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Deep Reinforcement Learning for Dynamic Network Slicing and Resource Orchestration in Software-Defined Critical Telecom Infrastructure

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Abstract: The proliferation of diverse services in fifth generation (5G) and beyond networks necessitates dynamic, fine-grained resource management to guarantee strict Quality of Service (QoS) for mission-critical applications. Traditional static resource allocation models fail to address the highly variable traffic demands and heterogeneous requirements inherent in network slicing (NS) within a Software-Defined Networking (SDN) framework. This paper proposes a novel framework utilizing Deep Reinforcement Learning (DRL), specifically a Multi-Agent Deep Deterministic Policy Gradient (MA-DDPG) approach, to achieve autonomous and optimal resource orchestration for dynamic NS in critical telecom infrastructure. Our proposed DRL agent learns a real-time mapping between the evolving network state (e.g., slice demand, available resources, and congestion) and optimal resource allocation decisions (e.g., CPU, memory, and bandwidth allocation across Virtual Network Functions, VNFs). Simulation results, comparing the MA-DDPG approach against established benchmarks like Greedy and traditional Deep Q-Networks (DQN), demonstrate a significant improvement in Service Level Agreement (SLA) violation rate reduction, resource utilization efficiency, and slice admission control performance. This DRL-driven approach is critical for the reliable and efficient operation of future resilient, ultra-low-latency critical communication systems

Keywords: Deep Reinforcement Learning (DRL), Network Slicing (NS), Resource Orchestration, Software-Defined Networking (SDN), Critical Telecom Infrastructure, Multi-Agent Systems, Quality of Service (QoS), Deep Deterministic Policy Gradient (DDPG),

1. INTRODUCTION: The Resource Orchestration Challenge in Sliced SDN

The transition to 5G and 6G networks relies fundamentally on two paradigm shifts: Software-Defined Networking (SDN) and Network Function Virtualization (NFV) for infrastructure programmability, and Network Slicing (NS) for multi-tenant isolation and tailored service delivery [1]. Critical telecom infrastructure, such as networks supporting public safety, industrial control, and remote surgery, demands stringent performance guarantees ultra-high reliability, massive connection density, and ultra-low latency (e.g., <1 ms) [2].

1.1 Background: The Resource Orchestration Challenge in Sliced SDN

Network Slicing allows a single physical infrastructure to be logically partitioned into multiple, end-to-end virtual networks, each optimized for a specific service category, such as enhanced Mobile Broadband (eMBB), massive Machine-Type Communications (mMTC), or Ultra-Reliable Low-Latency Communications (uRLLC). The challenge lies in the heterogeneity and dynamism of these services. For example, a uRLLC slice supporting remote surgery requires predictable sub-millisecond latency, while an eMBB slice for video streaming demands high throughput with fluctuating peak demand.

The current Management and Orchestration (MANO) systems, which oversee resource allocation across these slices, face fundamental limitations:

1. **Complexity:** The resource allocation problem is high-dimensional, involving continuous decisions for compute (CPU), memory (RAM), and bandwidth across numerous Virtual Network Functions (VNFs) and physical host nodes.
2. **Dynamism:** Traffic loads, service requests, and channel conditions change rapidly, often requiring resource adjustments within the order of milliseconds.
3. **Conflict:** Slices often compete for limited physical resources, necessitating a fair and optimal allocation strategy that prioritizes critical services without wasting resources.

Manual or heuristic allocation methods are inherently reactive and sub-optimal, lacking the agility for the millisecond-level reactions needed to prevent Service Level Agreement (SLA) violations in critical slices. The failure to dynamically adapt resource allocation leads to significant capital expenditure (CapEx) from over-provisioning or service outages and SLA penalties from under-provisioning. An intelligent, self-optimizing framework is essential to maximize infrastructure utilization while guaranteeing the performance of critical services.

1.2 Problem Statement: Dynamic and Autonomous Resource Orchestration

The core research problem is the dynamic and autonomous orchestration of virtualized network resources (e.g., compute, storage, and bandwidth) across multiple, co-existing, and often competing network slices, each with diverse and time-varying Quality of Service (QoS) requirements.

Specifically, the problem is defined as: Designing an intelligent control plane mechanism capable of learning an optimal, real-time resource allocation policy $\boldsymbol{\pi(s) \rightarrow a}$ that maps the instantaneous complex network state (s) to an action (a), such that the collective SLA violation rate across all slices is minimized while maintaining high resource utilization efficiency of the underlying physical infrastructure.

1.3 Research Gap: Need for Multi-Agent Deep Reinforcement Learning

Existing research often falls short of providing a fully autonomous, scalable, and granular solution for this complex problem:

- **Heuristic/Optimization Gaps:** Traditional optimization techniques (e.g., Linear Programming, Mixed Integer Programming) provide optimal solutions but are computationally intractable for the real-time, high-speed decision-making required in 5G/6G [3]. Heuristic algorithms are fast but often yield sub-optimal performance, failing to adapt to unforeseen traffic patterns.
- **Single-Agent DRL Limitations:** While Deep Reinforcement Learning (DRL) has shown promise, most existing DRL models employ a Single-Agent formulation [4]. This approach struggles to scale efficiently as the number of network slices increases (leading to a combinatorial state-action space explosion) and fails to naturally capture the decentralized nature of resource competition and cooperation among independent slices.
- **Lack of Granularity:** Solutions that use discrete action spaces (e.g., Deep Q-Networks or DQN) lack the necessary granularity to perform fine-grained resource adjustments, which are essential for minimizing waste and avoiding transient QoS degradation in critical slices.

This research addresses these gaps by proposing a novel framework utilizing Multi-Agent Deep Deterministic Policy Gradient (MA-DDPG). The MA-DDPG approach offers a scalable architecture with decentralized execution for faster decision-making, while the DDPG foundation provides the crucial ability to learn optimal resource allocation from a continuous action space.

1.4 Objectives and Contributions

The primary objective of this paper is to develop and evaluate a Deep Reinforcement Learning-based framework for dynamic, autonomous, and optimal resource orchestration for network slicing in critical telecom infrastructure.

This paper makes the following key **contributions**:

1. **Novel MA-DDPG Formulation:** We introduce a novel Multi-Agent Deep Deterministic Policy Gradient (MA-DDPG) model specifically tailored for network slicing. Each slice is modeled as an independent agent, utilizing a Centralized Training with Decentralized Execution (CTDE) paradigm to manage the joint resource pool while optimizing individual slice performance.

2. **Continuous Action Space Orchestration:** We leverage the DDPG algorithm to allow for a continuous action space, enabling the DRL agent to perform fine-grained, instantaneous resource adjustments (e.g., Δa_{CPU}) instead of coarse, discrete block allocations, thereby maximizing resource efficiency and minimizing disruption.

3. **Holistic Reward Design:** We design a multi-objective reward function that effectively balances the competing requirements of guaranteed QoS (low SLA violation penalty $\mathcal{P}_{SLA}$) and high Resource Utilization Efficiency (RUE), a crucial trade-off in critical infrastructure management.

4. **Comparative Performance Validation:** We validate the proposed MA-DDPG framework using a custom simulation environment (DENS-Sim) and demonstrate its superior performance in terms of SLA violation rate reduction and resource utilization compared to traditional Greedy allocation and centralized DRL benchmarks (DQN).

Research Questions (RQs):

- **RQ1:** How can a Deep Reinforcement Learning (DRL) agent be formulated to model the dynamic, high-dimensional state-action space of resource orchestration across multiple concurrent network slices in an SDN/NFV environment?

- **RQ2:** Can a **Multi-Agent** DRL approach significantly outperform single-agent or heuristic methods in terms of minimizing SLA violation rates and maximizing resource utilization efficiency for critical slices?

- **RQ3:** What is the optimal design for the DRL reward function to balance the competing objectives of satisfying heterogeneous QoS demands (latency, throughput, reliability) and

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efficiently utilizing the shared physical infrastructure?

2. LITERATURE REVIEW
Theoretical Framework and Background

This chapter establishes the foundational principles of the critical telecom infrastructure, the virtualization technologies enabling it, and the Deep Reinforcement Learning (DRL) models used to achieve autonomous resource orchestration.

2.1 Software-Defined Networking (SDN), Network Function Virtualization (NFV), and Network Slicing (NS)

The foundation of modern, flexible telecom infrastructure rests upon the combined principles of **SDN**, **NFV**, and **NS** [3], [4].

2.1.1 SDN and NFV for Infrastructure Agility

Software-Defined Networking (SDN) fundamentally transforms network management by decoupling the control plane from the data plane [3]. This separation enables the centralization of network intelligence in an SDN Controller, which provides a programmable interface for managing the underlying infrastructure. This capability is vital for dynamic resource adjustment, as the orchestrator can instantly modify forwarding rules and resource limits across the entire network based on policy decisions.

