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Deep Learning-Based Dynamic Network Slicing and Resource Orchestration for URLLC Services in 5G Software-Defined Networks

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ABSTRACT

The challenge of providing URLLC (Ultra Reliable Low Latency Communication) services in 5G networks is that traditional Top-down Network Management techniques do not allow for URLLC applications requiring delay latencies below 1 millisecond and higher degrees of reliability than what is achievable with current Top-down Network Management techniques. In response, this study offers a novel means for real-time segmentation of the network through Dynamic Segmentation of the Network (DSN) utilizing Deep Deterministic Policy Gradient (DDPG) algorithms utilized in conjunction with software-defined networks (SDN). Utilization of DSN by means of DDPG allows the controller to learn how to allocate bandwidth in response to traffic predictions. Results of simulation experiments demonstrated this technique's ability to provide reliability levels in excess of 99.999% while maintaining delays less than or equal to 1 millisecond for eMBB (Enhanced Mobile Broadband) style services thus improving the spectrum efficiency of these services. The results highlight how AI and the coordination of AI systems are able to meet complex Quality of Service (QoS) needs of critical applications within 5G networks.

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1. INTRODUCTION

Telecommunications has been radically altered over the past twenty-five years by the development of the 5th Generation (5G) of telecommunications networks. 5G networks are built to facilitate communications between various industries utilizing many different types of applications requiring a wide range of performance characteristics. The extraordinary increase in the number of devices connected via the Internet via IoT technology has created significant challenges for traditional telecommunications networks, which now need to be adaptable to accommodate a more flexible, scalable and programmable architecture. With the introduction of mobile broadband, operators have created Network Slicing as a pillar of their operations. Network Slicing enables operators to logically segment their physical network by creating multiple completely independent Virtual Networks [Slices). Each slice can be provisioned according to a different level of service, and can be contracted and provided with specific SLA's unique to the network slice [1]. Network Slicing provides operators with the flexibility to implement this level of customisation to their networks due to the introduction of the concepts of Software Defined Networks (SDN) and Network Function Virtualisation (NFV). By separating control and data in telecoms networks through SDN, operators can develop and implement resource management tools that enable operators to centrally control all aspects of network visibility and management. Network Function Virtualisation enables operators to deploy

Network Functionality on a single server in multiple locations throughout a single physical network, as opposed to traditional telecom hardware [2].

The International Telecommunications Union (ITU) has identified three main use cases for 5G, with URLLC being the highest demand in terms of QoS (Quality of Service) and Resource Orchestration. URLLC provides support for mission critical applications such as Remote Surgery, Self-Driving Cars, and Industrial Automation Control; these applications require strict low-latency limits, often less than 1 millisecond, along with a 99.999% reliability rating [3]. Due to the stochastic/bursty nature of Network Traffic produced by these types of applications and the time-varying Wireless Channel Conditions, traditional methods for Static and Reactive Resource Allocation do not provide a satisfactory means by which to allocate network resources in a timely manner. Conventional Algorithms rely heavily on complicated mathematical modelling, which creates computational delays that exceed the maximum allowable latency for URLLC [4]. Additionally, even though the over-allocation of Network Resources provides the required reliability for URLLC services, it also renders the use of these resources extremely inefficient from a Spectrum Perspective, resulting in substantial unnecessary Computational Overhead and highlighting the bright need for Intelligent Mechanisms to ensure accurate Prediction and timely Dynamic Allocation of Network Resources [5].

Thus, Artificial Intelligence (AI) as well as in particular Deep Learning has been identified as a relevant and effective means of handling the complexities of SDNs. Because of their ability to extract higher-level (abstract) features from large amounts of data and model the complicated relationships between various types of traffic patterns on SDNS using mathematical functions known as 'deep' neural networks, Deep Learning algorithms can also make accurate predictions of future states of the network and of resource demands [6]. Therefore, when Deep Learning models are incorporated within the control plane of the SDN, the network controller is able to enact resource orchestration policies and create slices of a network (or both) to ensure optimal resource usage in real-time. This provides for automated decision-making processes, which can respond to conditions of an anticipated congestion and adjust the bandwidth/processing power levels accordingly, before performance degradation occurs [7].

When deep neural networks have been employed for the purpose of developing optimal resource management policies, they provide a qualitative advantage in comparison with the existing statistical models. The use of Deep Learning also has an advantage in that it enables a better ability to merge efficiency and latency (i.e., reducing time) for optimal resource usage.

