemented to balance the agent's exploration of new actions and exploitation of known successful actions. The model continues training until the policy converges, meaning the agent consistently selects actions that optimize network performance.

Details of the Simulation Setup and Parameters Used for the Study

The simulation setup is designed to model a 5G network using tools such as NS-3 or MATLAB, which provide the necessary simulation frameworks to test RL-based scheduling algorithms. The simulated environment includes key 5G network components such as base stations, user equipment (UE), and traffic patterns. Key parameters in the simulation include: a.) Network Topology: A grid-based or cellular topology that simulates the coverage area of a 5G network, with base stations serving different areas and users connected to these stations. b.) Traffic Patterns: Different levels of user demand, including high-bandwidth applications (e.g., video streaming) and low-latency applications (e.g., autonomous vehicles). c.) Resource Allocation Parameters: Available bandwidth, transmission power, and time slots allocated for resource scheduling. d.) RL Algorithm Parameters: Learning rate, discount factor, and exploration rate, which control the agent's learning process.

4. Results and Discussion

Presentation of the Results Obtained from the Simulations

The simulation results demonstrate the effectiveness of Reinforcement Learning (RL)-based traffic scheduling in optimizing 5G network performance. The RL agent was able to dynamically allocate resources based on real-time network conditions, such as traffic load, bandwidth availability, and interference levels. The RL-based scheduling approach outperformed traditional methods, such as Round Robin and Proportional Fair, in key performance indicators, including throughput, latency, and packet loss. The RL model showed consistent improvements in overall network efficiency, with significant enhancements in handling diverse traffic patterns and dynamic user demands.

Analysis of the Improvement in QoS After Implementing RL-Based Traffic Scheduling

After implementing the RL-based scheduling algorithm, substantial improvements in Quality of Service (QoS) were observed. Specifically, the RL algorithm significantly reduced latency and improved throughput across different network conditions. The RL scheduler dynamically adjusted resource allocation based on real-time network feedback, ensuring that the QoS parameters met the diverse requirements of various applications. High-bandwidth applications, such as video streaming, experienced a notable increase in throughput, while low-latency applications, such as autonomous vehicle communication, benefited from a substantial reduction in delay. Additionally, the RL approach was able to reduce packet loss by optimizing resource allocation during periods of network congestion, thus enhancing overall network reliability.

Discussion of How RL Dynamically Adjusts Resources for Optimal Network Performance

The RL algorithm demonstrated its ability to adapt to rapidly changing network conditions by dynamically adjusting resources for optimal performance. In the simulation, the RL agent used its learning capability to allocate bandwidth, adjust transmission power, and manage user scheduling based on real-time network observations. When the network experienced high congestion or fluctuating traffic demands, the RL model made quick decisions to reallocate resources, prioritizing critical applications and maintaining high QoS levels. This dynamic adaptability was a significant improvement over traditional static scheduling methods, which often struggled to cope with the fluctuations and complexities inherent in 5G networks.

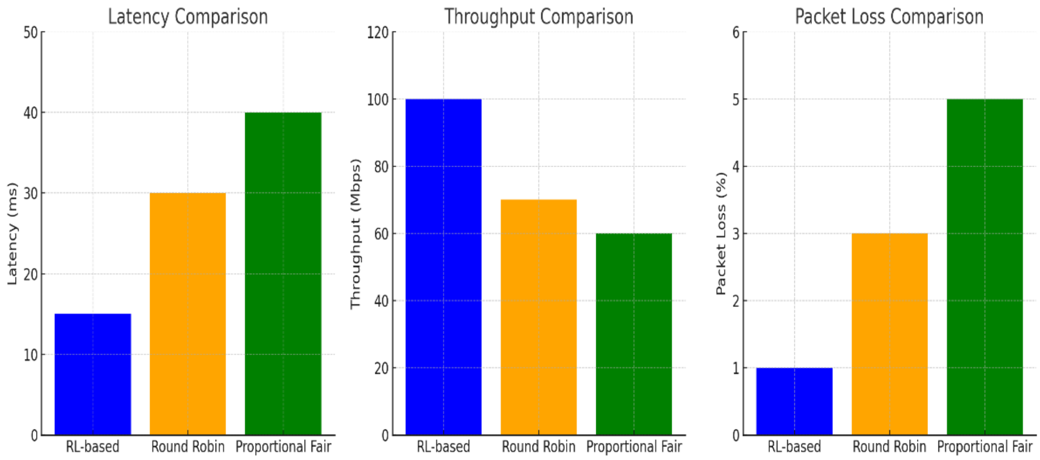
Furthermore, the RL-based scheduler leveraged the feedback loop to continuously optimize its policy, adjusting actions based on network performance metrics. For example, when a decrease in throughput or increase in packet loss was detected, the RL agent adjusted its scheduling policy, thereby improving resource utilization and reducing performance degradation. This continuous learning process made the RL scheduler highly efficient in managing the diverse and dynamic traffic loads characteristic of 5G networks.