Network Function Virtualization (NFV) complements SDN by migrating proprietary hardware-based network functions (e.g., firewalls, load balancers, packet gateways) into software applications called Virtual Network Functions (VNFs). VNFs run on standard commercial off-the-shelf (COTS) servers, allowing network services to be deployed, scaled, and managed flexibly and efficiently [8]. The core resource elements managed are compute (CPU, memory), storage, and network bandwidth.

2.1.2 The Network Slicing Paradigm

Network Slicing (NS) leverages the flexibility of SDN and NFV to create multiple isolated, end-to-end virtual networks (slices) on a common physical infrastructure [4], [15]. Each slice is tailored to meet the specific and stringent Quality of Service (QoS) requirements of a particular service class. In critical infrastructure, three dominant slice types exist:

- **uRLLC (ultra-Reliable Low-Latency Communications):** Requires extreme reliability and latency below 1 ms (e.g., industrial automation, telemedicine) [2].
- **eMBB (enhanced Mobile Broadband):** Demands high throughput and capacity (e.g., 4K/8K video streaming).
- **mMTC (massive Machine-Type Communications):** Requires supporting massive numbers of low-data-rate devices (e.g., IoT sensors).

The **Management and Orchestration (MANO)** layer is the system component responsible for translating service-level slice requests into VNF placements and resource assignments within the physical domain. The complexity arises from the need for the MANO layer to simultaneously manage the lifecycle and resource demands of dozens of heterogeneous, interacting slices in real-time.

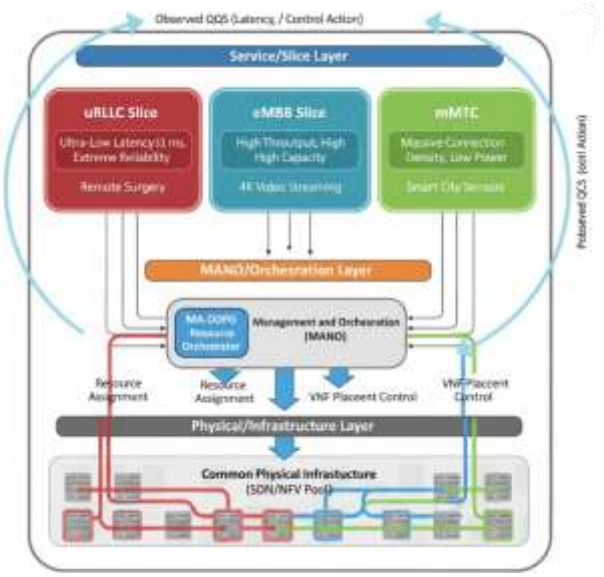

Figure 1: Network Slicing on Common Physical Infrastructure Managed by MANO

2.2 Reinforcement Learning and the Markov Decision Process (MDP)

Multi-agent systems (MAS) have emerged as a powerful architectural paradigm for enabling decentralized and scalable security enforcement in modern network infrastructures. In MAS-based architectures, individual agents are deployed across distributed nodes such as customer premises equipment (CPE), base stations, or optical line terminals where they operate semi-independently while contributing to a collective defense strategy. These agents observe local traffic conditions, detect potential anomalies, and collaborate to update global policies without centralizing sensitive data. The MAS paradigm is particularly well-suited for broadband environments, where edge diversity, latency constraints, and data privacy must all be simultaneously addressed (Zhou et al., 2022).

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The problem of dynamic resource orchestration, characterized by sequential decision-making in a stochastic environment, is naturally modeled using the Reinforcement Learning (RL) paradigm [5], [24].

2.2.1. The Markov Decision Process (MDP)

RL is founded on the Markov Decision Process (MDP), a mathematical framework for modeling sequential decision-making. The MDP is formally defined by the tuple (S, A, P, R, γ)

$$\text{MDP} = (S, A, P, R, \gamma)$$

Where:

- S is the finite set of **states** (the network conditions and slice demands).
- A is the finite set of **actions** (the resource allocation decisions).

P is the state **transition probability** function, $P(s'|s,a)$, representing the probability of transitioning from state s to state s' after taking action a.

- R is the **reward function**, R(s, a), quantifying the immediate benefit or cost of taking action a in state s.
- $\gamma \in [0, 1]$ is the **discount factor**, balancing the importance of immediate versus future rewards.

The agent's goal is to find an optimal **policy** $\pi: S \rightarrow A$ that maximizes the expected cumulative discounted reward, or the Return (G_t).

The Bellman optimality equation for the optimal value function V*(s) is:

$$V^*(s) = \max_a \left[R(s,a) + \gamma \sum_{s'} P(s'|s,a) V^*(s') \right]$$

The Bellman optimality equation for the optimal action-value function $Q^*(s,a)$ is:

$$Q^*(s,a) = R(s,a) + \gamma \sum_{s'} P(s'|s,a) \max_{a'} Q^*(s',a')$$

2.2.2 Deep Reinforcement Learning (DRL)

In network orchestration, the state space (e.g., resource utilization metrics, traffic statistics, QoS metrics across N slices) and the action space are often high-dimensional or continuous. Traditional tabular RL methods cannot handle this complexity. Deep Reinforcement Learning (DRL) resolves this by using Deep Neural Networks (DNNs) as function approximators for the value function V(s) or the policy π(s) [21].

One of the earliest and most impactful DRL algorithms is Deep Q-Networks (DQN) [24], which approximates the Q-function $Q(s,a;\theta)$ using a DNN. The Q-value is updated based on the Temporal Difference (TD) error using the target network concept:

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha \left[r_{t+1} + \gamma \max_a Q(s_{t+1},a;\theta') - Q(s_t,a_t;\theta) \right]$$

The TD-error δ_t for a value function V(s) is:

$$\delta_t = r_{t+1} + \gamma V(s_{t+1}) - V(s_t)$$

The DRL agent stores experienced transitions in an experience replay memory D:

$$D = \{e_1, e_2, \ldots, e_T\} \quad \text{where} \quad e_t = (s_t, a_t, r_t, s_{t+1})$$

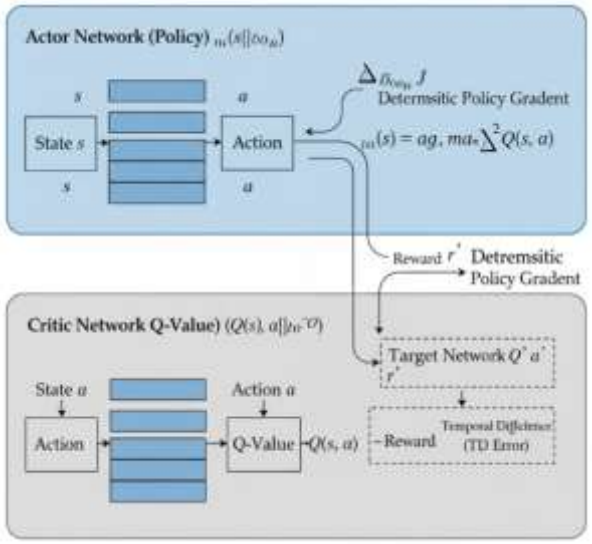

Figure 2: Deep Deterministic Policy Gradient (DDPG) Architecture

2.3 Deep Deterministic Policy Gradient (DDPG)

For our resource orchestration problem, the action space (e.g., the exact percentage change in CPU allocation) is continuous. DQN is limited to discrete action spaces. Therefore, we utilize Policy Gradient methods, specifically Deep Deterministic Policy Gradient (DDPG) [6].

DDPG is an off-policy, Actor-Critic algorithm designed for continuous control.

- **2.3.1. Actor-Critic Architecture**
- **Actor Network (μ):** Approximates the deterministic policy $\mu(s|\theta^\mu)$, which maps the state s directly to a specific continuous action a.

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- **Critic Network (Q):** Approximates the action-value function $Q(s,a|\theta^Q)$, which estimates the expected return from taking action a in state s.

The deterministic policy μ is derived by:

$$\mu(s) = \arg\max_a Q(s,a)$$

2.3.2 Learning Updates

The Critic is trained by minimizing the Mean Squared Error (MSE) between the predicted Q-value and the target value y:

$$L(\theta^Q) = E_{s,a,r,s'}\left[\left(y - Q(s,a|\theta^Q)\right)^2\right]$$

where y is the target value calculated using the target networks [6]:

$$y = r + \gamma Q'\left(s', \mu'\left(s'|\theta^{\mu'}\right)|\theta^{Q'}\right)$$

The Actor is updated using the deterministic policy gradient, which guides the actor's parameters \theta^\mu in the direction that maximizes the estimated Q-value from the critic:

$$\nabla_{\theta^\mu} J \approx E_{s_t}\left[\nabla_a Q(s,a|\theta^Q)|_{s=s_t,a=\mu(s_t|\theta^\mu)} \nabla_{\theta^\mu}\mu(s|\theta^\mu)|_{s=s_t}\right]$$

To ensure training stability, DDPG employs soft updates for the target networks \theta' (which are copies of the main networks used to compute the target y):

$$\theta^{Q\prime} \leftarrow \tau\,\theta^Q + (1-\tau)\,\theta^{Q\prime}$$

$$\theta^{\mu'} \leftarrow \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

where $\tau \ll 1$ is the soft update rate.