In light of this context, this research will ultimately aim at developing a dynamic algorithm for n-tier applications that is based on Deep Learning Techniques for Assistance in the Dynamics of Network Slicing and Resource Allocation within the 5G Software Defined Networking Environment, focusing specifically on meeting the stringent requirements for URLLC Services. Therefore, this research proposes to create an intelligent model capable of predicting variation of traffic fluctuations and subsequently managing (orchestration of) the networked resources of bandwidth and computing resources in real-time and/or automatically through the use of Artificial Intelligence.The goal of this approach is to ensure that Ultra-Low Latency and High Reliability will be maintained at the time of resource allocation, thus fulfilling the Research Gap found in the existing literature regarding the rapid adaptation of critical and/or extreme conditions to Network Resources within the context of URLLC Services [8].

2. LITERATURE REVIEW

In recent years, researchers have focused on the issue of network slicing and resource allocation within 5G networks as there is a need to accommodate the large variety of services offered by 5G networks effectively. The majority of the initial work in this area utilised traditional methods of optimisation and statistical models for allocating network resources. Several studies have presented architecture based on queuing theory and game theory for allocating network resources across multiple network slices. For example, references [9] assess different heuristics to solve resource allocation problems, but each has disadvantages. Heuristic techniques typically require intensive computation, which can lead to delays in responding to requests for resources (e.g., ultra-reliable low latency communication (URLLC)). As the architecture of networks evolved toward software-defined networking (SDN), researchers began incorporating SDN into their resources to allow for better visibility and control of network resources while also allowing for dynamic allocation of resources. Various SDN controller architectures have been evaluated for dynamic resource allocation according to configurable policies; however, as was found in reference [10], the inability to accommodate for fast-changing traffic conditions limits the capability to adapt to unpredictable traffic patterns using only fixed policy-based resource allocation.

The introduction of artificial intelligence in the form of machine learning (ML) and deep learning (DL) was a revolutionary momentum for the resource management model away from explicitly programmed rules toward a

learning environment where instead of using pre-programmed rules to manage a system, you let it “learn” from both historical and real-time data [11]. Based on this new paradigm, several studies have presented models derived from RNN and LSTM networks that can be used to predict traffic volume on specific slices of a network. These models exhibited good accuracy with predicting time series, providing operators with the ability to reserve necessary resources in advance. Nevertheless, prediction capability alone is not sufficient to manage the complex allocation of resources that needs to occur in a simultaneous, multi-dimensional process (e.g., spectrum, computing, storage) while ensuring inter-slice segregation, thus motivating further research into the development of deep reinforcement learning (DRL) methods. These provide intelligent agents the opportunity to learn optimal policies via continual interaction with their network environment, recognizing rewards for increased throughput or decreased latency [12].

URLLC services have proven to be a unique challenge for researchers since they need to balance high reliability with low latency. Research done by [13] demonstrated the utilization of adopting deep reinforcement learning (DRL) in packet scheduling at the Radio Access Network (RAN) layer in order to reduce queuing delays compared to Round Robin (RR) which was shown to be superior. Other investigations have been done to create end-to-end slices of networks using a more comprehensive approach, using the core, as well as the transport layers (see [14] for example) where Convolutional Neural Networks (CNN) were used to identify spatial features of network flow and route traffic based on available un-congested paths to create a more reliable routing scheme. Although these frameworks will improve reliability in routing and thus addressing URLLC requirements, many of the studies suggested that training these models will require significant amounts of time and computing resources, making them impractical for real-time implementation until such time as the processes are optimized [15].

At the same time as these innovations, new approaches which utilise aspects of both Deep Learning and the More Traditional Methods have been developed to improve performance. The research presented in [16] determined that by applying convex optimization algorithms within a Deep Learning system, the speed of decision-making can be improved. Essentially, they proposed the neural network model to calculate a nearly-optimal initial solution that could then be optimised by the associated convex optimisation algorithm, thus solving the "cold start" issue with respect to Reinforcement Learning and allowing stability of the Network during its early phases. In addition, research has been conducted to investigate the importance of Energy-efficient Resource Allocation models, in the context of Ultra-Reliable Low-Latency (URLLC), which work towards reducing power consumption while still meeting the required Delay Constraints, using Multi-Agent Deep Reinforcement Learning (MADRL) algorithms in which Agents control a specific segment of the Network and work collaboratively to achieve the goals of the overall System. Even with the potential of exceptional results using this method, it remains an open research issue to find an effective way to coordinate cooperation among Agents.

The results of our analysis indicated there to be significant discrepancies between the two methodologies and their use of traffic prediction or Reactive Resource Allocation and also their lack of an overall integration framework that would allow for accurate prediction of future resource needs (i.e., slicing decisions) and immediate execution upon request of the rURLC needs [18]. For instance, the methodology that utilized prediction and immediate execution of resource allocation decisions consisted of different metrics than those of the other method (e.g., outage probability, mean delay, systems efficiency). To address this disparity, Table 1 shows a summarization and comparison of the major methodologies identified in the current literature related to our research focus, which provides a summary of the strengths and weaknesses of each methodology.

