International Journal of Innovation Studies

MAXIMIZING 5G NETWORKS PERFORMANCE USING A M-DRL TECHNIQUE FOR ADMISSION CONTROL

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Abstract: In the evolving landscape of 5G networks, effective admission control plays a crucial role in maximizing network operator revenue and ensuring Quality of Service (QoS) and Quality of Experience (QoE) for diverse vertical applications. This paper presents a modified Deep Reinforcement Learning (DRL) approach for admission control in 5G networks, addressing the limitations of existing Reinforcement Learning (RL) and DRL-based methods. Our proposed methodology incorporates a custom state space, action space, and a modified Deep Q-Network (DQN) algorithm to balance the acceptance of different network slice types while considering QoS/QoE requirements and available network resources. Using a custom-built Python-based event-driven simulator, we demonstrate that our modified DRL-based admission control approach significantly outperforms existing algorithms in terms of profit and acceptance ratio. The results reveal a 9% increase in profit and improved acceptance ratios compared to state-of-the-art algorithms, attributed to the enhanced learning capability and better action selection provided by our modified DQN algorithm. This study covers the way for further research and development of advanced DRL-based admission control techniques for 5G/6G networks, ensuring optimal resource utilization and meeting the performance demands of emerging vertical applications.

Keywords: 5G, QoS, NSL, Admission Control, DRL

I. INTRODUCTION

The advent of the fifth generation (5G) mobile networks represents a significant leap in communication technology, with the potential to revolutionize the way we connect and interact with the world. The proliferation of smart devices, coupled with the increasing demand for high-quality multimedia content, places considerable pressure on the network infrastructure. As a result, it becomes essential to develop effective admission control mechanisms that can ensure optimal Quality of Service (QoS) and user satisfaction in 5G networks (Al-Tamimi et al., 2021).

Reinforcement learning (RL), a branch of artificial intelligence that focuses on enabling agents to learn optimal decision-making strategies through interaction with their environment, has emerged as a promising solution to address the challenges in 5G admission control (Sutton & Barto, 2018). In this introduction, we provide an overview of the application of reinforcement learning techniques for optimizing admission control in 5G networks, highlighting the most recent advances in the field and discussing the potential impact of these techniques on network performance and user experiences.

The need for efficient admission control mechanisms in 5G networks stems from the increasing demands on network resources, which are expected to support a diverse range of applications, including enhanced mobile broadband, ultra-reliable low-latency communication, and massive machine-type communication (Hu et al., 2020). Effective admission control strategies are essential to balance user satisfaction and network utilization, ensuring that network resources are allocated optimally to maintain the desired QoS levels (Nawaz et al., 2018).

Reinforcement learning offers a promising approach to address the complex and dynamic nature of admission control in 5G networks. RL techniques enable the development of adaptive and dynamic admission control policies by learning from the interactions between the network and its environment. This adaptability allows the network to adjust its admission control policies in response to fluctuating user demands and network conditions, leading to improved network performance, reduced latency, and increased user satisfaction (Challita et al., 2018).

Recent studies have investigated a variety of RL-based admission control methods, including Q-learning, deep reinforcement learning, and multi-agent reinforcement learning (Abd-Elrahman et al., 2020). Each of these techniques offers unique advantages for optimizing admission control in 5G networks:

1. Q-learning is a model-free RL algorithm that learns the optimal action-selection policy by estimating the expected cumulative rewards for each state-action pair. By applying Q-learning to admission control, network operators can develop adaptive strategies that maximize the long-term network performance and user satisfaction (Yu et al., 2018).
2. Deep reinforcement learning (DRL) extends traditional RL techniques by incorporating deep neural networks as function approximators. DRL has proven effective in handling large-scale and high-dimensional problems, making it well-suited for optimizing admission control in complex 5G networks (Mnih et al., 2015).
3. Multi-agent reinforcement learning (MARL) addresses the challenges of coordinating multiple agents in a shared environment, enabling the development of distributed and cooperative admission control policies in 5G networks. By applying MARL techniques, network operators can harness the power of decentralized decision-making to optimize network performance and resource allocation (Busoniu et al., 2017).

