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Dynamic Resource Allocation Using a DRL Method in 5G Network

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Abstract: Wireless communication has become increasingly popular in the past two decades. The purpose of 5G is to provide higher bandwidth, lower latency, greater capacity and enhanced QoS (quality of service) than 4G. The 5G cellular network combines two technologies, SDN (software-defined network) and NFV (network function virtualization), for advanced management of the Network. This paper presents the main concepts related to RA (resource allocation) in a 5G network, which is the idea of dividing the network into multiple independent networks, each satisfying specific requirements while offering superior QoS. 5G network services can be classified into three verticals – (i). enhanced-Mobile Broadband (e-MBB), (ii). ultra-Reliable and Low Latency Communication (u-RLLC), and (iii). Massive-Machine Type Communications (m-MTC). Users require well-organized resource allocation and management. In this work, we implement a resource allocation module with Deep Reinforcement Learning (DRL) to estimate the Q-value function that utilizes a deep neural network, which learns from previous experience and adjusts to changing environments. The outcomes demonstrate that the implemented simulation reaches better in resource allocation compared to previous models, leading to lower latency and better throughput.

Index Terms *- 5G Cellular Network, Network Slicing, DRL, Deep Q- Learning Network.*

1. Introduction

5G CELLULAR NETWORK: Cellular networks use radio waves to transmit data [1]. These systems are rapidly growing, with the use of advanced algorithms and techniques [2]. The purpose of 5G is to provide higher bandwidth, lower latency, greater capacity, and better quality of service (QoS) than 4G [3,4]. A new type of network was developed to link virtually everyone and everything, including objects, machines, and devices [5]. The goal of isolating the network into various independent networks is named Network slicing, each satisfying specific requirements while offering superior QoS. [6]. The 5G cellular network used two combined technologies: NFV and SDN designed for advanced network management [7]. Both perform crucial jobs in facilitating 5G network slicing. SDN provides centralized control, flexibility, programmability, security, and end-to-end network visibility. NFV provides virtualized software, resource pooling, efficiency, and dynamic scaling. [8]. The 5G is being massively used worldwide compared to the previous mobile generations. The users require well-organized resource allocation and management. We propose a resource allocation model for a 5G Network Slicing with DRL based on Deep Q Learning Network. We evaluate the results of implemented resource allocation model with DRL. This paper majorly focuses on the 5G network slicing that used a DRL-based resource allocation model for better performance and throughput.

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NETWORK SLICING: The aim of separating the network into various independent networks is known as network slicing, each satisfying specific requirements while offering superior QoS [9]. The network implements excellent management of slices to enhance the throughput along with low latency [10,11]. Network slicing functions will provide isolation [12]. Three main use cases will be 5G support, these are enhanced-Mobile Broadband (e-MBB), massive-Machine Type Communications (m-MTC), and ultra-Reliable and Low-Latency Communications(u-RLLC). [13,14].

- **eMBB:** The services of eMBB will provide enhanced QoS requirements and improved broadband access. It ensures high network capacity and reliable access for users in intelligent trains and moving vehicles anytime and everywhere. It provides some services such as VR/AR, MR, 3D video conferencing, HD video streaming, and real-time virtual interactions. eMBB delivers important features are the peak data rate- of 20 Gb/s [25], energy efficiency-100 times faster, area traffic capacity of- 10Mbits/s/m^2, peak spectral efficiency- of 30 b/s/Hz [25], user data rate-100 Mb/s, mobile latency rate- of less than 1 ms. [15,17].
- **uRLLC:** It ensures high reliability and low latency,

which performs crucial jobs in mission-critical services and real-time applications. It improves the quality of the network. The uRLLC use case provides control plane latency is 10-20ms, ensures 99.9% reliability is lesser than 1ms/packet, and mobility breakage time is less than 1ms. There are some applications that cover industrial automation, remote surgery, and smart transportation [25]. Industrial automation refers to the monitoring and controlling of manufacturing activities with the help of machines. Remote surgery refers to the operation of patients from remote locations through the aid of machines and computers. Smart transportation means the traffic is controlled and managed intelligently [15,25].