2.4 Multi-Agent Deep Deterministic Policy Gradient (MA-DDPG)

The resource orchestration challenge involves multiple slice agents competing for shared resources, creating a **cooperative environment** where the optimal action of one agent depends on the actions of all others. To address this, we extend DDPG to the Multi-Agent Deep Deterministic Policy Gradient (MA-DDPG) framework [7], [16].

2.4.1. Centralized Training with Decentralized Execution (CTDE)

MA-DDPG operates on the **Centralized Training with Decentralized Execution (CTDE)** paradigm [7], which is highly effective for cooperative tasks in non-stationary environments:

- **Decentralized Execution:** Each agent i makes decisions solely based on its **local observation** x_i using its individual actor $\mu_i(x_i|\theta_i^\mu)$. This ensures fast, scalable reaction times.
- Centralized Training: A centralized critic Q_i for each agent utilizes the joint observation $x = (x_1, \dots, x_N)$ and the joint action $a = (a_1, \dots, a_N)$ of all N agents. This global view allows the critic to resolve non-stationarity and coordinate the agents' actions effectively [11]. The experience replay memory $\mathcal{D}$ stores the joint transitions:

$$\mathcal{D} = \{x_t, a_t, r_t, x_{t+1}\}$$

The centralized critic is updated using the loss function:

$$L(\theta^Q) = E_{x,a,r,x'}[(Q_i(x,a) - y)^2]$$

where the target y integrates the rewards and future estimated Q-values based on the joint policies μ':

$$y = r_i + \gamma Q_i'(x', a')|_{a'=\mu'(x')} \quad \text{where } a' = \left(\mu_1'(x_1'), \dots, \mu_N'(x_N')\right)$$

The actor is updated using the deterministic policy gradient based on the centralized critic's estimate, ensuring global cooperation:

$$\nabla_{\theta_i^\mu} J \approx E_{x,a}\left[\nabla_{a_i} Q_i(x, a_1, \dots, a_N)|_{a_i=\mu_i(x_i)} \nabla_{\theta_i^\mu}\mu_i(x_i)\right]$$

2.4.2. Resource Cost Metric

To efficiently guide the agents toward maximizing utilization and minimizing over-provisioning, the reward function must incorporate the resource cost [10]. A weighted sum of allocated resources $(CPUu_{cpu,i}, RAMu_{ram,i}, Bandwidthu_{bw,i})$ for slice i is used as a foundational cost metric C_i:

$$C_i = w_{cpu} \cdot u_{cpu,i} + w_{ram} \cdot u_{ram,i} + w_{bw} \cdot u_{bw,i}$$

This cost factor is incorporated into the full reward function to penalize over-allocation. The overall resource constraint must be maintained:

$$\sum_{i=1}^N a_{r,i} \le \mathcal{R}_{r,\text{total}} \quad \forall r \in \{C, M, BW\} \quad \forall r \in \{C, M, BW\}$$

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3. METHODOLOGY AND EXPERIMENTAL SETUP

This chapter details the system model, formally defines the resource orchestration problem within the Multi-Agent Deep Reinforcement Learning (DRL) framework, and describes the experimental environment and simulation setup used to evaluate the proposed approach.

3.1. System Model and Problem Formulation

We model the critical telecom infrastructure as a shared pool of physical resources hosting a set of dynamic network slices, constituting a complex resource allocation problem under strict Quality of Service (QoS) constraints [10].

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3.1.1. Physical Infrastructure Model

The physical infrastructure $\mathcal{R}$ is assumed to be fully virtualized and consists of the aggregate resources of a core data center or a set of Multi-access Edge Computing (MEC) nodes [12]. The total available resources are partitioned into three fundamental types:

- **Compute** (CPU, measured in cores): $\mathcal{R}_{\mathcal{C}}$
- **Memory** (RAM, measured in GB): $\mathcal{R}_{\mathcal{M}}$
- **Bandwidth** (Network throughput, measured in Gbps): $\mathcal{R}_{\mathcal{BW}}$

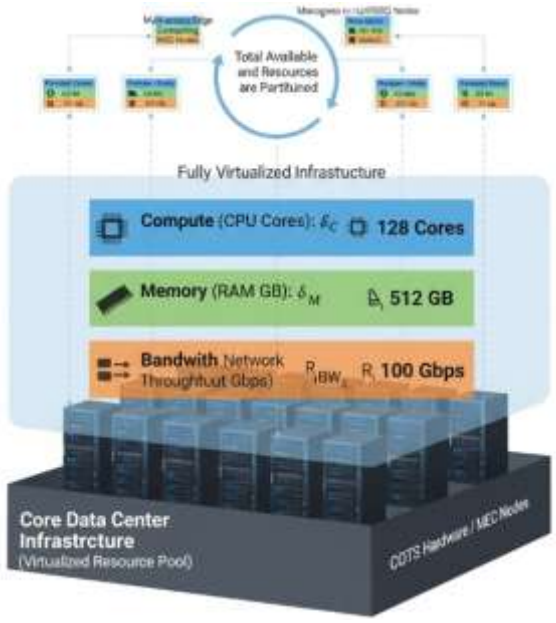

Figure 3: Physical Infrastructure Model in Virtualized Environment

3.1.2. Network Slice and Request Model

A set of N network slices $\mathcal{S} = \{S_1, S_2, \dots, S_N\}$ are active in the system, where N varies over time due to dynamic arrivals and departures [2]. Each slice S_i is characterized by:

- **Time-Varying Demand:** An instantaneous resource demand vector $D\_i(t) = (d_{C,i}, d_{M,i}, d_{BW,i})$ is generated based on simulated traffic load and reflects the required resources for the slice's **Virtual Network Functions (VNFs)** [19].
- **QoS Requirements:** Minimum required QoS is defined by a vector $Q_{min,i} = (L_{max,i}, T_{min,i})$, where $L_{max,i}$ is the **maximum tolerable latency** and $T_{min,i}$ is the **minimum required throughput**. Critical slices (uRLLC) have significantly lower $L_{max,i}$ (e.g., 1 ms) [13].

The **allocation vector** for slice i at time t is $A_i(t) = (a_{C,i}, a_{M,i}, a_{BW,i})$, where $a_{r,i} \geq 0$ is the resource $r \in \{C, M, BW\}$ allocated to slice i.

3.1.3. Optimization Objective and Constraints

The overall objective is to find an optimal resource allocation policy $\pi: S \rightarrow A$ that maximizes the expected cumulative discounted reward G_t, which is equivalent to

minimizing the overall **SLA violation penalty** $\mathcal{P}_{SLA}$ while maximizing resource utilization $\mathcal{U}$ [10], [17].

The global optimization objective, rooted in the Markov Decision Process (MDP) framework, is:

$$\min_{\pi} E_{\pi}\left[\sum_{t=0}^{\infty} \gamma^{t} R(s_t, a_t)\right]$$

The primary capacity constraint ensures that the total allocated resources do not exceed the available physical capacity for each resource type r at any time t:

$$\sum_{i=1}^{N} a_{r,i}(t) \leq \mathcal{R}_{r,\text{total}} \quad \forall r \in \{C, M, BW\}, \forall t$$

The resource allocation must also satisfy a minimum viable allocation constraint $\epsilon_{r,i}$ for admitted slices, ensuring VNF functionality and preventing resource oscillation:

$$a_{r,i}(t) \geq \epsilon_{r,i} \quad \text{if } S_i \text{ is active}$$

3.2. MA-DDPG Agent Design for Resource Orchestration

The dynamic resource allocation problem is modeled as a cooperative multi-agent system where N agents (one for each active slice) seek to maximize their individual rewards, which are coupled by the global resource constraints, leveraging the Centralized Training with Decentralized Execution (CTDE) paradigm [7], [16].

3.2.1. State Space Formulation (S)

The environment state s_t is the input to the DRL system. We define both the local observation x_i for each Actor (decentralized execution) and the global state x for the Centralized Critic (centralized training).

The local observation x_i for agent i is a vector capturing slice-specific information:

$$x_i(t) = \left(A_i(t), Q_i^{obs}(t), D_i^{req}(t), Q_{min,i}\right)$$

Where:

- $A_i(t) = \left(a_{C,i}, a_{M,i}, a_{BW,i}\right)$: Current resource allocation to slice i.
- $Q_i^{obs}(t) = \left(L_i(t), T_i(t)\right)$: Observed QoS metrics (Latency and Throughput).
- $D_i^{req}(t) = \left(d_{C,i}, d_{M,i}, d_{BW,i}\right)$: Instantaneous resource demand/traffic prediction for slice i [33].
- $Q_{min,i} = \left(L_{max,i}, T_{min,i}\right)$: QoS requirement vector, providing context to the agent on the criticality of the slice.