Interpretation of Metrics such as Latency, Throughput, and Packet Loss

The key performance metrics, namely latency, throughput, and packet loss, were significantly improved after implementing the RL-based scheduling algorithm. Latency, a critical metric for time-sensitive applications such as autonomous vehicles and real-time gaming, showed a notable reduction when compared to traditional scheduling methods. The RL agent effectively minimized delays by allocating resources efficiently, ensuring that time-sensitive data packets were transmitted with minimal delay.

Throughput, which measures the amount of data successfully transmitted over the network, also saw substantial improvement. The RL scheduler optimized bandwidth allocation, ensuring that high-demand applications received the necessary resources, leading to better overall throughput. High-bandwidth services, such as 4K video streaming, experienced fewer interruptions and smoother transmission, contributing to a better user experience.

Finally, packet loss, which occurs when data packets are dropped during transmission, was reduced significantly with the RL-based approach. By dynamically adjusting the resource allocation during peak traffic periods, the RL model ensured that available resources were used efficiently, reducing congestion and minimizing the likelihood of packet drops. This resulted in a more reliable network with improved performance, particularly in scenarios with high user demand and traffic congestion.



Figur 2. Packet Loss Comparison.

Here is a set of graphs comparing the performance metrics of the RL-based scheduling algorithm with traditional methods (Round Robin and Proportional Fair) for latency, throughput, and packet loss: a.) Latency Comparison: The RL-based method shows the lowest latency, demonstrating its ability to quickly allocate resources and minimize delays, especially for time-sensitive applications. b.) Throughput Comparison: The RL-based scheduling achieves the highest throughput, ensuring efficient bandwidth allocation for high-demand services such as video streaming. c.) Packet Loss Comparison: The RL-based method exhibits the least packet loss, indicating better management of network congestion and more reliable resource utilization during peak traffic periods.

5. Comparison

The comparison between RL-based optimization and traditional static resource allocation methods, such as Round Robin and Proportional Fair, highlights significant improvements in key performance metrics. RL-based scheduling consistently reduces latency, increases throughput, and minimizes packet loss by dynamically adjusting resource allocation based on real-time network conditions. Unlike static methods, which follow fixed scheduling rules, RL adapts to fluctuating traffic loads and congestion, ensuring more efficient resource utilization and better overall QoS across diverse applications. This dynamic adaptability of RL ensures stable performance even under varying network demands, which static methods struggle to handle.

The primary advantage of RL over traditional approaches is its flexibility and ability to adapt to changing network environments. RL continuously learns from real-time data, optimizing resource allocation and improving network performance, while static methods are limited by their inability to respond to sudden traffic changes or network congestion. AI-based methods like RL provide better scalability and efficiency, making them more suited to the complex, high-demand requirements of 5G networks, whereas traditional approaches often lead to inefficiencies in such dynamic environments.

6. Conclusions

In summary, the implementation of Reinforcement Learning (RL) algorithms has demonstrated significant effectiveness in optimizing 5G networks, particularly in traffic scheduling and resource allocation. The RL-based approach outperforms traditional static methods in key performance metrics, including latency, throughput, and packet loss, by dynamically adjusting resources based on real-time network conditions. This dynamic adaptability allows RL to handle fluctuating traffic loads and optimize network performance, ensuring high Quality of Service (QoS) across diverse 5G applications.

