National Journal of Antennas and Propagation, ISSN: 2582-2659 Vol. 7, No. 2, 2025 (pp. 8-13)

RESEARCH ARTICLE

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Development of A Novel Resource Allocation Algorithm for 5G Ran Using Reinforcement Learning and Game Theory

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KEYWORDS:
Reinforcement learning,
5G,
Game Theory,
Deep learning

ARTICLE HISTORY:

Received 29-01-2025
Revised 23-03-2025
Accepted 12-05-2025

DOI:
https://doi.org/10.31838/NJAP/07.02.02

Abstract

In this, the implemented DRL based DDQN-CASA algorithm for resource allocation with to approximate Deep Q-function with uses of double deep neural network, that gains from existing experience and adapts to changing environments. The results prove that the proposed simulation delivers improved Resource Allocation with DRL based technique compared to existing models, leading to reduced latency and improved output. Effectively, the DRL-based DDQN algorithm provided 13% higher profit than existing techniques. This learning covers further way of development and research in progressive DRL based Admission Control and resource allocation methods used for 5G/6G, it is providing better resources utilization and allocation, their developing vertical services meets performance demands. In this, compare performance of implemented modules with various existing modules based on factor latency, utilization rate and throughput. At last, we also include the conclusion and future directions of our related work.

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How to cite th is article: Biswas D, Tiwari A, Puri S, Development of A Novel Resource Allocation Algorithm for 5G Ran Using Reinforcement Learning and Game Theory, National Journal of Antennas and Propagation, Vol. 7, No.2, 2025 (pp. 8-13).

Introduction

Wireless networks use radio waves to transmit data. 5G has been initiated by many organizations. The advance development of the 5G cellular network provides higher bandwidth. 5G offers lower latency, higher speed, and greater capacity..[1] 5G could address drawbacks of existing technologies. 5G is offering higher broadcasting capacity ranging from many more Gb that maintaining many thousand connections at the same time. 5G provides more security than 4G Network, it is also upgrading bi-directional frequency shaping. Apart from speed, the channel for 5G network is quite high so we are moving from 4G to 5G. Over the long periods, the background of wireless communication technology from 1G to 4G, wireless technology has accomplished huge advances in data transmission.[2] 5G can be a great innovate network technology which can achieve better performance.[9] The main purpose of 5G is to provide faster data speeds, wide coverage area, admission policy, reliability, security, support for wearable devices, and service of HD multimedia broadcasting. It has been demanding concern to meet the requirements of QoS for any network services. The network technologies would be able to back the constant revolution network functions of the latest network structure, like merges with new applications, dynamic resource allocation, admission control network, superior QoS, and effective packet transferring licensed user.

RELATED WORK

The fifth generation (5G) of wireless communication technology has ushered in a new era of connectivity, promising higher speeds, ultra-low latency, and massive connectivity.[3] However, with the increased adoption of 5G and the advent of future communication technologies, ensuring robust security measures is of paramount importance. Researchers provide a comprehensive overview of the security challenges and solutions in the context of 5G and beyond.[13] begins by emphasizing the critical role of security in the 5G ecosystem, considering the diverse range of applications and the proliferation of connected devices.The authors provide an overview of the security requirements and threats in 5G networks, highlighting the need for comprehensive security measures to protect against attacks such as eavesdropping, data manipulation, and denial-of-service (DoS).[4] The article delves into the various security mechanisms proposed for 5G networks.[10] These mechanisms include encryption algorithms, authentication protocols, key management schemes, and intrusion detection systems.Ahmad et al. also examines the role of standardization organizations and regulatory bodies in addressing the security needs of 5G and beyond. Researchers highlight the efforts of organizations such as the 3rd Generation Partnership Project (3GPP) in defining security standards and protocols for 5G networks.[13] The authors discuss ongoing research initiatives aimed at addressing the security challenges and potential solutions for future communication technologies, including 6G.[5] The review highlights the importance of a multi-layered security approach, emphasizing the need for encryption, authentication, and intrusion detection mechanisms.