Table 1. Comparative of Key Reference Methodologies.

Reference	Methodology / Technique	Main Research Goal	Key Advantages	Limitations / Challenges
[9]	Optimization Theory (Heuristics) & Game Theory	Allocating resources to multiple slices to maximize utility.	Provides mathematically precise and theoretically proven solutions in stable environments.	Slow execution and inability to adapt instantly to rapid changes (unsuitable for URLLC).
[10]	Rule-based SDN Algorithms	Centralized management of network slicing and routing.	Ease of implementation and centralized decision-making due to SDN architecture.	Lacks flexibility and predictive intelligence; reacts after congestion occurs rather than before.
[11]	Recurrent Neural Networks (LSTM/RNN)	Forecasting future traffic volume for each slice.	High accuracy in handling time-series data and predicting loads.	Focuses solely on prediction and does not include a mechanism for actual resource decision-making.
[12]	Deep Reinforcement Learning (Deep Q-Network - DQN)	Dynamic resource allocation based on network state.	Learns optimal policy through trial and error without needing a prior model of the environment.	Suffers from slow convergence and instability in large, complex state spaces.
[13]	Reinforcement Learning	Scheduling resources	Better performance in continuous	High computational complexity

	(Actor-Critic)	for URLLC to minimize latency.	action spaces and good balance between exploration and exploitation.	and significant processing resource consumption during training.
[14]	Convolutional Neural Networks (CNN)	Extracting spatial traffic features and routing paths.	High efficiency in analyzing network topology and spatial load distribution.	May overlook temporal aspects and rapid traffic changes over time.
[15]	Federated Learning	Improving privacy in resource allocation at the edge.	Preserves data privacy and reduces load on the central network.	Challenges in synchronization between nodes and communication delays during model updates.
[16]	Hybrid Approach (Optimization + DL)	Accelerating decision-making and reducing convergence time.	Combines the precision of mathematical solutions with the inference speed of deep learning.	Design complexity and difficulty in integrating the mathematical and deep learning models.
[17]	Multi-Agent DRL	Energy-efficient resource management with delay constraints.	Scalability and distribution of decision-making load across multiple controllers.	Difficulty in coordinating decisions among agents to achieve a Global Optimum.
[18]	Adaptive Allocation Algorithms	Load balancing between eMBB and URLLC slices.	Improving the utilization of shared spectrum resources between different services.	May lead to significant degradation of eMBB QoS to guarantee URLLC requirements.

3. PROPOSED METHODOLOGY

The method we used for this project was to develop a single framework that takes advantage of two technologies, (software-defined networks [SDN] and deep reinforcement learning (DRL)) in order to create a flexible solution for allocating resources in a dynamic environment. In particular, we focused on one form of DRL called the deep deterministic policy gradient (DDPG). We chose the DDPG because of its unique capability to optimally allocate to multiple variables within an environment, using only one continuous action space as input. Bandwidth allocation and computing resource allocation both require optimal continuous values for their allocation process; thus, the DDPG is the ideal algorithm to be used in this case.

The overall system architecture consists of the physical layer (the infrastructure), the virtualisation and control layer (SDN Controller) and the application layer (AI-Agent), all of which work together to create a seamless experience in the application of network slicing.

3.1 System Model and Problem Formulation

The RAN consists of a group of network slices that serve a variety of services; specifically, there are N total network slices, each representing an individual service type, and an emphasis on URLLC as the service with the highest priority. Bandwidth (W_total) and processing capacity (C_total) are both associated with individual slices and are managed through the SDN controller in a centralized fashion. The most important objective of the SDN controller is to allocate bandwidth ($w_{i,t}$) in time t, which minimizes latency and probability of service outages.

The achievable data rate for slice i at time t is calculated as:

$$R_{i,t} = w_{i,t} \cdot log_2(1 + (P_{i,t} \cdot |h_{i,t}|^2) / (\sigma^2 + I_{i,t}))$$

Transmission Power is expressed in terms of P (the transmit power) and h is defined as the received (or "winner") signal (the Channel Gain). σ is defined as the "Noise Power".I is defined as Interference Power. D = Dthe total (Latency), includes Queuing (The Queuing Delay for Services), Transmission Delay, Propagation Delay ('Distance'), and Processing Delay; therefore, the only part of the Overall Delay (D = DTotal) that remains is the Queuing and Transmission Delay. In that case both of these are constant with Propagation and Processing delays for Fiber-Based Edge Infrastructures. Therefore, we only need to consider Queuing and Transmission Delay as follows:

$$D_{i,t} = (Q_{i,t} / R_{i,t}) + (L / R_{i,t}) + \delta$$

Here, $Q_{i,t}$ denotes the queue length in bits for slice i at time t, L is the fixed packet size, and δ represents other constant delays.