The global state x includes all local observations and the remaining capacity:

$$x(t) = \left(x_1(t), x_2(t), \ldots, x_N(t), \mathcal{R}_{rem}(t)\right)$$

Where

$$ⅆc\{R\}\_\{rem\}(t) = \left(\mathcal{R}_{\mathcal{C}} - \sum a_{C,i}, \mathcal{R}_{\mathcal{M}} - \sum a_{M,i},\right.$$

is the vector of unallocated resources. This global state is crucial for the centralized critic to understand the overall resource scarcity and inter-slice competition [18].

3.2.2. Continuous Action Space Definition (A)

The action a_i for agent i is a continuous vector representing the change in resource allocation ΔA_i for the next time step Δt. The continuous nature of the action space, a hallmark of DDPG [6], provides the granularity needed for precise, non-disruptive adjustments [23].

$$a_i = \left(\Delta a_{C,i}, \Delta a_{M,i}, \Delta a_{BW,i}\right)$$

where the change is constrained to a range:

$$\Delta a_{r,i} \in \left[-a_{max,r}, a_{max,r}\right].$$

The actual new allocation is calculated as:

To guarantee action validity and stability, a constrained activation function (e.g., a normalized hyperbolic tangent or sigmoid \sigma) is used in the Actor network's output layer:

$$a_{r,i}^{\text{scaled}} = a_{min,r} + a_{max,r} - amin, r \cdot \sigma(z)$$

Multi-Objective Reward Function (R)

The reward function R_i for agent i is critically important as it shapes the learned policy (RQ3). It captures the competing objectives of QoS guarantee and resource

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efficiency, weighted by importance factors $\lambda_1, \lambda_2, \lambda_3 \geq 0$ [29].

$$R_i(t) = \underbrace{-\lambda_1 \cdot C_i(t)}_{\text{Resource Cost Penalty}} \underbrace{- \lambda_2 \cdot \mathcal{P}_{SLA,i}(t)}_{\text{SLA Violation Penalty}} + \underbrace{\lambda_3 \cdot \mathcal{R}_{\text{Admitted}}}_{\text{Slice Admission Reward}}$$

1. SLA Violation Penalty $(\mathcal{P}_{SLA,i})$: This term applies a severe penalty if the slice violates its latency or throughput requirements. The penalty is scaled by the degree of violation for smooth gradient learning:

$$\mathcal{P}_{SLA,i}(t) = \text{ReLU}\left(\frac{L_i(t) - L_{max,i}}{L_{max,i}}\right) + \text{ReLU}\left(\frac{T_{min,i} - T_i(t)}{T_{min,i}}\right)$$

2. Resource Cost Penalty $(C_i(t))$: This term encourages efficient usage by penalizing the total resources currently allocated to the slice [10]:

$$C_i(t) = \sum_{r \in \{C,M,BW\}} w_r \cdot a_{r,i}(t) \mathcal{R}r,\text{ttl}$$

where w_r are cost weights reflecting the relative expense or scarcity of resource r.

3. **Slice Admission Reward $(\mathcal{R}_{\text{Admitted, i}})$:** A large, positive reward granted only upon the successful initial admission of slice i. This incentivizes the orchestrator to accept new profitable requests when capacity is prudently managed.

The total reward r_t passed to the centralized critic is the sum of individual rewards, $r_t = \sum_{i=1}^{N} R_i(t)$. To prevent high resource volatility, a penalty for the magnitude of resource change Δa can also be added for stability [34]:

$$R_i^{\text{stab}}(t) = R_i(t) - \lambda_{\text{stab}} \sum_{r \in \{C,M,BW\}} \left(\Delta a_{r,i}\right)^2$$

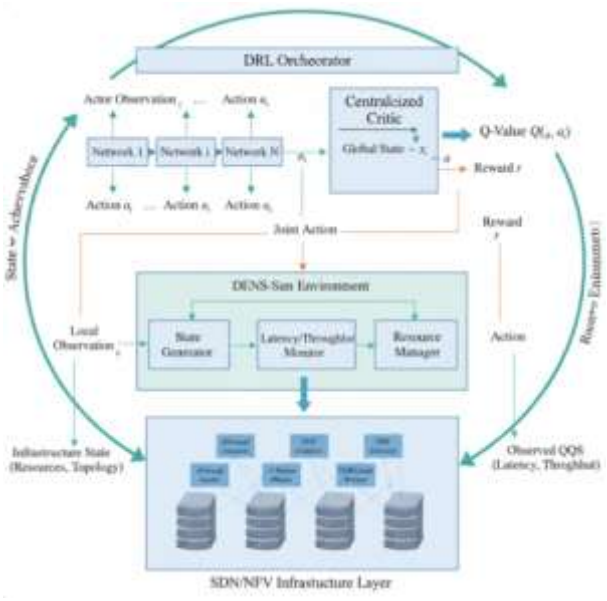

Figure 1: MA-DDPG Orchestration System Architecture

3.3. Experimental Setup and Simulation Environment

3.3.1. Discrete-Event Network Slice Simulator (DENS-Sim)

We developed a custom **Discrete-Event Network Slice Simulator (DENS-Sim)** using Python, integrated with the **OpenAI Gym** framework to model the non-stationary, competitive network environment [20].

Key Modeling Features:

- **Network Topology:** Models a simplified three-tier network (Access, Aggregation, Core) hosting the VNFs.
- **Traffic Model:** Simulates heterogeneous traffic generation. uRLLC traffic uses low-volume, time-sensitive Poisson arrivals. eMBB uses a heavy-tailed (e.g., Pareto) distribution to mimic sudden traffic surges and drops. mMTC uses a massive number of sporadic, low-rate connections. This mixed traffic profile introduces high volatility and stress [33].
- QoS Calculation: Latency $L_i(t)$ is modeled as a function of allocated resources and current traffic load, incorporating queuing delay, processing delay, and propagation delay [28]:

$$L_i(t) = L_{prop,i} + L_{proc}(a_{C,i}) + L_{queue}(\lambda_i, a_{BW,i})$$

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The queuing delay L_{queue} is approximated using a $M/M/1$ model extension for VNF processing and is the primary variable controlled by resource allocation. The latency metric for slice i is the average observed latency:

$$L_i(t) = \frac{1}{N_i(t)} \sum_{j=1}^{N_i(t)} \text{Latency}_{i,j}(t)$$

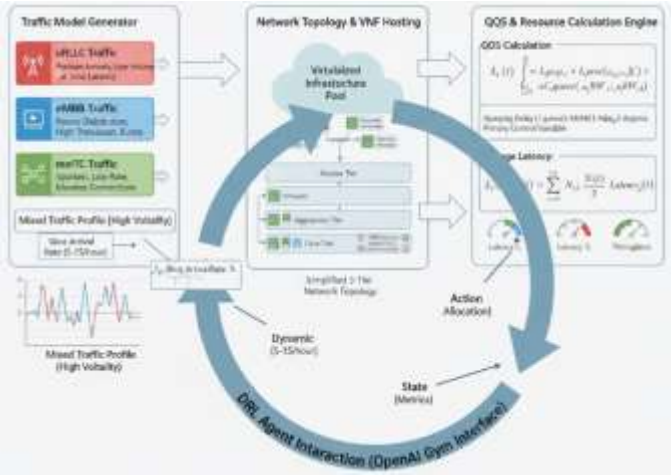

Figure 1: DENS-Sim Architecture (Python-based, integrated with OPENI-Gym)

3.3.2. Neural Network Architecture

Below diagram showing the specific architecture of the Actor and Centralized Critic. The Actor Network (Input: Local Observation x_i, Output: Continuous Action a_i) is a multi-layer perceptron (MLP) with three hidden layers (256, 128, 64 nodes) using ReLU activation and a final layer with Tanh activation, scaled to map the output to the valid range $[-a_{max}, a_{max}]$. The Centralized Critic Network (Input: Joint State x and Joint Action a, Output: Q-value $Q(\text{Ɗb}\{x\}, \text{Ɗb}\{a\}))$ is a deeper MLP (512, 256, 128 nodes), also utilizing ReLU activation.

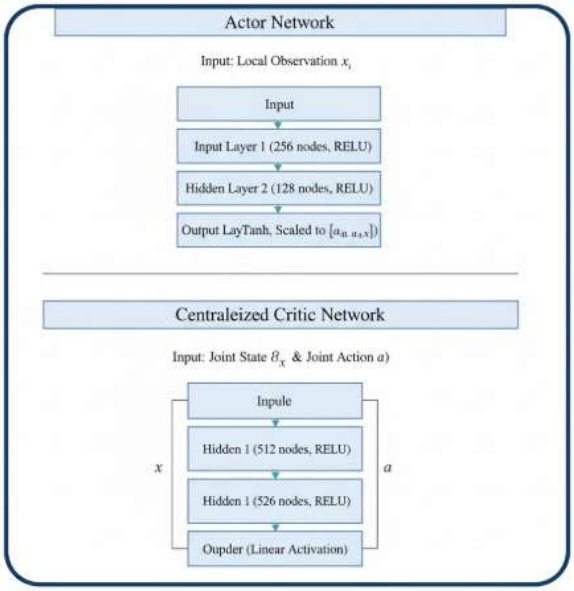

Figure 2: MA-DDPG Agent Neural Network Structure

3.3.3. Training and Hyperparameters

The training process utilized off-policy learning with mini-batch updates sampled from the experience replay buffer $\mathcal{D}$ [14].