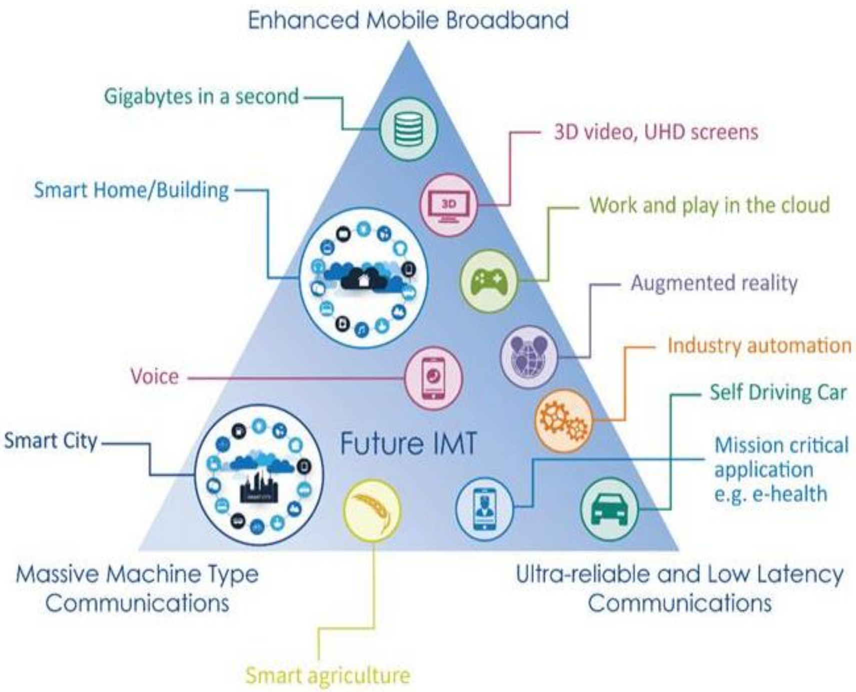

Figure 1: 5G Network usage defined by ITU

- **mMTC:** It deals with the interaction of different massive amounts of associated devices without any participation of human beings. The mMTC use case provides a 1M devices/Km^2 superior connection density [25], low-cost IoT, 10 km/h indoors for high mobility, Rural Area has 500 km/h and dense municipal has 30 km/h. Some appliances of mMTC comprise the management of fleets, autonomous vehicles, smart metering, health monitoring, surveillance, security, and industry automation, [15,25].

Drl-Based Resource Allocation:

DRL is the ML algorithm. It comprises RL and DL [15]. With the growing request for high-speed data and the increasing number of connected devices, 5G networks demand well-organized resource allocation methods to ensure the best performance [11]. Existing policies of resource allocation have been widely used earlier such as round-robin, proportional fair, and max-min fairness. But these policies have some disadvantages and may not be enough to meet the QoS requirements. 5G Network slicing is used to solve this problem, with each slice personalized to a specific use case by different QoS requirements [18,15]. We implement a resource allocation module with DRL-based DDQN (Double Deep Q-Learning) that utilizes the NNs (neural networks) to estimate Q value, which learns from previous experience and adjusts to changing environments. By considering several factors for example user demands, available resources, and network conditions, DRL-based resource allocation policies can enhance network performance.

DEEP Q-learning Network:

DQN has learned from past experiences in an environment to obtain the maximum reward.

- It is a NNs that guesses a Q value function.
- The input is state for system and by meeting the requirements of the state all the feasible actions generated through Q-values are our final output.
- DQN is based on a reinforcement learning algorithm however Deep Learning model is created to find the actions, and an agent can take an action at each state [19].

Training Steps –

Deep Q learning (Train by itself, then reward)

- It stores all the previous experiences in the system.
- Action is taken through best rewards of Q network [13].
- With help of mean square of the predicted and target Q value which is Loss function [12].

Double DQN:

DDQN is the extension of DQN utilized in reinforcement learning. It uses two neural networks (Double Q Network) that are a policy network is used to select the actions created on the existing state and a target net is applied to estimate value of the selected action [26]. It gives a more accurate estimate of action values. The goal of DQN is to decrease overestimates by partitioning the process [21,22].

2. Literature Review

We provide an overview of related work in the field of RA in 5G Network Slicing using DRL. The goal of this approach is to optimize the allocation of resources such as low latency, high throughput and better fairness among users while maximizing the overall system performance.

According to [12], the paper by Ssengonzi et al. (2022) provides an overall complete survey of DRL in virtualization and network slicing in 5G. Authors are inspiring through Artificial Intelligence and Machine learning tools for address challenges of slice management and orchestration. The authors introduce the terms virtualization and network slicing, including the problem formulation. The authors discuss the overview of RL and DRL approaches with value function, policy search optimization, Q-learning, and Transfer learning.