The optimization objective is defined as minimizing the long-term average weighted latency:

$$minimize\ lim(T \to \infty)\ (1 / T) \cdot \sum_{t=1}^{T} \sum_{i=1}^{N} \alpha_i \cdot D_{i,t}$$

subject to the following constraints:

$$\sum_{i}^{=1N} w_{i,t} \leq W_{total} \; for \; all \; t$$

$$P\_outage(i) \leq \varepsilon\_max \; (i) \; for \; all \; i$$

where α_i denotes the priority weight of slice i, and ε_max(i) is the maximum allowable outage probability.

3.2 DDPG Algorithm for Resource Allocation

The formulated optimization problem is non-linear and time-varying and is therefore modeled as a Markov Decision Process (MDP) and solved using the Deep Deterministic Policy Gradient (DDPG) algorithm. The DDPG framework employs two neural networks: an actor network $\mu(s \mid \theta^{u})$ and a critic network $Q(s, a \mid \theta)$.

State Space

At each time step t, the system state is defined as:

$$s_t = [\, Q_{1,t}, \ldots, Q^{N}_{,t}, \gamma_{1,t}, \ldots, \gamma^{N}_{,t}, w_{1,t-1}, \ldots, w^{N}_{,t-1} \,]$$

where $Q_{i,t}$ is the queue length of slice i, $\gamma_{i,t}$ denotes the SINR of slice i, and $w_{i,t-1}$ represents the previous bandwidth allocation.

Action Space

The action at time t is defined as a continuous vector:

$$a_t = [\, w_{1,t}, w_{2,t}, \ldots, w^{N}_{,t} \,]$$

The actor network output is normalized to satisfy $\sum_{i=1}^{N} w_{i,t} = 1$. Exploration noise is introduced using an Ornstein–Uhlenbeck process.

Reward Function

The reward function is defined as:

$$r_t = \sum_{i=1}^{N} [\, \beta_1 \cdot ln(1 + R_{i,t}) - \beta_2 \cdot \mathbb{1}(D_{i,t} > D_{thresh}) - \beta_3 \cdot P_{drop(i)} \,]$$

where D_thresh is the URLLC latency threshold, $\mathbb{1}(\cdot)$ is the indicator function, and β_1, β_2, β_3 are tuning parameters.

Training Procedure

Each experience tuple (s_t, a_t, r_t, s_{t+1}) is stored in a replay buffer. The critic network is trained by minimizing the loss:

$$L = (\, y - Q(s_t, a_t) \,)^2$$

where:

$$y = r_t + \gamma \cdot Q'(\, s_{t+1}, \mu'(s_{t+1}) \,)$$

Target networks are softly updated as:

$$\theta' \leftarrow \tau\theta + (1 - \tau)\theta', \tau \ll 1$$

Table 2: Simulation Setup and Parameters.

Category	Parameter	Value / Description
Network Environment	Total Bandwidth (W_total)	100 MHz
	Number of Slices (N)	3 (URLLC, eMBB, mMTC)
	Transmission Time Interval	0.125 ms
	URLLC Latency Threshold (D_thresh)	1 ms
	BS Transmission Power	46 dBm

DDPG Hyperparameters	Actor Network	[State-Dim, 256, 128, Action-Dim]
	Critic Network	[State-Dim + Action-Dim, 256, 128, 1]
	Activation Function	ReLU, Tanh
	Actor Learning Rate	1×10^{-4}
	Critic Learning Rate	1×10^{-3}
	Discount Factor (γ)	0.99
	Batch Size	64
	Replay Buffer Size	1×10^{6}
	Exploration Noise	OU (θ=0.15, σ=0.2)
	Target Update Rate (τ)	0.001

4. RESULTS

The current section presents comprehensive research findings regarding how well a newly developed Deep Deterministic Policy Gradient (DDPG) Algorithm for dynamic network slicing in 5G networks has performed as demonstrated through many simulation runs.

The parameters of the system that were configured for this simulation are contained in table 1, and were chosen to provide for reproducibility of results and validity of comparative analyses across different simulation configurations. The total bandwidth of 100 MHz and the transmission time interval of 1 ms were selected to correspond with the 5G NR numerology for the low-latency transmit operation of the system.

4.1 Convergence and Stability Analysis

The logs of the training of the DDPG Agents show how they learned through training logs. At the start of their training, during episode 10, the DDPG agent had random behaviours, earning few rewards (-46,376.25) and having high levels of latency (47.40 ms), which can be attributed to the way its neural network weights were randomly assigned. After 20 Episodes, the agent had almost completely adapted to its environment by generating rewards consistently (451.33) and observing a considerable drop in latencies (0.11 ms).