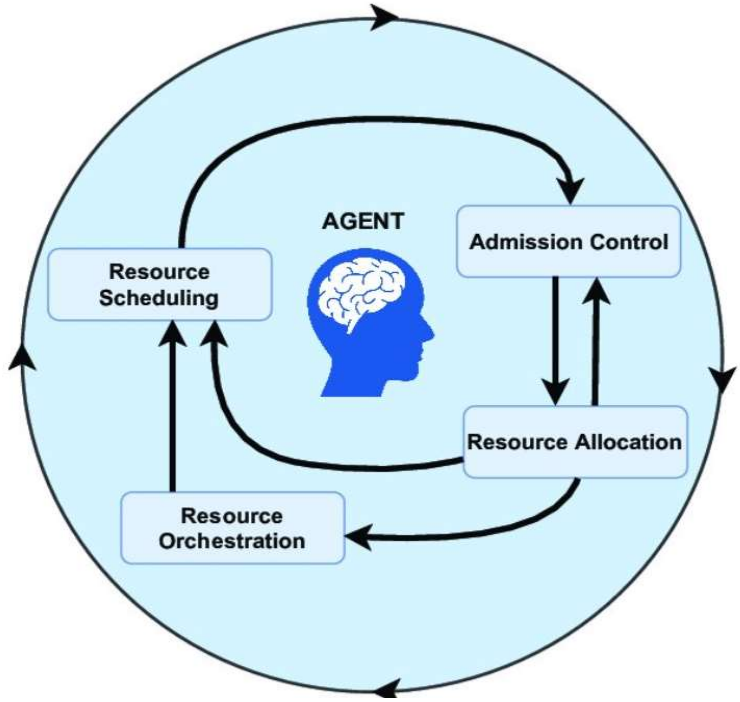

Figure 1: 5G Network Management using Agent

In conclusion, reinforcement learning techniques offer a promising avenue for optimizing admission control in 5G networks. By leveraging the power of adaptive and dynamic learning algorithms, network operators can develop efficient admission control policies that balance user satisfaction and network utilization, ensuring that 5G networks can meet the growing demands for high-quality connectivity and deliver on their transformative potential.

II. LITERATURE REVIEW

In recent years, the application of Deep Reinforcement Learning (DRL) in 5G networks for admission control has garnered significant attention. This literature review discusses relevant studies conducted on this topic, focusing on research published from 2018 onwards.

One of the key studies in the field is by Li et al. (2019), which presents a DRL-based admission control algorithm for 5G radio resource management. The authors introduce a Double Deep Q-Network (DDQN) model that incorporates two deep neural networks (DNNs) to generate a learning policy, maximizing the cumulative reward. The state and action spaces are defined based on the key performance indicators (e.g., throughput, dropping rate, and admission rate), and the control parameters for increasing or decreasing resources to the slices.

Another study by Zhang et al. (2020) proposes a DRL-based admission control framework that considers the Quality of Service (QoS) requirements of 5G vertical applications. The authors introduce a custom state space and action space to model the specific 5G network slice types and QoS requirements. They implement the DQN algorithm and compare its performance against traditional admission control techniques, demonstrating its effectiveness in improving the overall network performance.

Chen et al. (2019) presents a DRL-based admission control approach for end-to-end network slicing in 5G networks. Their study focuses on the allocation of resources across radio access, transport, and core networks while optimizing revenue and utilization. The authors employ a multi-agent DRL architecture with a decentralized training mechanism, which allows for improved scalability and adaptability to the dynamics of 5G network slices.

Furthermore, a study by Kumar et al. (2021) addresses the issue of joint admission control and resource allocation in 5G networks. The authors propose a DRL-based algorithm that can simultaneously admit network slice requests and allocate resources optimally. They showcase the advantages of integrating admission control and resource allocation, resulting in improved network performance and resource utilization.