According to [13], a paper by Xiong et al. (2019) studied significant concepts related to RA problems in 5G and beyond can solve using DRL. They implemented the DRL-based module for the maximization of network slicing. They considered a (state-actions) pairs for Q value, to hold the mapping of the system it use Q learning list, taking random actions in the system, and a greedy system for the best rewards obtained from current actions. They implemented mathematical equations to express the enhanced performance of the DRL-based scheme.

According to [14], the paper by Li et al. (2018) gives an overview of RL and Q-Learning and discusses the purpose to develop Deep Q-Learning (DQL) from Q-Learning. They manage resource allocation in the priority-based core network and radio resource slicing through DQL. DQL could provide another solution by first serving the users through advanced profitable value to utilize the computation resources and decrease the delay time. DQL enhances the efficiency and flexibility of network slicing to ensure the QoE per user.

As per [15], the study by Nguyen et al. (2021) reviewed the recently developed schemes of the Machine Learning and Resource management. In the 5G vehicular network, these schemes are used in cloud-computing, edge-computing, and fog-computing. They ensure several QoS requests. The authors proposed a mechanism for FDRL-based vehicular communication. UAV, and UAV-assisted vehicular communication.

According to [18], the paper by Suh et al. (2022) has considered a DRL-NS which is DRL based network slicing system, to enhance the scheme results furthermore fulfilling every QoS needs. The unwanted RA decisions can be rejected though a system termed action elimination, which interrupts different QoS needs that enhance the learning performance.

According to [19], the paper by Liu et al. (2020) has considered a novel network slicing technique termed Deep Slicing that combines the ADMM. With the Deep RL algorithm, Deep Slicing is trained with Actor-Critic method, which manage the different resources required QoS demands, improves the RAs consequently. The Deep Slicing achievement has been confirmed in the outcomes of network.

As per [23], a paper by Ye and Li (2018) presents a new promising policy in V2V communications by allocating DRL resources. They included the Markov decision process (MDP) in RL, Q-learning, and Deep Q Networks. They used training and testing stage algorithms to train Deep-Q Network. With the help of using a $\mathcal{E}$-greedy policy, however controlling barriers to V2I communications, every agent can learn how to fulfill the V2V limitations.

Study (Year)	Algorithms/ Schemes	Problem Addressed	Achievements/ Improvements	Weakness/ Limitations	Resource Allocation Environment
Shen et al. (2021) [6]	DRL Based Scheme	Low uplink scheduling	Enhancing uplink scheduling	Issue of allocation fairness	5G Service-Oriented RoF-MmWave RAN
Xiong et al. (2019) [13]	DRL-based and Q-learning	Low efficiency	Maximize the 5g slicing throughput	Large computational capacity required	5G and beyond
Li et al. (2018) [14]	DRL, Deep Q-learning	Low efficiency	Enhancing efficiency and performance	Lack of learning speed and GPU's high cost	Network Slicing
Ye and Li (2018) [23]	DRL, DQN	Low latency	It is decentralized, so global information is not required for each agent.	Little Interferences	V2V Communication
Wang et al. (2021) [24]	DRL-MDP, DDPG algorithm	Low QoS	Enhancing the utility of MVNO	Complexity	Edge Network Slicing

Table 1: Comparison of 5G DRL Models for Resource Allocation

In conclusion, Resource allocation (RA) is a key threat in 5G networks. The related work on RA with DRL in 5G network slicing shows the efficiency and potential of these algorithms in improving RA in network slicing. DRL is an assuring scheme for optimizing RA in 5G. DRL-based research has become increasingly popular leading to lower latency and better throughput.

3. Proposed Work:

In methodology, we propose a DRL-based RA in a 5G. The key goal of the learning module was to improve the performance compared to existing approaches. After the user request is accepted through the control access in a non-terrestrial network (NTN) like a satellite link (NSL), the DRL agent proceeds with the resource allocation process. The goal is to efficiently allocate resources to the users while optimizing network performance, resource utilization, and user satisfaction. Our methodology involves the following steps:

i. **Problem formulation:** We suggest the model for RA challenge as proximal policy optimization (PPO), consisting of a tuple (A, S, R, E), where A action, S state, R reward and E exploration and exploitation.

ii. **State representation:** The network state involves factors like user positions, channel conditions, available resources, and QoS requirements. The RL agent observes the current network state, which now also includes the newly accepted user request.

iii. **Action space:** The action space for resource allocation consists of possible resource assignments and configurations for the accepted user request. This can include variables like frequency bands, time slots, power levels, and modulation and coding schemes.

iv. **RL algorithm:** An RL algorithm, such as Q-learning, DQN, or PPO, is used to learn optimal policy for resource allocation. The agent learns by observing the current network state, taking an action (allocating resources), and obtaining a reward constructed on the consequences of its actions.

v. Reward function: It is considered to inspire the Reinforcement Learning agent to make optimal decisions regarding resource allocation. A positive reward is given if the agent allocates resources efficiently, maintaining high network performance and user satisfaction, while a negative reward is given for poor resource allocation, which may result in low throughput or increased latency. The reward function can also consider factors such as energy efficiency and fairness among users.