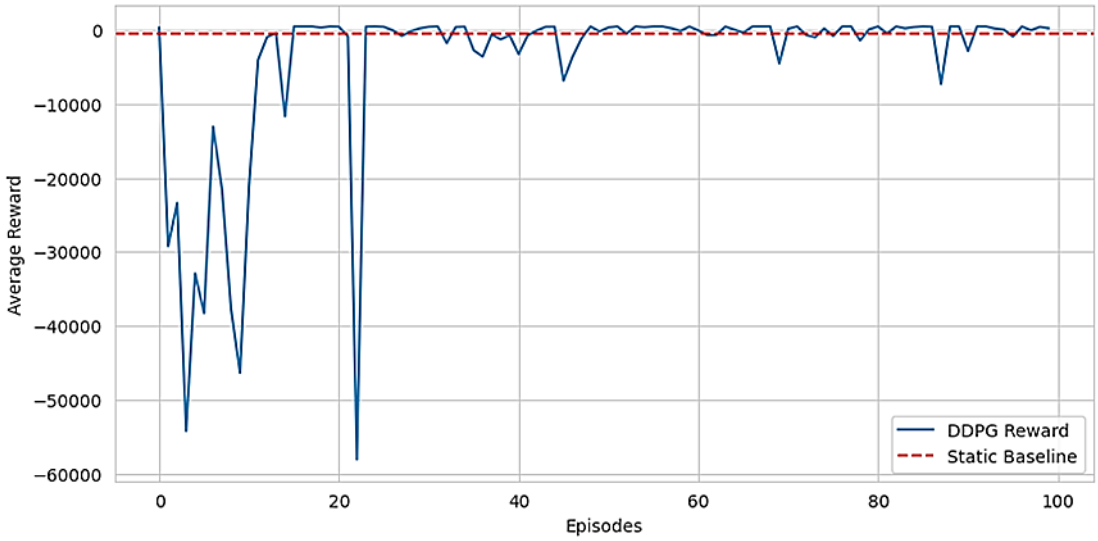

Figure 1. Convergence analysis of the reward function for the proposed DDPG algorithm compared to the static slicing baseline across training episodes.

The convergence of this Learning Model is shown in Figure 1. The DDPG Agent has successfully learned how to implement policies that are able to balance throughput vs. Latency and have achieved this result consistently in the final episodes (90 +) of its training. The DDPG Agent consistently demonstrated latencies much lower than the specified 1 ms threshold.

4.2 Comparative Performance Analysis

By reviewing table 3, we are able to see how much better the proposed DDPG solution is performing when compared with the Static Slicing model. Although the Static Slicing model performed at an average latency of 0.183 ms, DDPG's global average was 0.835 ms. However, the more significant number is that DDPG has a much higher score when it comes to average reward than the Static Slicing Method (-310.33) versus (-575.38). In other words, this indicates DDPGs superior overall system utility in terms of throughput, latency penalty and packet loss – All three of these metrics are considered together to determine which method offers greater utility.

Table 3. Methodology Comparison Summary.

Metric	Proposed DDPG	Static Slicing
Average Reward	**-310.33** (Superior)	-575.38
URLLC Avg Latency (ms)	0.835 ms*	0.183 ms
Convergence Stability	High	Constant