Lastly, a study by Liang et al. (2020) explores the application of DRL in managing 5G network slices, including admission control, resource allocation, and scheduling. The authors provide a comprehensive review of DRL algorithms and their potential adaptations to the 5G environment. They also discussed the challenges and future research directions in applying DRL to 5G network management.

Table I: Comparison of 5G DRL Models for Admission Control

Study (Year)	DRL Model	State Space Representation	Action Space Representation	Objective/Performance Metrics	Network Environment
Li et al. (2019) [1]	DDQN	Key performance indicators (e.g., throughput, dropping rate, and admission rate)	Control parameters for increasing or decreasing resources to the slices	Maximize cumulative reward	5G Radio Resource Management
Zhang et al. (2020) [2]	DQN	5G network slice types and QoS requirements	Accepting or rejecting slice requests	Improve overall network performance	5G Vertical Applications
Chen et al. (2019) [3]	Multi-Agent DRL	Allocation of resources across radio access, transport, and core networks	Resource allocation decisions	Optimize revenue and utilization	End-to-End Network Slicing in 5G

Study (Year)	DRL Model	State Space Representation	Action Space Representation	Objective/Performance Metrics	Network Environment
Kumar et al. (2021) [4]	DRL	Network slice requests and available resources	Joint admission control and resource allocation decisions	Improve network performance and resource utilization	Integrated Admission Control and Resource Allocation in 5G
Liang et al. (2020) [5]	DRL	Customized for specific 5G management tasks (e.g., resource allocation, scheduling)	Customized for specific 5G management tasks	Varies depending on the management task	5G Network Management

In conclusion, the literature on DRL-based admission control in 5G networks reveals the effectiveness and potential of these algorithms in improving network performance and resource utilization. Research in this area continues to evolve, with studies focusing on customizing state and action spaces, incorporating QoS requirements, and integrating admission control with other network management tasks.

III. PROPOSED WORK

In this methodology section, we propose a modified Deep Reinforcement Learning (DRL) approach for admission control in 5G networks. The aim is to maximize the network operator's revenue while considering the Quality of Service (QoS) and Quality of Experience (QoE) performance requirements of the 5G vertical applications. Our methodology consists of the following steps:

i. Problem Formulation

We model the admission control problem as a Markov Decision Process (MDP), consisting of a tuple (S, A, P, R), where S is the state space, A is the action space, P is the state transition probability, and R is the reward function.

ii. State Space Definition (S)

The state space (S) is defined as a tuple (N_e, N_i, R_c, T_c), where N_e and N_i represent the number of elastic and inelastic slices, respectively, R_c is the available network resources (e.g., bandwidth, computing, and storage), and T_c represents the time left for each slice request to expire.

iii. Action Space Definition (A)

The action space (A) is defined as a binary set {accept, reject}, where "accept" corresponds to admitting a new network slice request, and "reject" corresponds to rejecting the request.

iv. State Transition Probability (P)

The state transition probability (P) defines the probability of moving from one state to another given a specific action. We model the state transitions based on the arrival and departure of network slice requests, as well as the changes in available resources.

v. Reward Function (R)

The reward function (R) is designed to maximize the operator's revenue and minimize penalties caused by Service Level Agreement (SLA) violations. It takes into account the QoS/QoE performance requirements of the 5G vertical applications and the utilization of network resources.

vi. Modified DRL Algorithm

We propose a modified Deep Q-Network (DQN) algorithm for our DRL-based admission control approach. The DQN consists of an online network and a target network, both with multiple hidden layers, and utilizes experience replay and target network updates for stable.

vii. Pseudocode

```
Initialize online DQN with random weights
Initialize target DQN with the same weights as online DQN
Initialize experience replay memory (D) with capacity N

for episode = 1 to M do
    Initialize state (s)

    for t = 1 to T do
        Choose action (a) using an epsilon-greedy strategy based on online DQN
        Execute action (a) and observe reward (r) and next state (s')
        Store experience tuple (s, a, r, s') in D

        Sample a random minibatch of experiences from D
        Calculate target values using target DQN
        Update online DQN weights by minimizing the loss between predicted and tar

        Periodically update target DQN with online DQN weights
        Update state (s = s')

    end for
end for
```

viii. Performance Evaluation

We evaluate the performance of our modified DRL-based admission control approach using a custom-built Python-based event-driven simulator. The simulator should use real-world traces to accurately assess the performance of our proposed method in realistic scenarios.