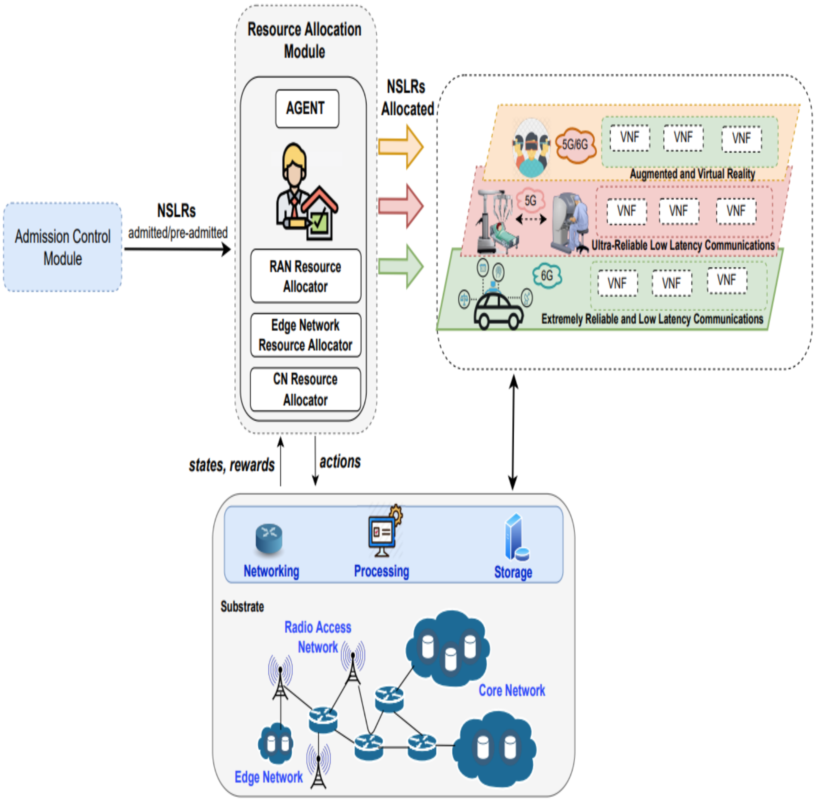

Figure 2: DRL-Based Resource Allocation in 5G

vi. Exploration and exploitation: The RL agents need to balance exploration (trying new resource allocation strategies to discover their effects) and exploitation (choosing the best-known resource allocation strategy) to learn the optimal policy. This balance is crucial in a dynamic environment like a 5G NTN, where network conditions and user demands can change frequently.

vii. Training and deployment: The RL agents are trained using historical or synthetic data in a simulated environment or a real-world testbed. Once the agent has learned the optimal policy for resource allocation, it can be deployed in the 5G NTN to autonomously allocate resources to the users.

When a user request is accepted, the DRL agent observes the updated network state and chooses a RA strategy formed on its learned program. The agent then assigns resources such as frequency bands, time slots, and power levels to the user while considering the current network state, user requirements, and other constraints.

By leveraging Deep reinforcement learning, the 5G network model can adapt to dynamic conditions in non-terrestrial networks, making resource allocation decisions that optimize network performance, resource utilization, and user satisfaction.

Algorithm Used: DRL algorithms provide an assuring solution to the issues of RA in 5G networks by allowing intelligent decision-making in real time. With the help of DRL, the network can learn through its own experience and constantly improve its resource allocation policy to improve network performance.

Algorithm 1: DRL Based Resource Allocation in 5G Network

Here's an outline of the Reinforcement Learning algorithm for resource allocation in 5G after NSL admission, using Q-Learning.