The Authors offer a comprehensive analysis of the security challenges and solutions in the context of 5G networks.[8] The review provides valuable insights into the security requirements, vulnerabilities, and potential mechanisms for ensuring robust security in 5G and future communication technologies.[15] However, while the article covers various security mechanisms, it would have benefited from a more detailed evaluation of their effectiveness and practical implementation challenges. Additionally, the article could have provided further insights into the trade-offs between security and performance in 5G networks.[11] According to,[5] the paper by Dogra, A. et al. (2020) titled “A Survey on Beyond 5G Network with the Advent of 6G: Architecture and Emerging Technologies”.[6] As the deployment of 5G networks continues to expand, researchers and industry experts are already looking towards the future of wireless communication technology. Researchers provide a comprehensive survey of the emerging technologies and architectural considerations for beyond 5G networks, with a focus on the anticipated 6G era. Authors start by discussing the current 5G networks and the need for further advancements in the form of 6G. The authors highlight the key drivers behind the development of 6G, such as the exponential growth of data traffic, the increasing demand for ultra-high-speed communication, and the integration of emerging technologies like artificial intelligence (AI), Internet of Things (IoT), and edge computing.

METHODOLOGY

This research work follows a systematic methodology and adopts a comprehensive approach to develop an adaptive resource allocation model with integrated admission control mechanisms in 5G networks using deep reinforcement learning. The following steps will be undertaken to achieve the research:

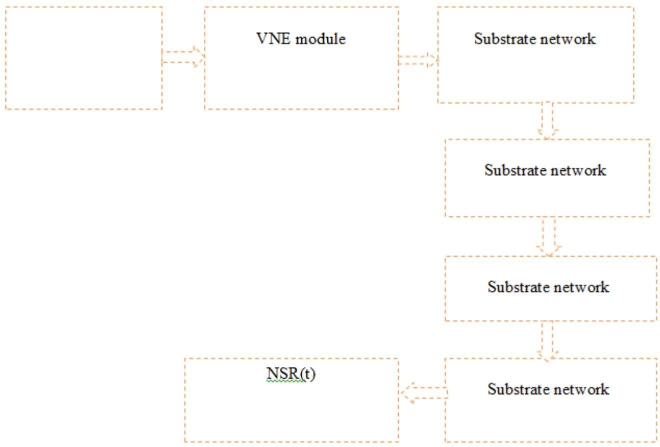

Fig. 1: Admission Control and Virtual Network Embedding

The network slicing can show a dynamic character in facilitating a variety of 5G appliances, verticals, and facilities.[14] Network slicing capabilities will give start to finish detachment between cuts with a capacity to tweak each cut in light of the help requests (transfer speed, inclusion, security, idleness, this work predominantly focuses on a clever AC and RA module for 5G organization cutting in view of Profound RL[12] The proposed Deep DQN algorithm trains RA modules with trial-and-error contacts with network surroundings, including terms for instance user QoE/QoS, accessible resources, lower latency, and network circumstances. The model outcomes show that this method improves performance than conventional methods based on throughput, latency, and fairness of the network. This technique could deliver a basis for upcoming research in the same region and improve throughput of 5G networks. The scheme estimates Q-Value with the Deep DQN, which approximates the predictable reward of every action assumed by the present network state. Commonly, this technique DDQN-CASA delivers an advance in addressing the challenge of efficient Resource Allocation in a 5G network which provides 13% higher profit than conventional techniques and improved QoS and customer understanding. Reliability, etc.).

Preserving allotment of machines, traffic stream, and organization highlights among cuts is fundamental in safeguarding network association plans. Its requests and new highlights assist progressing and composite corporate necessities with having assembled existing approaches to organize wellbeing flawed. In this work, the fostered a Brain Organization based control access module utilized for Organization Cutting and to recognize and wipe out dangers in light of approaching associations before they plague the 5G center organization. 'Secure 5G' is a versatile model that isolates the dangers guaranteeing start to finish security from device(s) to the center organization, and to any of the outside organizations. In this, the planned model empowered the organization administrators to offer organization cutting as-a-administration to serve different administrations effectively over a solitary foundation with high security and dependability. The proposed ES system. Which incorporates two modules: an air conditioner module and a VNE module. AC Module in view of a RL/DRL calculation and performs confirmation control of NSRs. This module concludes which NSRs occupants acknowledge or dismiss in view of the need. The second VNE Module depends on an ILP (Whole number Direct Programming) and heuristic calculation and accomplishes RA on Network Slice. This module involves mapping virtual network requests onto the physical infrastructure efficiently. It is important in the 5G networks to ensure optimal resource utilization. The anticipated ES agendas are planned below.