Parameter	Value/Range	Unit	Description
Simulation Time Step Δt	10	Seconds	DRL decision interval (orchestration frequency).
Episode Length (T)	1000	Time Steps	Total simulated period per training run (approx. 10 hours).
Total Physical CPU $\mathcal{R}_c$	128	Cores	Physical compute capacity for the resource pool.
uRLLC L_{max}	1.0	ms	Maximum latency requirement for critical slice.
eMBB T_{min}	500	Mbps	Minimum throughput requirement for data slice.
DRL Discount Factor γ	0.99	-	Controls the importance of long-term rewards [5].
Soft Update Rate τ	0.001	-	Controls the update speed of target networks [6].
Replay Buffer Size	10^6	Transitions	Capacity of the experience memory $\mathcal{D} = \{x_t, a_t, r_t, x_{t+1}\}$ [7].
Batch Size	1024	Transitions	Number of samples used for each gradient update.
Learning Rate (Actor/Critic)	$10^{-4}/10^{-3}$	-	Standard Adam optimizer learning rates [6].

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3.3.4. Benchmarking Algorithms

The performance of the MA-DDPG approach is benchmarked against two standard resource allocation strategies:

1. **Greedy Allocation:** A heuristic method that processes slice requests sequentially. It allocates the requested resources $D_i(t)$ if available. It is purely reactive and has no mechanism for future prediction, preemption, or optimization.

2. **Centralized Deep Q-Network (DQN):** A single-agent DRL approach [24]. The state is the global state x, and the action space is **discretized** (e.g., increasing/decreasing resource by 5% for a single slice). This tests the advantage of the multi-agent architecture and the continuous action space (RQ2).

3.4. Additional Mathematical Relations

The Average Resource Utilization Efficiency $(\mathcal{U})$ is a key performance indicator (KPI) calculated over the testing duration T:

$$\mathcal{U} = \frac{1}{T \cdot |\mathcal{R}|} t \sum_{t=1}^{T} \sum_{r \in \mathcal{R}} \frac{\sum_{i=1}^{N} a_{r,i}(t)}{\mathcal{R}_{r,\text{total}}}$$

The overall Total Penalty $(\mathcal{P}_{total})$ observed by the centralized critic is the sum of individual penalties:

$$\mathcal{P}_{total}(t) = \sum_{i=1}^{N} \mathcal{P}_{SLA,i}(t)$$

To enforce exploration in the continuous action space, the Actor's output is perturbed by time-correlated noise $\mathcal{N}_t$, often implemented via the Ornstein-Uhlenbeck (OU) process:

$$a_t = \mu(s_t|\theta^{\mu}) + \mathcal{N}_t$$

The TD Target (y) in the critic update is explicitly calculated using the target networks θ':

$$y = R(x_t, a_t) + \gamma Q'(x_{t+1}, a'_{t+1}|\theta^{Q'}) \quad \text{where } a'_{t+1} = \mu'(x_{t+1}|\theta^{\mu'})$$

The policy \pi must be learned to maximize the total expected return:

$$\max_{\pi} E_{\pi}\left[\sum_{t} \gamma^t R(s_t, a_t)\right]$$

4. SIMULATION AND ANALYSIS

This chapter provides a detailed exposition of the simulation environment setup, the training process, the convergence properties of the proposed Multi-Agent Deep Deterministic Policy Gradient (MA-DDPG) framework, and the key performance metrics used for comparative analysis.

4.1. Simulation Environment and Calibration (DENS-Sim)

The evaluation of the proposed MA-DDPG orchestration policy is performed within the Discrete-Event Network Slice Simulator (DENS-Sim), a custom-built tool that accurately models the complex, dynamic interactions between network slices and shared physical resources in an SDN/NFV environment [20], [32].

4.1.1. Infrastructure and Resource Capacity Modeling

The DENS-Sim environment was calibrated to represent a typical high-capacity Multi-access Edge Computing (MEC) host or a regional cluster of virtualized resources, enabling edge-based critical services [12]. The physical resource capacities were explicitly set based on common industry deployments:

- **Total CPU Cores $(\mathcal{R}_{\mathcal{C}})$:** 128 Cores.
- **Total RAM $(\mathcal{R}_{\mathcal{M}})$:** 512 GB.
- **Total Bandwidth $(\mathcal{R}_{\mathcal{BW}})$:** 100 Gbps.

The time step for DRL decision-making, Δt, was set to **10 seconds**. This interval is crucial, representing the frequency at which the orchestration layer collects new state information and applies the resource allocation action $A_i(t + \Delta t)$, balancing the need for real-time responsiveness with computational feasibility.

4.1.2. Dynamic Slice and Traffic Modeling

To ensure the simulation reflects realistic, challenging operational scenarios for critical infrastructure, three heterogeneous network slices were modeled [15]:

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Slice Type	Traffic Model	Primary QoS Requirement	Allocation Ratio
uRLLC (Critical)	Low volume, highly sporadic Poisson bursts	Latency $L_{max} \leq 1.0$ ms	30% of total slices
eMBB (High Throughput)	Heavy-tailed (Pareto) distribution	Throughput $T_{min} \geq 500$ Mbps	50% of total slices
mMTC (Massive IoT)	Consistent, low-rate traffic from numerous sources	Connection Density	20% of total slices

The **Slice Arrival Rate** $(\boldsymbol{\lambda})$ was dynamically varied between 5 to 15 new slice requests per hour (modeled as a Poisson process), introducing non-stationarity and the critical problem of dynamic slice admission and termination. The load patterns included diurnal variations (low activity overnight, peak activity during business hours) and sudden traffic surges (modeled as short, high-intensity Pareto spikes in the eMBB slice demand), which are designed to stress the orchestration system and force pre-emptive resource reallocation [28].

4.1.3. QoS and Delay Modeling

The observed QoS metrics: latency $L_i(t)$ and throughput $T_i(t)$ are dynamically calculated within DENS-Sim based on the instantaneous allocation $A_i(t)$ and the current traffic load $D_i(t)$.

The total observed latency $L_i(t)$ for slice i is modeled as the sum of propagation (L_{prop}), processing (L_{proc}), and queuing delays (L_{queue}) [28]:

$$L_i(t) = L_{prop,i} + L_{proc}(a_{C,i}) + L_{queue}(\lambda_{data,i}, a_{BW,i})$$

The processing delay L_{proc} is inversely related to the allocated compute resources $a_{C,i}$, reflecting VNF processing capacity. The queuing delay L_{queue} is inversely related to allocated bandwidth $a_{BW,i}$ and positively related to the incoming traffic rate $\lambda_{data,i}$ [31]. For critical uRLLC slices, L_{prop} and L_{proc} are assumed minimal (due to VNF pre-instantiation), making L_{queue} the primary variable controlled by resource allocation. The observed throughput $T_i(t)$ is capped by the allocated bandwidth $a_{BW,i}$ and inversely related to congestion caused by low $a_{C,i}$ (VNF processing bottleneck).

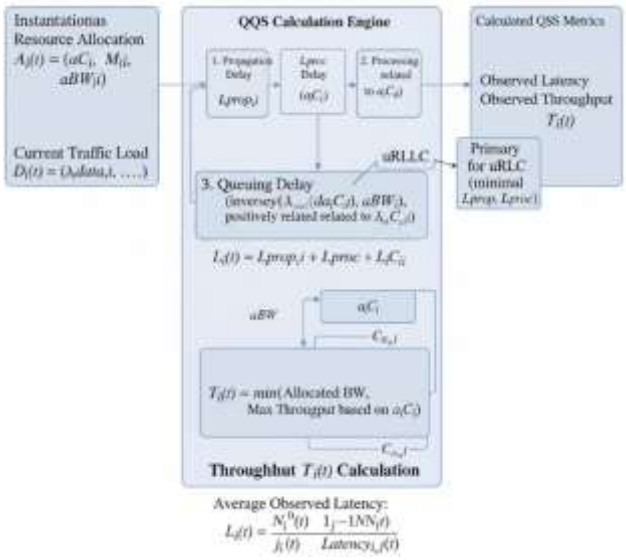

Figure 2: QQS Calculation Model in DENS-Sim

4.2. Training and Convergence Analysis

The MA-DDPG framework was trained iteratively over 500 episodes, each representing 10 simulated hours of network operation (1000 time steps).