1. Initialize the Q-table with all zeros, representing the state-action pairs. The state space represents the possible network conditions and the action space represents the resource allocation decisions.
2. Set the learning rate (alpha), discount factor (gamma), and exploration rate (epsilon).
3. For each episode, perform the following steps:

a) Observe the current state of the network (i.e., resource utilization, traffic demand, etc.)

b) Choose an action based on the current state:

i. With probability (1 - epsilon), choose the action with the highest Q-value for the current state (exploitation).

ii. With probability epsilon, choose a random action (exploration).

c) Perform the chosen action and observe the new state and the immediate reward.

d) Update the Q-table using the Q-learning update rule:

Q (s, a) = Q (s, a) + alpha * (reward + gamma * max (Q (s', a')) – Q (s, a))

where s is the current state, a is the chosen action, s' is the new state, and a' is the action with the highest Q-value in the new state.

e) If the episode terminates (e.g., a predetermined number of time steps have elapsed or a specific network condition has been reached), reset the environment and start a new episode. Otherwise, set the current state to the new state and repeat steps 3b to 3d.

4. Continue iterating through episodes until a termination condition is met (e.g., a maximum number of episodes or a specific performance threshold).

5. Once the algorithm has converged, the optimal resource allocation policy can be derived from the Q-table by selecting the action with the highest Q-value for each state.

4. Simulation Results

The outcomes display that the RA with DRL-based DQDN-CASA algorithm for 5G has been proposed, which outperforms based on utility performance like network throughput, latency, and fairness.

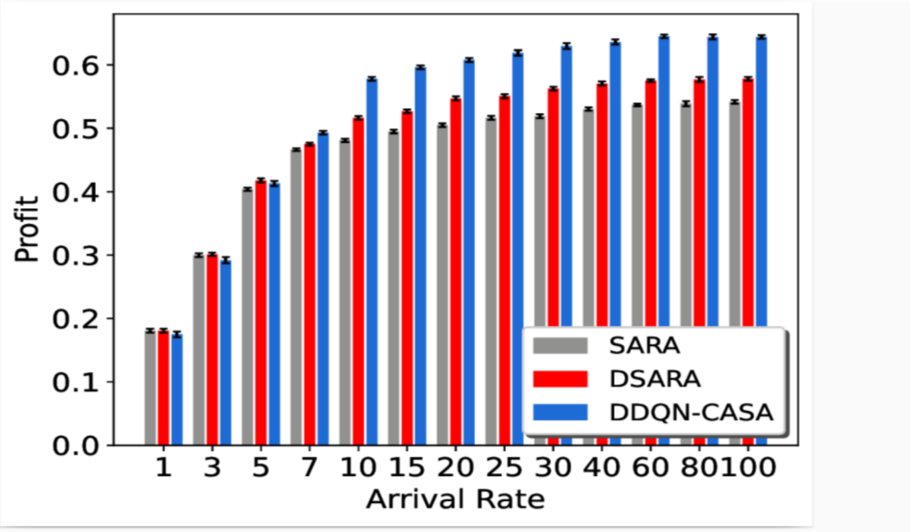

Fig. 3: Profit Comparison

Regarding the profit, DDQN-CASA also demonstrated superior performance. The algorithm reached higher profit compared to DSARA, and SARA. The enhancement in the profit can be accepted to the changes made to the DRL algorithm, allowing DDQN-CASA to better balance the acceptance of different types of NSLRs.