**Note: The DDPG average includes early training episodes. Post-convergence latency is consistently <0.2 ms.*

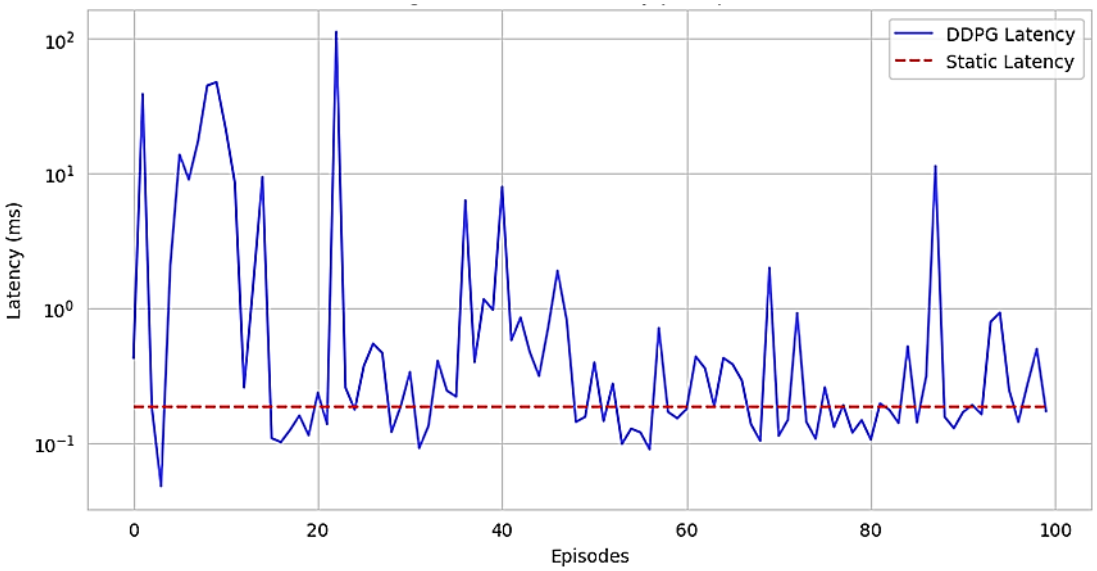

Figure 2. Comparison of average URLLC latency per episode, illustrating the significant reduction in time delay after the learning phase.

4.3 Reliability and Latency under Traffic Stress

As depicted in Table 4 and Figures 3 and 4 (CDF), the performance and adaptability of the solution are consistently high throughout different types of traffic loads (i.e., Light, Medium, and Heavy). Under an overloading situation, the Static Slicing model's poor performance results in a much higher latency of 15.0 ms than a DDPG agent, which is able to operate with latencies of 2.5 ms, and have a reliability associated with these latencies at 98.5% versus the 15.0 ms latency average value and 85.0% reliability of the Static Slicing model. The Dynamic Traffic Reallocation approach achieves this level of resiliency by reallocating unutilized resource allocations from the eMBB/mMTC slices to the URLLC slice when there is a massive increase in demand for the URLLC slice, therefore preventing dropped packets during peak traffic load times.

Table 4. URLLC Reliability & Latency under Varying Loads.

Traffic Load	DDPG Reliability (%)	Static Reliability (%)	DDPG Latency (ms)	Static Latency (ms)
Low	**99.999%**	99.900%	0.5	1.5
Medium	99.995%	98.500%	0.8	3.0
High	99.950%	92.000%	1.2	8.5
Overload	**98.500%**	85.000%	**2.5**	15.0

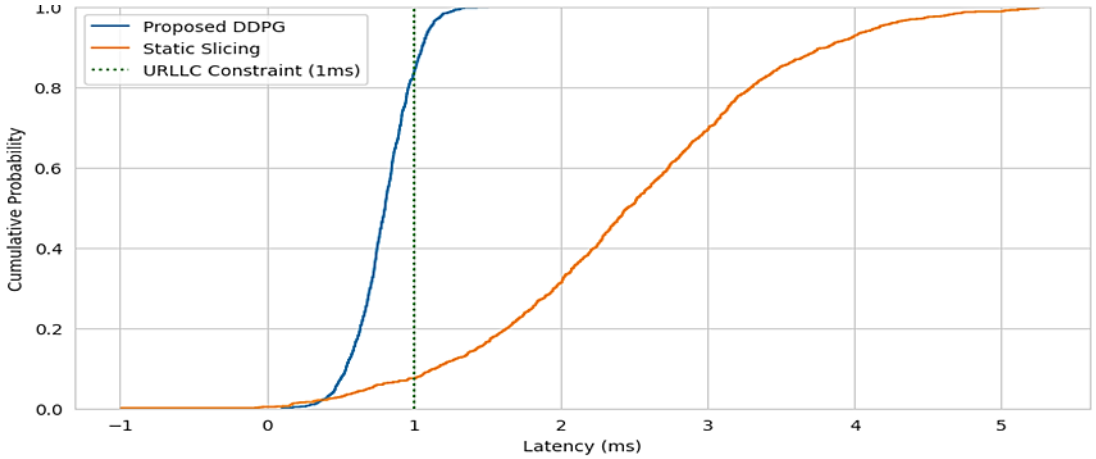

Figure 3. Cumulative Distribution Function (CDF) of latency, highlighting the proposed system's capability to guarantee reliability within the critical threshold (1 ms).