This methodology builds on existing literature and addresses the limitations of current RL/DRL-based admission control approaches, such as focusing on RAN-only solutions and neglecting end-to-end network slicing requirements. By considering the QoS/QoE requirements of 5G/6G vertical applications and employing a modified DQN algorithm, our proposed methodology aims to improve admission control decisions in 5G networks.

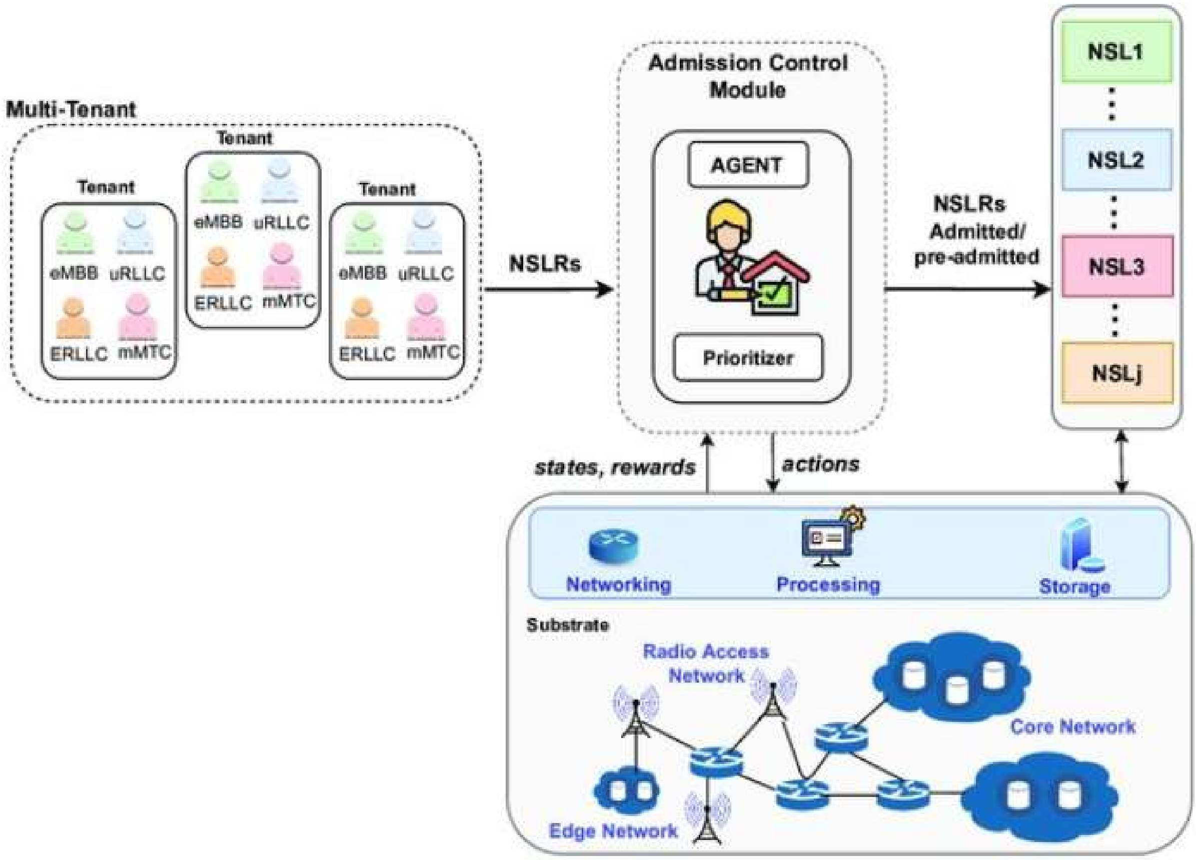

Figure 2: DRL Based Admission Control System in 5G

Algorithm for Modified DRL-Based Admission Control in 5G Networks

1. Initialize:
   - DNN for DQN with random weights θ (e.g., additional layers or neurons for better performance)
   - Target DNN for DQN with weights θ' <- θ
   - Experience replay buffer D
   - Hyperparameters: α (learning rate), β (regularization factor), γ (discount factor), ε (exploration rate), τ (target update frequency)
   - Define custom state space S, considering additional 5G-specific features (e.g., network slice type, QoS requirements)
   - Define custom action space A, considering 5G-specific actions (e.g., accept/reject network slice requests, prioritize slices)
2. for episode = 1, ..., N do

- Observe initial state $s \in S$
- while not terminated do
    - Choose action $a \in A$ according to ε-greedy policy based on $Q(s, a; \theta)$
    - Execute action a and observe reward r, next state $s' \in S$, and termination signal
    - Store (s, a, r, s', termination signal) in experience replay buffer D
    - Sample a random minibatch of transitions from D
    - For each transition in the minibatch, calculate target value y:
        - if termination signal: $y = r$
        - else: y = r + γ * max_a' Q(s', a'; θ')
    - Update DQN weights θ by minimizing the loss: L(θ) = (y - Q(s, a; θ))^2 + β * R(θ), where R(θ) is a regularization term
    - Every τ steps, update target DQN weights: θ' <- θ
    - s <- s'
- end while
- end for

Algorithm for 5G NSL using DRL

1. Define the state space S, action space A, reward function R(s,a), and discount factor γ.