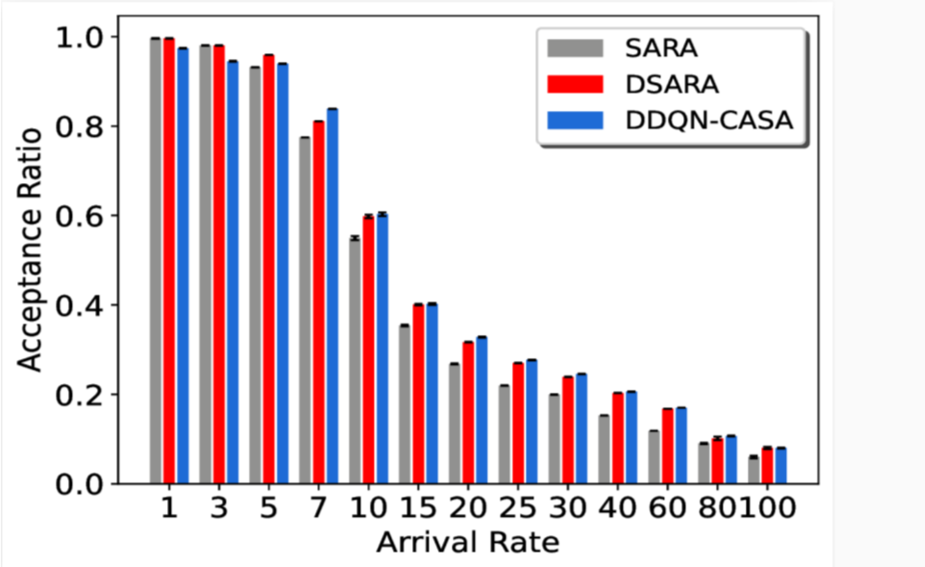

Fig. 4: Acceptance Ratio Comparison

The profit has increased with the algorithm, leading to better profit which provides improved performance and selection of actions in overall profit as exposed in Figure. Through stating an advanced proportion of more profitable NSLRs, such as URLLC, while including eMBB and M-IoT requests.

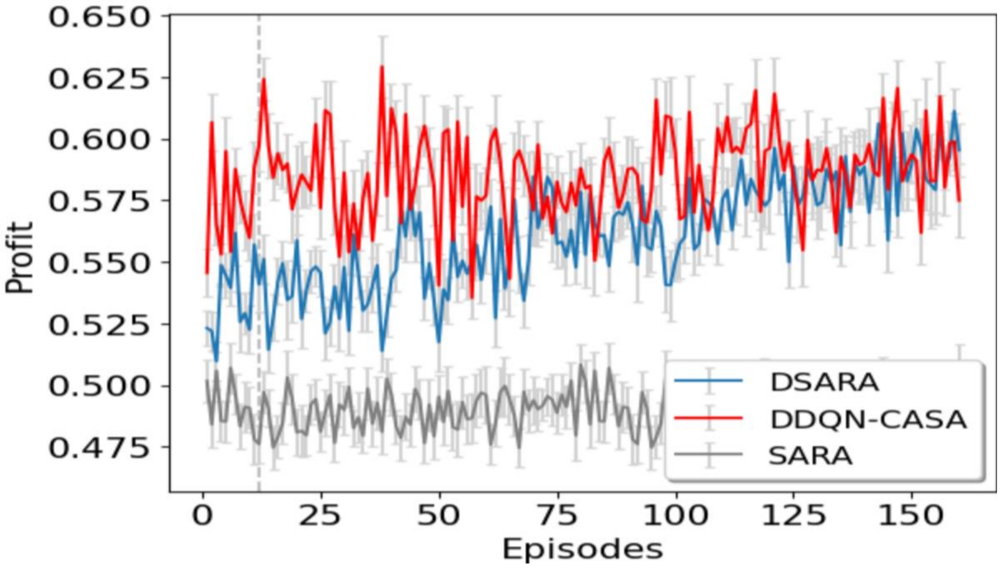

Fig. 5: Profit Comparison with Episodes

In summary, in all the episodes of trial executes, the DDQN system mainly reaches the superior reward, delivering as a minimum 13% higher profit, higher network throughput, and lower latency related to existing approaches. Furthermore, our approach reaches better fairness among users and all users receive appropriate service.

5. Conclusion

This work majorly focuses on a new resource allocation module for 5G network slicing using DRL. The implemented DDQN algorithm learns the best resource allocation policy through trial-and-error interactions with the network environment, considering factors such as user demands, available resources, and network conditions. The simulation results prove that this technique is betters than existing resource allocation techniques related to network throughput, latency, and fairness. Our approach can provide a foundation for future research in this area and enhance throughput of 5G networks. The system approximates Q-function using a DDQN, which estimates the expected reward of each action given the current network state. Specifically, the DRL-based DDQN algorithm can achieve up to 13% higher network throughput, up to 10% lower latency, and up to 10% better fairness among users. Generally, this method provides a step forward in addressing challenge of well-organized RA in 5G network slicing and has the capability to increase the QoS and user experience.

Future Scope

In the future, DRL perform crucial jobs in the development of intelligent RA with DDQN algorithms for 5G network slicing. Its future scope is endless, with many possible applications. Its main advantage is to enhance resource allocation policies dynamically. As the conditions change in Network, DRL can learn and adapt resource allocation policies to ensure the best resource utilization. DRL could be beneficial in QoS optimization. It can also be used to increase network security by learning resource allocation policies that manage network security and prevent cyber-attacks. It could be operated to control network resources more intelligently and automatically, which reduces the need for human intervention. As DRL technology becomes more advanced, we can anticipate seeing many new and innovative uses for it in the field of network slicing.

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