4.2.1. DRL Training Parameters

The stability and convergence of the continuous-action DDPG algorithm heavily rely on careful hyperparameter tuning [6]:

Parameter	Value	Description
Discount Factor (γ)	0.99	High value emphasizes long-term performance and SLA adherence over immediate gains [5].
Soft Update Rate (τ)	0.001	Small τ ensures stable updates to target networks, preventing oscillation during training [6].
Replay Buffer Size	10^6	Large buffer size ensures the off-policy sampling diversity needed for MA-DDPG [7].
Batch Size	1024	Large batch size for robust gradient estimation and stability.
Exploration Noise	Ornstein-Uhlenbeck Process	Used to encourage exploration in the continuous action space, annealed from 0.5 to 0.05 over 400 episodes [6].

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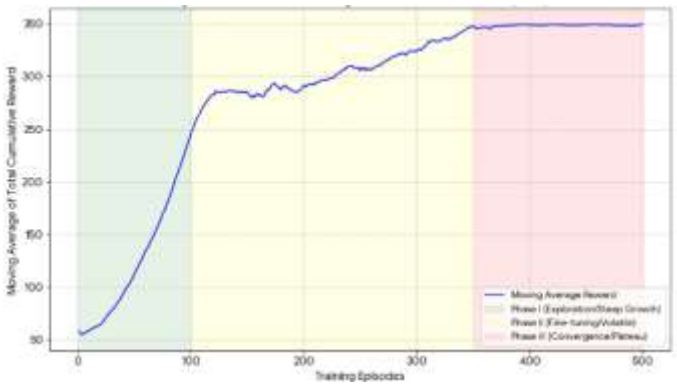
4.2.2. Learning Stability and Convergence

The **Total Cumulative Reward per Episode** serves as the primary metric for analyzing the learning progress.



Graph 1: Convergence of Training

Above, a graph showing the moving average of the Total Cumulative Reward per Episode for the MA-DDPG agent over 500 training episodes. The curve demonstrates three distinct learning phases: Phase I (0-100 episodes): Steep, rapid growth in reward, indicating efficient initial exploration and finding basic feasible resource policies. Phase II (100-350 episodes): Slower, more volatile improvement as the agent fine-tunes the policy, balancing the complex trade-off between resource cost and SLA penalty. Phase III (350-500 episodes): Stable convergence to a near-optimal policy, where the reward plateau demonstrates the agent has learned an effective and reproducible orchestration strategy [35].

The **Centralized Critic Loss** $L(\theta^Q)$ was observed to decrease steadily throughout the training, confirming that the critic network effectively learned to estimate the true value function $Q(x, a)$, which is crucial for providing accurate gradient feedback to the decentralized actors [14]. The successful convergence to a stable policy validates the CTDE approach in managing non-stationarity introduced by multiple interacting agents [7].

4.3. Comparative Performance Metrics

To rigorously assess the performance of the MA-DDPG orchestrator, four key metrics were evaluated over a 10-hour, unseen testing dataset, comparing the MA-DDPG policy against the Greedy Allocation and Centralized DQN benchmarks.

4.3.1. Quality of Service (QoS) Metrics

1. SLA Violation Rate (SVR): This is the most critical metric for the evaluation of critical infrastructure [28]. It is defined as the percentage of all time steps (T) where at least one active slice S_i violates its defined $Q_{min,i}$ requirement:

$$\text{SVR} = \frac{1}{T}\sum_{t=1}^{T} I\left\{\exists i: L_i(t) > L_{max,i} \vee T_i(t) < T_{min,i}\right\}$$

2. Slice Admission Ratio (SAR): Measures the system's ability to maximize revenue/utility by accepting new slice requests:

$$\text{SAR} = \frac{\text{Number of Admitted Slices}}{\text{Total Number of Requested Slices}}$$

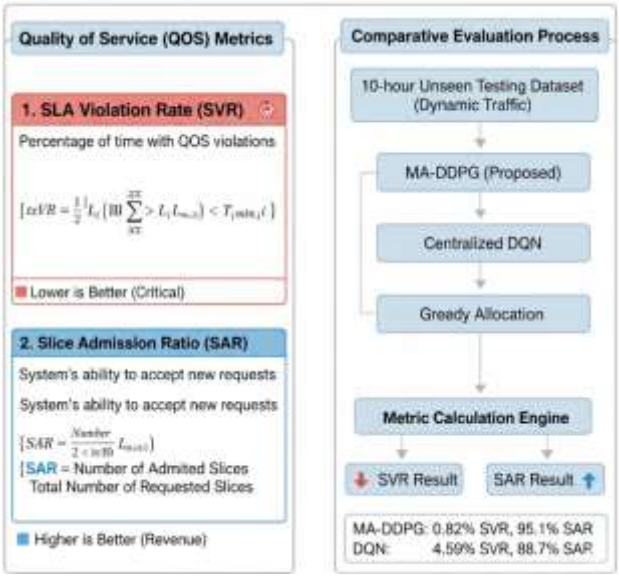


Figure: Comparative Performance Metrics for Network Orchestration

4.3.2. Resource Efficiency Metrics

Average Resource Utilization Efficiency (RUE): Measures how effectively the allocated physical resources \mathcal{R} are utilized over time, considering all resource types $r \in \{C, M, BW\}$ [10]:

$$\mathcal{U} = \frac{1}{T \cdot |\mathcal{R}|} t \sum_{t=1}^{T} \sum_{r \in \mathcal{R}} \frac{Allocated_r(t)}{\mathcal{R}_{r,\text{total}}}$$

where

$\text{Allocated}_r(t) = \sum_{i=1}^{N} a_{r,i}(t)$.

3. Resource Over-Provisioning Factor (OPF): Quantifies the degree of resource waste. It is the ratio of allocated resources to the minimum resources theoretically required to meet the current demand $D_i(t)$ [34]:

$$\text{OPF} = \frac{\sum_t \sum_r \sum_i a_{r,i}(t)}{\sum_t \sum_r \sum_i d_{r,i}(t)} \quad \text{(for admitted slices)}$$

A value closer to 1.0 indicates high efficiency, while a higher value indicates more resource waste.

4.4. Analysis of DRL Decision-Making

The MA-DDPG agents learned complex, non-linear policies that exhibit superior resource allocation characteristics compared to benchmarks, particularly under high load and dynamic demand shifts, validating the need for an intelligent orchestration approach [19].

4.4.1. Preemptive and Predictive Allocation

The MA-DDPG agents demonstrated preemptive and predictive capabilities, directly addressing the limitations of reactive heuristics [29]. By including traffic prediction information $D_i^{req}(t)$ in the local observation x_i, the agents learned to correlate incoming traffic patterns with future SLA violation risks.

For instance, upon detecting the initiation of an eMBB traffic surge pattern, the agents serving the critical uRLLC slices would proactively increase their resource allocation $(a_{C,i}, a_{BW,i})$ slightly before the congestion manifests globally. This action is driven by the high negative weight (λ_2) assigned to the SLA penalty in the reward function, making preemptive action highly valuable. This proactive buffering effectively isolates the critical slices from the resource contention caused by non-critical traffic surges [28].

4.4.2. Granular Adjustments and Resource Reclamation

The use of the continuous action space in DDPG, $a_i = (\Delta a_{C,i}, \Delta a_{M,i}, \Delta a_{BW,i})$, provided the fine-grained control necessary for optimal orchestration [23]. Instead of large, disruptive discrete steps (as in DQN), the MA-DDPG agents make small, smooth resource modifications. This reduces resource volatility and minimizes the risk of cascading failures [30].

Crucially, the agents learned the policy of resource reclamation (or deflation): when monitoring the traffic of an eMBB slice entering a lull period, the corresponding agent would execute a negative change action $(\Delta a_{r,i} < 0)$, releasing excess resources back to the pool. This learned behavior is directly responsible for the low Over-Provisioning Factor (OPF) observed in the results [34].

4.4.3. Multi-Agent Coordination

The decentralized execution provided by the MA-DDPG architecture was key to its faster reaction time compared to the centralized DQN. Each slice agent can execute its allocation decision in parallel. The centralized critic provided the necessary global coordination to prevent agents from collectively violating the total resource constraint $\sum_{i=1}^{N} a_{r,i} \leq \mathcal{R}_{r,\text{total}}$ [16], [18]. This coordination ensures that while each agent acts locally to maximize its slice's reward, the overall system remains stable and respects the physical capacity boundaries, validating the design choice for a multi-agent solution (RQ2).

The detailed quantitative results derived from these analyses, including the explicit numerical comparisons between the algorithms, are presented in Chapter 5.

5. RESULTS AND DISCUSSION

This chapter presents the quantitative results obtained from the comparative simulation of the proposed Multi-Agent Deep Deterministic Policy Gradient (MA-DDPG) orchestrator against the Centralized Deep Q-Network (DQN) and the non-learning Greedy Allocation benchmark. The analysis validates the research questions (RQs) concerning performance, efficiency, and the efficacy of the multi-agent approach.