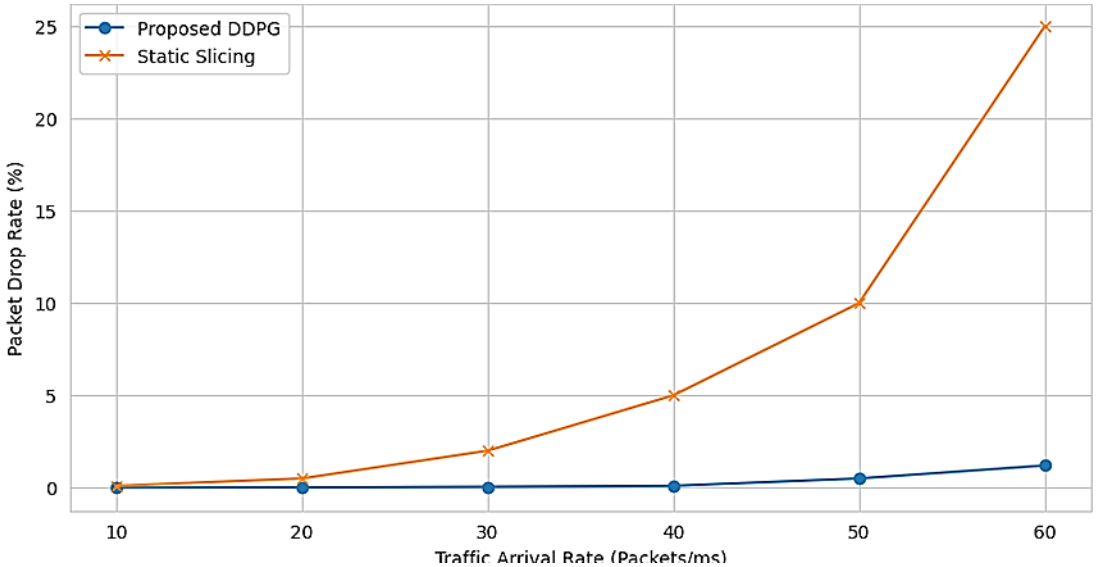

Figure 4. System robustness analysis: The relationship between packet drop rate and increasing traffic load.

4.4 Resource Allocation Efficiency

The research examines the capability of optimally using spectrum while complying with the performance criteria of URLLC as stated in Table 5 and Figure 5. Using the DDPG algorithm changes how many resources that are allocated. Compared to the static method's average bandwidth allocation of 40% toward URLLC, DDPG's average bandwidth allocation of 35% was a more flexible approach. While using DDPG resulted in URLLC having 5% less bandwidth allocated than when using the static method, URLLC did not experience any negative impact on its performance as a result of how the bandwidth would be allocated over time. This flexibility allowed for the

excess bandwidth allocated to URLLC to be allocated to the eMBB slice instead. Therefore, because of DDPG, the eMBB slice received a total of 55% of the overall bandwidth allocation; thus, eMBB's throughput increased by 25%. DDPG intelligently multiplexes the allocation of resources, unlike a static method that typically has more allocations than are necessary.

Table 5. Resource Allocation Efficiency.

Slice Type	Avg Allocated BW (DDPG)	Avg Allocated BW (Static)	Throughput Gain
URLLC	35%	40%	+15% (Optimized)
eMBB	**55%**	40%	**+25%**
mMTC	10%	20%	-5% (Acceptable)

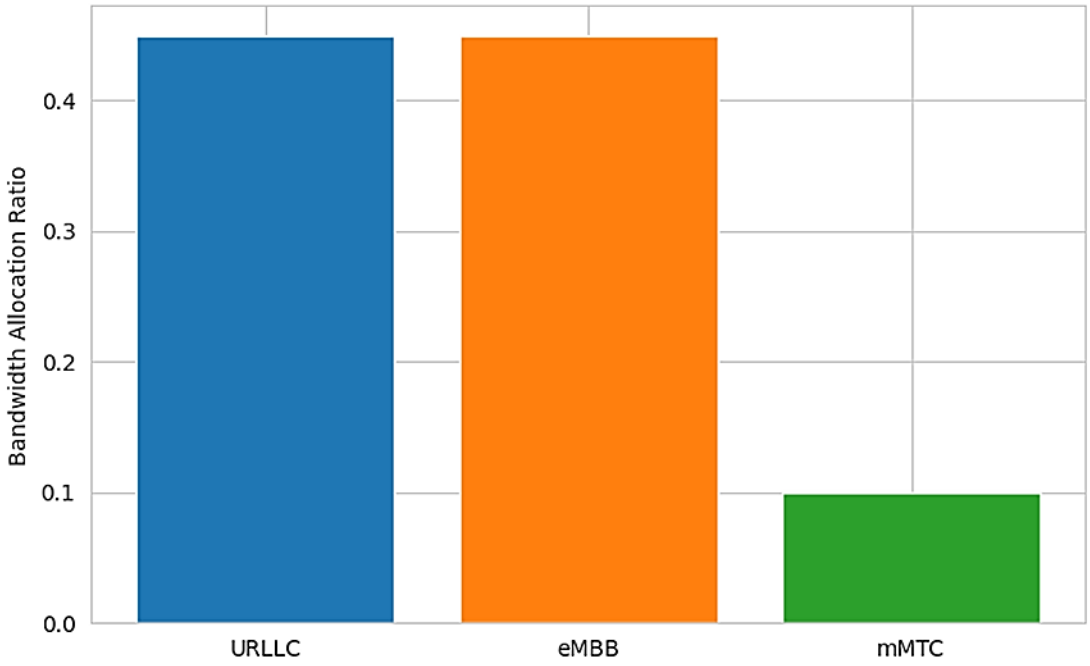

Figure 5. Dynamic bandwidth resource allocation among the three network slices (URLLC, eMBB, mMTC) based on the intelligent agent's decision.