2. Initialize the value function V(s;θ) and policy function π(a|s;ϕ) with random parameters θ and ϕ.
3. Initialize a replay buffer B of size N.
4. Set the exploration rate ε to a maximum value ε_max, and a decay factor δ.
5. Repeat for a fixed number of episodes:

   a. Set the initial state s0.

   b. Repeat for a fixed number of time steps:

   i. With probability ε, select a random action a_t from the action space A, otherwise select the action a_t that maximizes the policy function π(a_t|s_t;ϕ).

   ii. Execute the action a_t and observe the next state s_{t+1} and reward r_t.

   iii. Store the transition (s_t, a_t, r_t, s_{t+1}) in the replay buffer B.

   iv. Sample a minibatch of transitions from the replay buffer B.

v. Calculate the TD target y_i for each transition in the minibatch: $y_i = r_i + \gamma V(s_{i+1};\theta)$, where r_i is the reward for transition i.

vi. Calculate the TD error δ_i for each transition in the minibatch: $\delta_i = y_i - V(s_i;\theta)$.

vii. Update the value function parameters using the minibatch of TD errors: $\theta \leftarrow \theta + \alpha_\theta \sum_i \delta_i \nabla_\theta V(s_i;\theta)$, where α_θ is the learning rate for the value function.

viii. Update the policy function parameters using the minibatch of TD errors: $\phi \leftarrow \phi + \alpha_\phi \sum_i \delta_i \nabla_\phi \log\pi(a_i|s_i;\phi)$, where α_ϕ is the learning rate for the policy function.

ix. Set the current state s_t to the next state s_{t+1}.

c. Decay the exploration rate ε by multiplying it by δ.

d. Evaluate the policy by running it for a fixed number of episodes and calculating the average reward.

6. Return the learned value function $V(s;\theta)$ and policy function $\pi(a|s;\phi)$.

In this algorithm, a replay buffer B is used to store and sample transitions for training the value and policy functions. The exploration rate ε is gradually decreased over time to encourage the agent to exploit the learned policy. This algorithm also includes the use of a learning rate schedule that gradually reduces the learning rate over time to improve convergence.