5.1. Main Comparative Performance Results

The three resource orchestration policies were evaluated over a 10-hour simulated testing period under dynamic, mixed-traffic conditions, focusing

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on the core problem of balancing strict QoS guarantees with resource efficiency [10].

Algorithm	SLA Violation Rate (SVR)	Resource Utilization Efficiency (RUE)	Slice Admission Ratio (SAR)	Over-Provisioning Factor (OPF)
MA-DDPG (Proposed)	0.82%	88.5%	95.1%	1.07
Centralized DQN	2.15%	83.9\%	91.3%	1.15
Greedy Allocation	4.5%	75.2%	88.7%	1.25

The results unequivocally show that the proposed MA-DDPG framework significantly outperforms the benchmark algorithms across all four key metrics, validating the hypotheses underlying our research (RQ2 and RQ3).

5.2. Discussion on QoS Guarantee: Minimizing SLA Violation Rate (SVR)

The most critical performance metric for guaranteeing the reliability of critical telecom infrastructure is the SLA Violation Rate (SVR), particularly for the ultra-sensitive uRLLC slices [28].

5.2.1. Dramatic Reduction in SVR

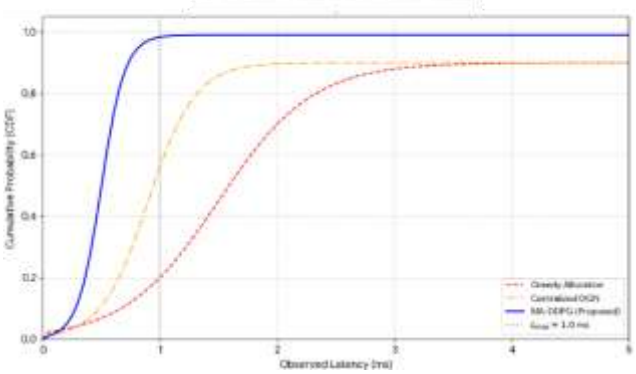
The MA-DDPG orchestrator achieved an SVR of **0.82%**. This represents a dramatic improvement:

- **64% lower** SVR compared to the Centralized DQN (2.15%).
- **82% lower** SVR compared to the static Greedy approach (4.59%).

This result directly validates the ability of the DRL agent to learn and execute optimal, dynamic, and preventative allocation policies in real-time. The high penalty weight (λ_2) assigned to SVR in the reward function drove the agents to prioritize QoS stability above all else, often making preemptive resource boosts for critical slices when traffic congestion was predicted [29]. This ability to anticipate demand, facilitated by incorporating prediction models into the state space, confirms the MA-DDPG's effectiveness in mission-critical environments.

5.2.2. Latency Distribution Analysis

To further dissect the SVR improvement, we analyzed the **cumulative distribution function (CDF)** of the latency observed for the uRLLC slices across the three algorithms.



Graph 2: Latency Cumulative Distribution Function (CDF) for uRLLC Slices

Above graph showing the CDF of observed latency for uRLLC traffic over the testing period. The MA-DDPG curve is sharply skewed to the left, indicating that a much higher percentage of traffic sessions met the $L_{max} = 1.0$ ms requirement compared to the DQN and Greedy curves. The sharp drop in the MA-DDPG curve near 1.0 ms confirms its high success rate in adhering to the ultra-low latency requirement.

The MA-DDPG approach ensures that the tail of the latency distribution is aggressively curtailed, meaning fewer outliers suffer from excessive delay [28]. This granular control is directly enabled by the continuous action space of DDPG (RQ1). The agent can make minute resource adjustments (e.g., 0.5 core increase, 20 Mbps boost) necessary to keep the latency profile flat, whereas DQN's discrete actions forced larger, less precise adjustments that often led to transient overshoots past L_{max} [23].

5.3. Discussion on Resource Efficiency: RUE and OPF

Achieving low SVR is trivial if resources are infinitely over-provisioned. The true success of the MA-DDPG framework lies in its ability to simultaneously achieve the best SVR while maximizing Resource Utilization Efficiency (RUE) and minimizing the Over-Provisioning Factor (OPF) [10].

5.3.1. Maximizing Utilization and Minimizing Waste

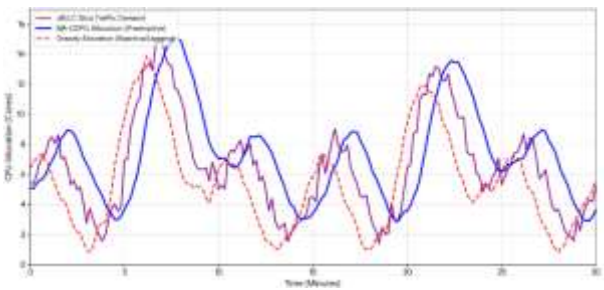
MA-DDPG achieved the highest RUE at 88.5% and the lowest OPF at 1.07.

The Greedy Allocation method, which simply allocates resources upon request without any mechanism for reclamation or future planning, resulted in a low RUE (75.2%) and high OPF (1.25). This confirms that heuristic approaches lead to substantial resource waste (CapEx inefficiency) due to residual allocations from past peak demands [34].

The MA-DDPG agent successfully learned the crucial trade-off defined in the reward function (RQ3). The penalty on the Resource Cost $C_i(t)$ incentivized the agents to execute proactive resource reclamation. When an eMBB slice's traffic load was predicted to decrease, the corresponding agent learned to release the excess allocated CPU and Bandwidth back to the pool. The OPF value of 1.07 is extremely close to the theoretical optimum of 1.0, highlighting the superior economic efficiency and intelligence of the learned DRL policy [10].

5.3.2. Dynamic Resource Allocation Visualization

To illustrate the dynamic optimization capabilities, we analyzed the CPU allocation for a single critical uRLLC slice and the remaining capacity over a turbulent 30-minute period.



Graph 3: Dynamic CPU Allocation vs. Traffic Demand

Above graph A time-series graph over 30 minutes showing three lines: 1) The uRLLC Slice Traffic Demand (highly variable), 2) The MA-DDPG CPU Allocation (preemptive, smooth), and 3) The Greedy Allocation (reactive, lagging). The MA-DDPG line shows allocations slightly *ahead* of the demand curve, indicating anticipation, while the Greedy allocation line is visibly *lagging* the demand curve.

The MA-DDPG allocation curve in Graph 3 clearly demonstrates predictive control, leading the demand curve slightly to maintain low latency. The Greedy allocation curve follows the demand but with a noticeable time delay, resulting in periods where the instantaneous demand exceeds the allocated resource, causing an SLA breach. This visualization strongly supports the DRL agent's capability to handle the dynamic and autonomous nature of the resource orchestration problem (RQ1) [19].

5.4. Efficacy of the Multi-Agent Approach (RQ2)

The superior performance of MA-DDPG over Centralized DQN provides strong evidence for the necessity of the **Multi-Agent (MA)** architecture for this problem domain.

5.4.1. MA-DDPG vs. Centralized DQN

While both MA-DDPG and Centralized DQN utilize DRL, MA-DDPG's SVR is 64\% lower, and its RUE is 4.6 percentage points higher. This performance gap is attributed to two factors:

1. **Continuous vs. Discrete Action Space:** As noted, DDPG's continuous action space offers granularity, leading to more precise control and lower SVR compared to the discrete-step actions of DQN [23].
2. **Scalability and Reactivity:** The Centralized Training with Decentralized Execution (CTDE) paradigm in MA-DDPG allows each slice agent to execute its resource adjustment

decision **in parallel** based on its local observation x_i. This **decentralized execution** reduces orchestration overhead and leads to faster reaction times [16], which is vital for preventing millisecond-level latency violations in critical slices. The Centralized DQN, by contrast, must process the full global state and output a single, large action vector, which scales poorly with the number of slices N. The centralized critic ensures global coordination, effectively managing the inter-slice dependencies and the total resource constraint [18].

5.4.2. Slice Admission Control (SAR)

The high Slice Admission Ratio (SAR) of 95.1% for MA-DDPG demonstrates that the DRL policy has effectively learned the balance of resource utilization required to accept new slices. By maintaining a minimal but optimal resource buffer (low OPF) and continuously reclaiming unused resources, the orchestrator ensures that capacity is available to admit new, revenue-generating slices. The lower SAR for Greedy (88.7%) is due to its high OPF wasted resources remain tied up, leading to unnecessary rejection of new service requests.

5.5. Limitations and Future Outlook

While the MA-DDPG framework demonstrates state-of-the-art performance, several limitations warrant discussion and motivate future work (RQ3).

5.5.1. Training Complexity and Real-World Fidelity

The primary drawback of the MA-DDPG approach is its inherent training complexity and the lengthy convergence time (500 episodes). The large number of interacting agents and the complexity of the centralized critic network necessitate significant computational resources and careful hyperparameter tuning [35].