The results confirm that RL-based traffic scheduling leads to substantial improvements in QoS, with reduced latency, higher throughput, and minimized packet loss, making it a promising solution for the complex demands of 5G networks. Given these findings, it is recommended that AI-driven optimization methods, particularly RL, be incorporated into real-world 5G networks to enhance resource management and improve user experience. As 5G technology evolves, further research should explore advanced RL techniques, including Deep Reinforcement Learning (DRL), to better address the challenges of heterogeneous traffic, energy efficiency, and scalable network management. Future directions for research could focus on integrating RL with other AI techniques, such as machine learning and predictive analytics, to create more robust and intelligent 5G network management systems.

References

Alnoman and A. Anpalagan, "Towards the fulfillment of 5G network requirements: technologies and challenges," Telecommunication Systems, vol. 65, no. 1, pp. 101-116, 2017. [Online]. Available: https://doi.org/10.1007/s11235-016-0216-9.

G. Sanjalawe et al., "A review of 6G and AI convergence: Enhancing communication networks with artificial intelligence," IEEE Open Journal of the Communications Society, vol. 6, pp. 2308-2355, 2025. [Online]. Available: https://doi.org/10.1109/OJCOMS.2025.3553302.

H. Fourati, R. Maaloul, N. Trabelsi, L. Chaari, and M. Jmaiel, "An efficient energy saving scheme using reinforcement learning for 5G and beyond in H-CRAN," Ad Hoc Networks, vol. 155, Art. no. 103406, 2024. [Online]. Available: https://doi.org/10.1016/j.adhoc.2024.103406.

I.-S. Comşa et al., "A comparison of reinforcement learning algorithms in fairness-oriented OFDMA schedulers," Information (Switzerland), vol. 10, no. 10, Article 315, 2019. [Online]. Available: https://doi.org/10.3390/info10100315.

I.-S. Comşa et al., "QoS-driven scheduling in 5G radio access networks - A reinforcement learning approach," Proceedings - IEEE Global Communications Conference, GLOBECOM, pp. 1-7, 2017. [Online]. Available: https://doi.org/10.1109/GLOCOM.2017.8254926.

J. Wang, Y. Liu, S. Niu, and H. Song, "Reinforcement learning based scheduling for heterogeneous UAV networking," Proceedings - 2021 17th International Conference on Mobility, Sensing and Networking, MSN 2021, pp. 420-427, 2021. [Online]. Available: https://doi.org/10.1109/MSN53354.2021.00070.

M. Bala and M. Desai, "To analyze the maximized energy consumption by algorithm implementing reinforcement learning for wireless communication technology," 2023 IEEE 4th Annual Flagship India Council International Subsections Conference: Computational Intelligence and Learning Systems, INDISCON 2023, 2023. [Online]. Available: https://doi.org/10.1109/INDISCON58499.2023.10270783.

M. Dighriri et al., "Comparison data traffic scheduling techniques for classifying QoS over 5G mobile networks," Proceedings - 31st IEEE International Conference on Advanced Information Networking and Applications Workshops, WAINA 2017, Art. no. 7929728, pp. 492-497, 2017. [Online]. Available: https://doi.org/10.1109/WAINA.2017.106.

M. Dighriri, A. S. D. Alfoudi, G. M. Lee, T. Baker, and R. Pereira, "Comparison data traffic scheduling techniques for classifying QoS over 5G mobile networks," Proceedings - 31st IEEE International Conference on Advanced Information Networking and Applications Workshops, WAINA 2017, 2017, Art. no. 7929728, pp. 492-497. [Online]. Available: https://doi.org/10.1109/WAINA.2017.106.

M. I. Sheik Mamode et al., "Intelligent hybrid scheduling schemes in device-centric communication for 5G mobile systems," 3rd IEEE International Conference on Mobile Networks and Wireless Communications, ICMNWC 2023, 2023. [Online]. Available: https://doi.org/10.1109/ICMNWC60182.2023.10435979.