- At time t, an NSR arrives at the AC module. It decides to accept or reject the NSR based on the output of the VNE module and the status of the SN at the previous time step.
- When the AC component gets an NS Request, it notifies the VNE component thus it could be inserted in the network slice and it could be rejected.
- Once the VNE module receives acceptance from the AC module, it performs the embedding procedure. If the NS Request embeds successfully, the VNE module sends positive feedback to the AC module; otherwise, it sends negative feedback. The latter is important for the AC module because it can learn to reject NSRs that cannot be embedded in advance.

In this work, the design of the proposed technique incorporates four modules-The Checking module, ACM (Confirmation Control Module), Slam (Asset Assignment Module), and Lifecycle module. The organization improvement has three verticals eMBB, uRLLC, and mMTC of 5G organization cutting. These modules contain two programming specialists, the RL and DRL based that thinking about the express, the activity, and the award climate as shown in figure 1. The methodology processes the showing up Organization Cut Solicitations (NSLRs) in groups gathered in time windows. The Checking module gathers data about asset openness in network substrates like hubs and connections. Occasionally, it conveys this data to the affirmation control.

Results and Analysis

In this research work, we implemented the M - DRL (Modified - Deep Reinforcement Learning) algorithm for admission control in 5G network slicing. It involves implementing a secure system for accepting or rejecting access to the network based on user or device authentication. The main motive of the M - DRL algorithm is to increase profit and enhance acceptance ratio related to conventional techniques.

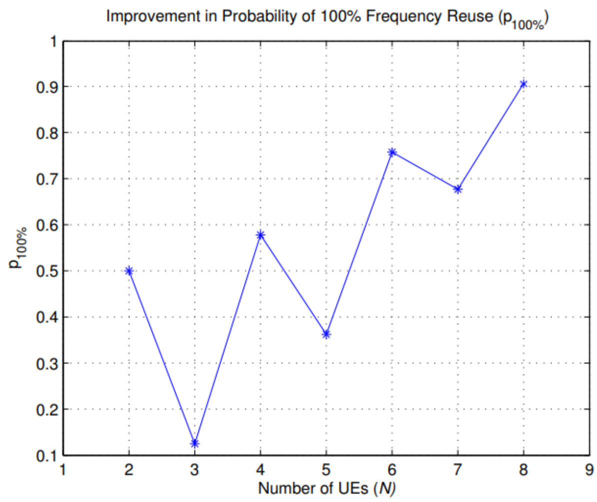

Fig. 2: Improvement in Probability of 100% Frequency Sharing (p100%)

The outcomes prove that the M - DRL algorithm is noticeably better than conventional techniques and algorithms. From the profit perspective, M - DRL reached incredible outcomes related to DSARA, SARA and AAR. This profit gained by M - DRL has 9% more than the conventional techniques.

One possible radio technology to help meet the growing need for cellular data capacity is IBFD. This paper examines a practical HICN with IBFD capable BS and older HD UEs, taking into account the intrinsic challenges involved in the realisation of IBFD transceivers. We have developed a general limited optimisation problem for resource allocation in order to improve sum-SE in an HICN. This is the first resource allocation mechanism for HICNs that we are aware of, and it does not require UEs

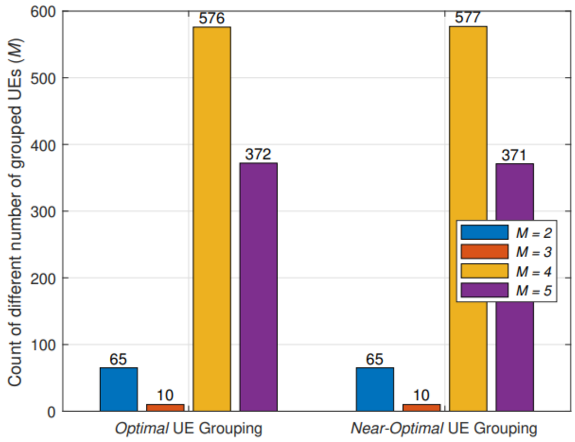

Fig. 3: Count of number of grouped UEs

to explicitly perform UE-to-UE SL CSI. In order to achieve the SL CSI, a location-aware technique presented here avoided the requirement for computational and signaling-intensive methods that have been used in the past.