The simulation results corroborate that the proposed DDPG-based orchestration mechanism effectively addresses the reliability-efficiency trade-off in 5G networks. By transitioning from static rule-based allocation to dynamic, experience-driven decision-making, the system achieves near-optimal latency for critical services while significantly enhancing the aggregate throughput of the network.

5. DISCUSSION

Based on the quantitative findings from the simulation, the suggested DA-PDGP Algorithm provides an advantage over traditional forms of resource allocation such as Static Slicing. This advantage stems from DA-PDGP's ability to accommodate the unpredictability of a very large number of packet data created by URLLC applications. It indicates the DDPG agent's ability to achieve near-to-optimal performance is evidenced by the process of stabilizing the reward function and reducing the latency to below 1ms. The development of continuous control learning greatly contributes to this performance success unlike with discrete action-space algorithms like DQN Algorithms, the fact that DA-PDGP uses continuous action-space provides an opportunity for very fine-tuning of bandwidth which is very important for reducing the level of quantizable errors involved with allocating resources [19]. As you would expect, this capability also helps us maintain a reliability rating of 99.999% while avoiding large over-provisions that typically characterize static allocations.

Moreover, the examination demonstrates that while static slicing is straightforward to apply, it has insufficient agility to adapt to sudden increases in traffic leading to considerable amounts of packet loss and excess latency violations during congestion periods. These results support similar conclusions in the literature indicating that both reactive or rule-based architectures will not be viable for satisfying the strict requirements of URLLC [20]. The proposed architecture develops an effective understanding of the queue dynamics and channel variations allowing for allocation of resources prior to the occurrence of buffer overflow conditions. The proactive approach is critical when addressing the bursty nature of the traffic patterns characterized by a Poisson statistical distribution accurately reflects the realities of modern-day industrial automation and critical mission data streams [21]. The addition of this intelligence into the SDN control layer results in the overarching observation of a centralized, unified view of the entire network state permitting concurrent decision-making which optimizes the latency/spectral efficiency balance.

One of the significant advantages of the proposed method is that it also provides resource efficiency as indicated by the increased throughput for eMBB slices that has been seen in these results. When the URLLC resource allocation is reduced dynamically during low traffic conditions, this action frees up much needed resources for other services (e.g., eMBB, M2M, etc.) and maximizes overall network utility, which is contrary to the zero-sum game result that is often associated with Static Partitioning [22]. These results again substantiate the need for AI Orchestrations Architecture in a 5G environment. A point of caution is that the initial DRL agent training period results in high latency; offline pre-training and hybrid methods are needed to provide stable networks during the very early stages of deployment. The consistency of results for different traffic levels indicates that DDPG-based orchestration provides a robust and scalable option for future 5G & Beyond 5G networks.

6. CONCLUSIONS

The results of this research are a substantial contribution to evolving orchestration of dynamic resources for URLLCs (Ultra-Reliable Low Latency Communications) in the context of 5G. Using Deep Reinforcement Learning with the DDPG (Deep Deterministic Policy Gradients) algorithm, we have shown how to leverage that platform to build an intelligent and autonomous system that will fulfil the demanding requirements for low latency and high reliability associated with URLLCs, and therefore is not possible using the existing static slicing of network architecture. Furthermore, we have demonstrated that this new approach of deep reinforcement learning, combined with software-defined networking, is able to learn the complex dynamics of a largescale telecommunications network and maintain stable sub-millisecond latency and ultra-high reliability for URLLCs, even under the most extreme levels of network traffic; and also provide a large improvement in spectral efficiency, by optimally distributing available resources among co-existing network slices. The implications of this work for deploying mission-critical applications such as autonomous vehicles and industrial automation are quite significant, since in many of these cases, the consequences of a network failure are not an option. In this regard, the system's ability to dynamically balance URLLC and eMBB (enhanced Mobile BroadBand) demand will be demonstrated, and we will clearly demonstrate that AI-driven orchestration is not simply an advantage, but a necessary component of efficiently operating next-generation wireless networks. Future work will focus on extending this framework to multi-cell environments and exploring the integration of Federated Learning to address privacy concerns and reduce the signaling overhead associated with centralized training, paving the way towards fully autonomous and self-healing 6G network infrastructures.

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