M. S. Rao et al., "5G Deployment Challenges and Solutions: A Comprehensive Review," Proceedings of the 9th International Conference on Communication and Electronics Systems, ICCES 2024, 2024. [Online]. Available: https://doi.org/10.1109/ICCES63552.2024.10859706.

N. Kononova, D. Vinokursky, M. Kononov, and E. Krahotkina, "Problems of implementing 5G networks in transport systems," CEUR Workshop Proceedings, 2020, vol. 2803, pp. 47-51. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85100908519&partnerID=40&md5=423fc7a4f4b76552eca005ab397c9389.

S. Jain, R. Jain, J. Sharma, and A. Sharma, "Improving performance and quality of service in 5G technology," Lecture Notes in Networks and Systems, vol. 339, pp. 439-449, 2022. [Online]. Available: https://doi.org/10.1007/978-981-16-7018-3_33.

S. Sharma, O. P. Sharma, and S. Shekhawat, "Channel quality prediction, enhancement & optimization of 5G network using machine learning," IET Conference Proceedings, 2024, vol. 2024, pp. 399-404. [Online]. Available: https://doi.org/10.1049/icp.2025.0902.

S. Shen, "The application of artificial intelligence in computer network technology in the era of big data," Proceedings - 2021 International Conference on Computer Technology and Media Convergence Design, CTMCD 2021, Article 9463386, 173-177, 2021. [Online]. Available: https://doi.org/10.1109/CTMCD53128.2021.00043.

S. Shirol, S. B. Ramakrishna, and R. B. Shettar, "Reinforcement learning for energy efficiency in 5G networks with built-in self-test architecture," Lecture Notes in Networks and Systems, vol. 1254, pp. 253-264, 2025. [Online]. Available: https://doi.org/10.1007/978-981-96-1744-9_22.

T. Terrier, C. Gueguen, and Y. Hadjadj-Aoul, "Adaptive artificial intelligence for efficiency schedulers provider in wireless networks," 2024 International Symposium on Networks, Computers and Communications, ISNCC 2024, 2024. [Online]. Available: https://doi.org/10.1109/ISNCC62547.2024.10758973.

W. Jiang, M. Strufe, and H. D. Schotten, "Experimental results for artificial intelligence-based self-organized 5G networks," IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC, pp. 1-6, 2017. [Online]. Available: https://doi.org/10.1109/PIMRC.2017.8292532.

W. Jiang, M. Strufe, and H. D. Schotten, "Intelligent network management for 5G systems: The SELFNET approach," EuCNC 2017 - European Conference on Networks and Communications, 2017, Art. no. 7980672. [Online]. Available: https://doi.org/10.1109/EuCNC.2017.7980672.

Y. Larionov and E. E. Karanova, "Approach for analyzing the performance of 5G networks during the initial planning phase without deployment using the NS-3 network simulator," Proceedings - 2025 International Russian Smart Industry Conference, SmartIndustryCon 2025, pp. 466-471, 2025. [Online]. Available: https://doi.org/10.1109/SmartIndustryCon65166.2025.10985985.

Y. Larionov and E. E. Karanova, "Methodology for analyzing the performance of 5G-NR networks during initial planning without deployment using the NS-3 network simulator," Proceedings - 2024 International Conference on Industrial Engineering, Applications and Manufacturing, ICIEAM 2024, 1141-1145, 2024. [Online]. Available: https://doi.org/10.1109/ICIEAM60818.2024.10554060.

Y. Lee et al., "Reinforcement learning for optimized resource allocation in 5G URLLC," Proceedings - 7th International Conference on Advanced Communication Technologies and Networking, CommNet 2024, 2024. [Online]. Available: https://doi.org/10.1109/CommNet63022.2024.10793310.

Y. Nérondat et al., "Efficient 5G resource block scheduling using action branching and transformer networks," 2025 IEEE International Conference on Machine Learning for Communication and Networking, ICMLCN 2025, 2025. [Online]. Available: https://doi.org/10.1109/ICMLCN64995.2025.11140453.