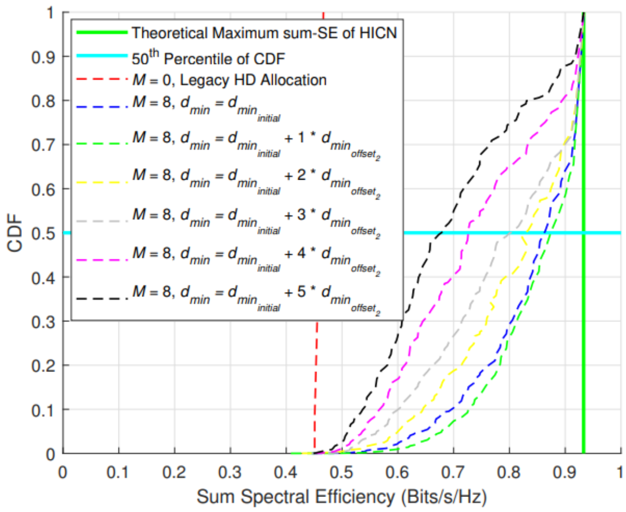

Fig. 4: Cumalative Distribution Function

We have created a power allocation algorithm that is non-iterative and does not cause convergence problems. The optimal set of UE groups to maximise frequency sharing among UEs in an HICN has been identified using a robust adjacency matrix approach that was established to capture the frequency sharing possibilities between UEs. As a result, the suggested group sharing strategy has outperformed current literature reference works in terms of sum-SE gain. Three different UE grouping algorithm variations can accommodate different time complexity and performance needs resulting from various deployment scenarios. It is demonstrated that a unified frequency allocation strategy can be used with either of the suggested UE grouping algorithms.

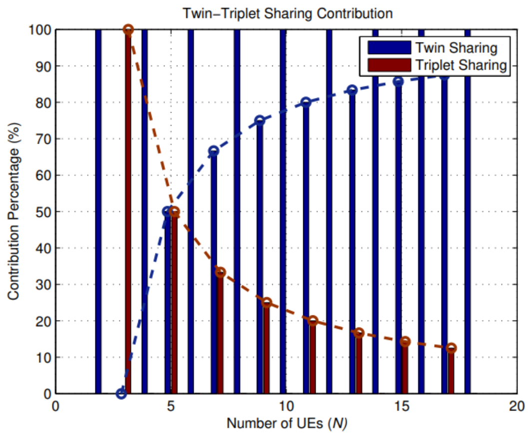

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Fig. 5: Twin-Triplet Sharing Contributions in p100%

The upgraded DRL algorithm used in M-DRL, which accepts advanced learning and selects actions relevant to the maximum profit, may be responsible for the increased profit. As shown in figure 6, the progressive learning capability enables quick identification of the most lucrative Network Slice Request (NSLR) groupings and acceptance of them, leading to a significant increase in overall profit.

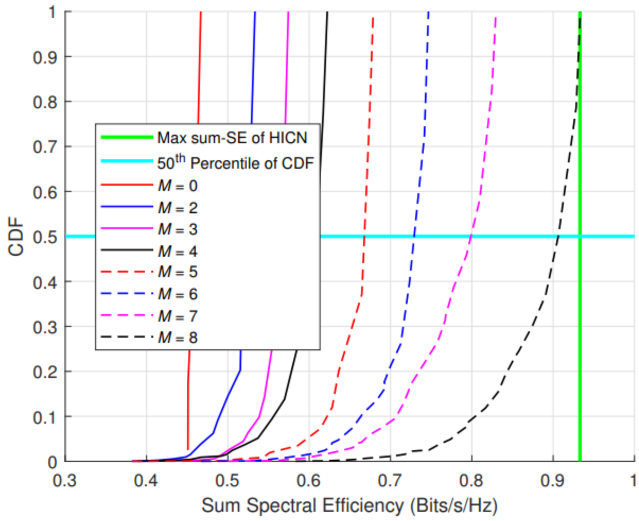

Fig. 6: Function of arrival rate

Figure 6 illustrates how profit and overall arrival rate work together. The number of network slice request entrances is insufficient to provide RL and DRL agents with useful information when the arrival rate is very low. Because of the higher-than-expected arrival rates, DDQN-CASA made more money.