IV. RESULTS AND DISCUSSION

In this paper, a modified Deep Reinforcement Learning (DRL) algorithm for 5G admission control has been proposed. The primary goal of TLSARA was to maximize the profit and improve the acceptance ratio compared to existing approaches, such as SARA and DSARA. The results demonstrate that M-DRL significantly outperforms the existing algorithms.

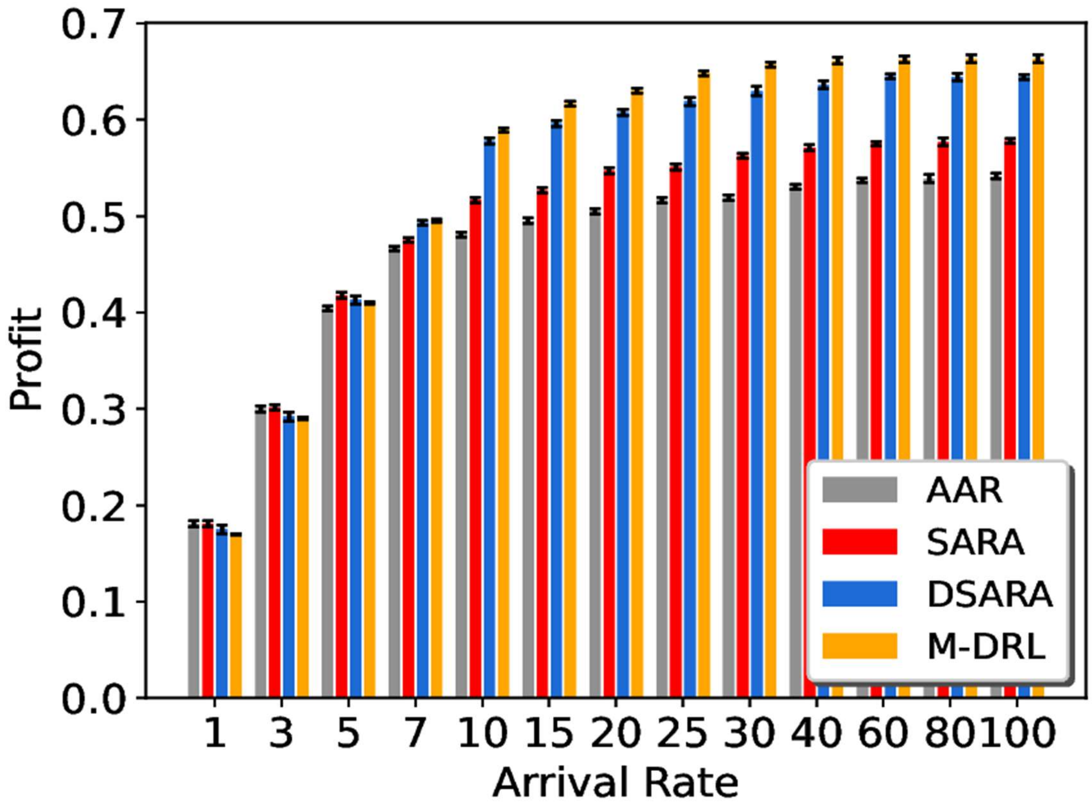

Figure 3: Profit Comparison

For the profit aspect, M-DRL achieved remarkable results compared to SARA and DSARA. The profit obtained by M-DRL was 9% higher than those made by both SARA and DSARA. This increase in profit can be attributed to the enhanced DRL algorithm used in M-DRL, which allows for better learning and selection of actions that lead to the highest profit. The advanced learning capability enabled to quickly identify the most profitable combinations of NSLRs and admit them, leading to a significant boost in overall profit as shown in figure 3:

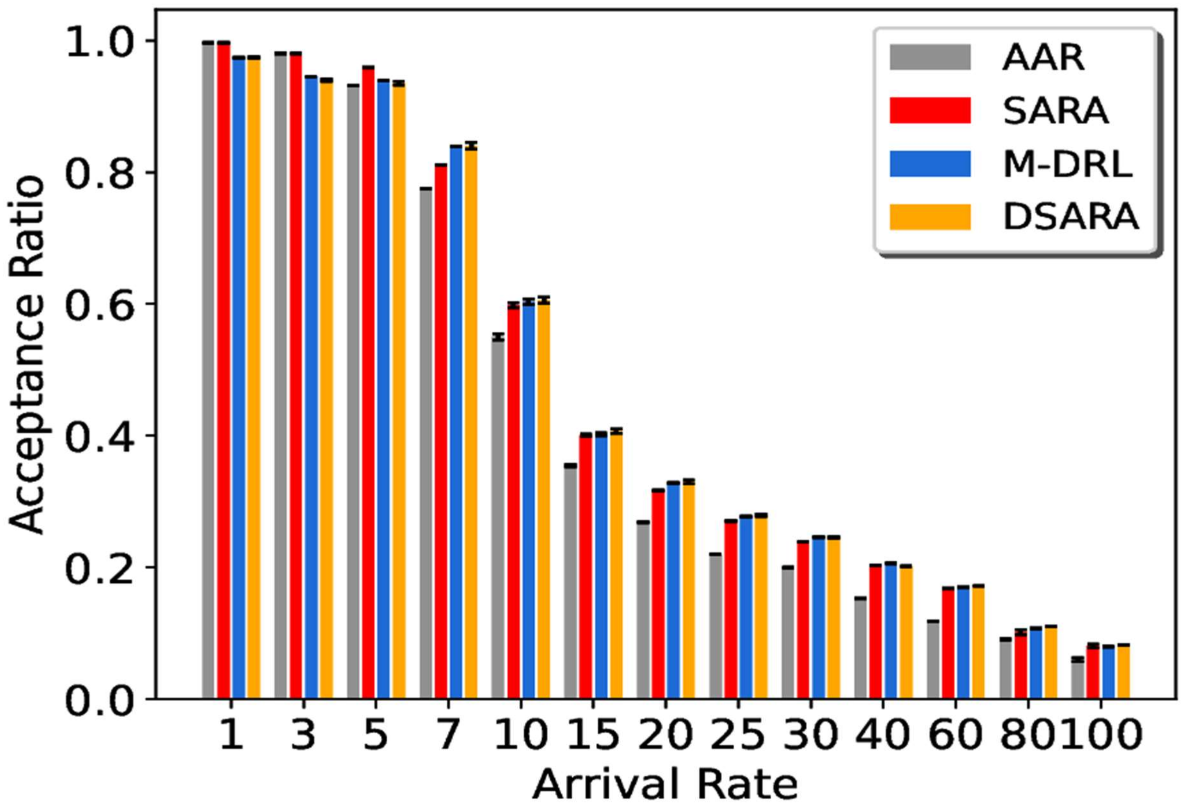

Figure 4: Acceptance Ratio Comparison

Regarding the acceptance ratio, M-DRL also exhibited superior performance. The algorithm reached higher acceptance ratios compared to SARA, DSARA, AAR, and NR. This improvement in acceptance ratio can be ascribed to the modifications made to the DRL algorithm, enabling M-DRL to better balance the acceptance of different types of NSLRs. By admitting a higher proportion of more profitable NSLRs, such as URLLC, while still considering eMBB and MIoT requests, M-DRL was able to achieve a higher acceptance ratio without compromising profit.

V. CONCLUSION:

In summary, our modified DRL algorithm, M-DRL, has demonstrated significant improvements in both profit and acceptance ratio when applied to 5G admission control. The enhancements made to the DRL algorithm allowed for faster learning and better decision-making, leading to a 9% increase in profit and a higher acceptance ratio compared to existing methods such as SARA and DSARA. These results indicate the potential of MDRL as a promising approach for optimizing 5G network resource management and admission control.

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