In typical cellular situations, including UE mobility, new time-complexity-saving strategies based on the idea of ineligible UEs and the correlation coefficient of the adjacency matrix have demonstrated a practical

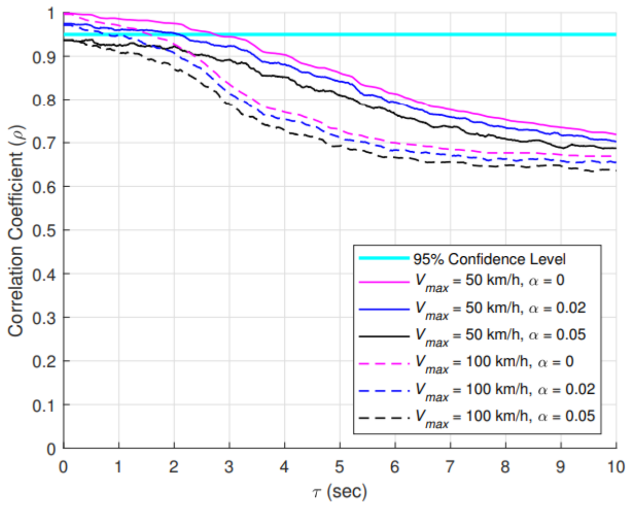

Fig. 7: Arrival Rate

ability to minimise the computational burden at BS. To demonstrate that our suggested method is appropriate regardless of cell size, we have tested it for three distinct BS classes with various coverage ranges. In a small cell Pico BS scenario, the computationally realistic near-optimal UE grouping algorithm—which is advised for real-time cellular systems—has demonstrated an impressive median sum-SE of 93.5% of the theoretical doubling maximum over the older HD systems, which is extremely pertinent for 5G.

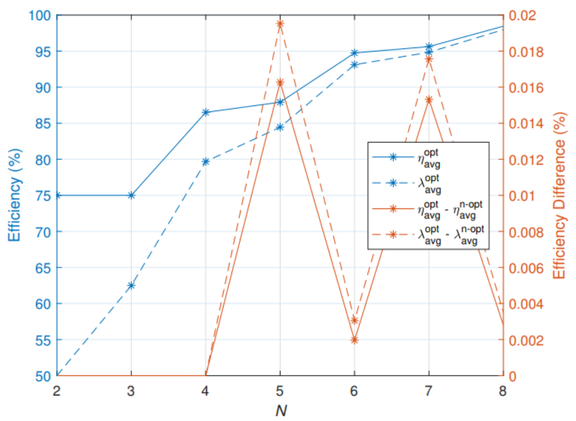

Fig. 8:Performance efficiency

The suggested sum-SE maximisation approach will be very appealing to the service providers since it can help to accommodate more UEs within the given spectrum, but the cost of obtaining additional spectrum is much greater. It is crucial to remember that the suggested approach keeps the legacy HD UEs and just needs IBFD functionality at the BS. Therefore, it can be implemented with the least amount of disturbance to current cellular systems. Additionally, this work has a broad reach and high applicability across all service verticals of future cellular networks because the assumptions established are reasonable and realistic. With these benefits, the suggested method to optimise sum-SE for HICN-type networks will be a solid and promising contender for cellular systems in 5G and beyond.

Conclusion

This work mainly concentrates on a novel AC and RA module for 5G network slicing based on Deep RL. The proposed Deep DQN algorithm trains RA modules with trial-and-error contacts with network surroundings, including terms for instance user QoE/QoS, accessible resources, lower latency, and network circumstances. The model outcomes show that this method improves performance than conventional methods based on throughput, latency, and fairness of the network. This technique could deliver a basis for upcoming research in the same region and improve throughput of 5G networks. The scheme estimates Q-Value with the Deep DQN, which approximates the predictable reward of every action assumed by the present network state. Commonly, this technique DDQN-CASA delivers an advance in addressing the challenge of efficient Resource Allocation in a 5G network which provides 13% higher profit than conventional techniques and improved QoS and customer understanding.

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