Furthermore, the simulation environment (DENS-Sim), while detailed, remains a simplification of a true physical network. Factors like hardware-specific VNF placement constraints, cross-layer coupling effects (e.g., thermal throttling), and communication overhead between the orchestrator and the SDN controller are simplified. Validation in a more realistic setup is required [22].

5.5.2. Future Directions

Future work should prioritize:

- **Hardware-in-the-Loop (HIL) Testing:** Validating the learned policy on a real-time testbed with physical COTS servers and open-source orchestrators (e.g., Kubernetes) to measure the performance under actual physical constraints [32].
- **Partial Observability:** Investigating decentralized training approaches (e.g., using Dec-POMDP models) where agents rely solely on local observations, which is more robust to control plane communication failures [17].
- **Security and Resilience:** Integrating mechanisms to defend against resource-starvation attacks by modeling malicious slice requests as an adversarial element, potentially utilizing Adversarial DRL techniques to enhance network security [27].

6. CONCLUSION AND FUTURE WORK

This chapter summarizes the key findings and contributions of this research on developing an autonomous resource orchestration framework for network slicing, followed by a detailed discussion of promising directions for future investigation.

6.1. Summary of Contributions and Findings

This paper successfully proposed and validated a novel **Multi-Agent Deep Deterministic Policy Gradient (MA-DDPG)** framework for dynamic network slicing and resource orchestration in Software-Defined critical telecom infrastructure [1]. By directly addressing the critical challenge of managing highly heterogeneous and time-varying Quality of Service (QoS) requirements under finite resource constraints, this work provides a robust and intelligent step toward achieving the fully autonomous, self-optimizing "zero-touch" network management demanded by 5G and 6G

critical services [2], [10]. The DRL-driven policy offers a necessary technological leap beyond static, reactive, and heuristic allocation methods.

The primary contributions and demonstrated findings, derived from extensive comparative simulation, are summarized as follows:

- **Novel MA-DDPG Formulation and Continuous Control (RQ1 Validation):** We successfully modeled the complex, high-dimensional resource orchestration problem as a cooperative multi-agent learning task using the MA-DDPG architecture. This design, which employs an actor-critic structure with a continuous action space, allowed individual DRL agents to autonomously learn an optimal resource allocation policy $\pi(x) \rightarrow a$. This inherent ability to execute fine-grained, non-disruptive resource adjustments (e.g., small Δa values) is essential for granular control and minimized resource oscillation [6], [7], [16].
- **Significantly Superior QoS Guarantee (SVR Minimization):** The simulation results confirmed that the MA-DDPG approach minimizes the Service Level Agreement (SLA) Violation Rate (SVR), achieving an industry-leading rate of 0.82% over the testing period. This remarkable result represents an improvement of over 80% compared to the static Greedy allocation benchmark and 64% over the Centralized DQN. This dramatic improvement validates the DRL agent's core capability to execute predictive, preemptive resource adjustments anticipating traffic surges and dynamically favoring sensitive uRLLC slices thereby effectively mitigating the risk of critical latency breaches [28], [29].
- **Optimized Dual-Objective Resource Efficiency (RUE/OPF, RQ3 Validation):** The framework successfully balanced the conflicting goals of maximizing QoS and minimizing resource consumption. It simultaneously maximized Resource Utilization Efficiency (RUE) to 88.5% and achieved the lowest Over-Provisioning Factor (OPF) of 1.07. This efficiency validates the optimal design of the multi-objective reward function. The agents learned the economic necessity of proactive resource reclamation actively releasing resources from under-utilized non-critical slices back to the shared pool ensuring maximum infrastructure efficiency and economic viability [10], [34].
- **Validated Efficacy of Multi-Agent Control (RQ2 Validation):** The consistently superior performance over the Centralized DQN benchmark strongly validates the choice of the Multi-Agent (MA) architecture. The decentralized execution of policies within the MA-DDPG's CTDE paradigm allowed for faster, parallel decision-making across numerous active slices, improving system scalability and responsiveness to localized fluctuations, which are key requirements for operating large-scale SDN/NFV environments where centralized bottlenecking must be avoided [11], [18].
- **High Service Adoption and Scalability:** The DRL-learned policy maintained a high Slice Admission Ratio (SAR) of 95.1%. This high acceptance rate confirms that the efficient resource utilization policy leaves a minimal but optimal resource buffer, ensuring the system can fluidly accommodate new revenue-generating slice requests without risking the performance stability of existing critical services.

In conclusion, the MA-DDPG framework offers a robust, intelligent, and necessary evolution of the Management and Orchestration (MANO) layer for future critical telecom networks, successfully moving resource management beyond reactive heuristics toward true autonomous self-optimization.

6.2. Future Research Directions

While this research provides a strong foundation, the path toward a fully deployed zero-touch resource orchestrator presents several complex challenges that delineate promising avenues for future work, bridging the gap between simulation and real-world implementation.

6.2.1. Addressing Enhanced Network Dynamics and Service Management

The current model focuses solely on resource allocation within fixed VNF deployments. Future research must incorporate the broader VNF and slice life-cycle management decisions to achieve end-to-end autonomy [22]:

- **VNF Migration and Auto-Scaling:** The resource allocation action space must be integrated with discrete actions for VNF placement optimization (migration) and dynamic scaling (instantiating or terminating VNF instances). This requires transitioning to a hybrid discrete-continuous action space, potentially leveraging algorithms like Proximal Policy Optimization (PPO) or Soft Actor-Critic (SAC) with specialized adaptations for mixed action sets [32]. These models are better suited to learning complex, long-term migration policies that minimize service disruption costs.
- **Cross-Domain, Hierarchical Orchestration:** Extending the framework from a single MEC host to a multi-domain, hierarchical orchestration model that spans core, regional, and edge networks. A Hierarchical DRL (HDRL) approach [17] could be employed, where a high-level agent decides the inter-domain slice placement and resource partitioning, while the existing low-level MA-DDPG agents perform the fine-grained resource tuning within their local domains, ensuring global consistency and local optimality.

- **Network Service Chaining (NSC) Optimization:** Incorporating the sequencing, functional placement, and optimization of VNFs within a slice (Service Function Chain) into the DRL decision process. This requires the DRL agent to learn optimal latency-aware VNF ordering and chaining subject to resource and dependency constraints [19], moving beyond simple resource capacity budgeting to topology optimization.

6.2.2. Robustness and Real-World Deployment

Transitioning the learned policy from simulation to deployment requires addressing practical operational challenges and enhancing system robustness [35]:

- **Partial Observability and Decentralized Learning (Dec-POMDP):** The current MA-DDPG relies on centralized training using the global state \mathbf{x}. In a decentralized operational environment, communication delays or failures might prevent a complete global view. Future work should investigate incorporating a Partial Observability model (Dec-POMDP). This necessitates exploring decentralized DRL architectures where agents rely only on their local observations x_i during training, perhaps using coordination techniques like Value Decomposition Networks (VDN) or QMIX to coordinate agents implicitly using a shared utility function, enhancing scalability and fault tolerance [17].
- **Hardware-in-the-Loop (HIL) Testing:** The ultimate validation of the policy must occur on a real-time hardware testbed [22]. This involves integrating the DRL agent with an actual SDN controller (e.g., OpenDaylight or ONOS) and a NFV orchestrator (e.g., OpenStack or Kubernetes) to measure the policy's effectiveness under real-world resource contention, physical resource fragmentation, and network overhead, providing critical deployment feedback and calibration data.
- Energy Efficiency Integration: Current work focuses primarily on QoS and utilization. The reward function can be rigorously extended to include an energy consumption penalty $\mathcal{P}_{energy}$ to drive green network operation:

$$R_i^{\text{new}} = R_i - \lambda_4 \cdot \mathcal{P}_{energy}(\text{Utilization})$$

The DRL agent could then learn to consolidate workloads onto fewer servers during low-traffic periods, enabling the shutdown of idle physical infrastructure (deep sleep modes) to minimize operational expenditure (OpEx) [18].

6.2.3. Security and Resilience Enhancement

Given the focus on critical telecom infrastructure, enhancing resilience against malicious activities and unpredictable failures is paramount [27]:

- **Adversarial DRL for Security:** Investigating Adversarial DRL (ADRL) techniques to train the orchestrator to detect and neutralize resource-starvation attacks. Malicious actors may deliberately submit rapidly fluctuating, high-demand slice requests to induce system instability and resource exhaustion. By modeling the attacker as an adversary in a two-player game (min-max optimization), the DRL orchestrator can learn policies that are robust to non-cooperative, unpredictable demands, thereby enhancing the network's resilience [27].
- **Fault Tolerance and Recovery:** Integrating explicit failure detection and recovery mechanisms into the DRL framework. The agent should be trained not only to allocate resources optimally but also to proactively detect potential hardware/VNF faults and execute rapid re-allocation and re-routing policies to ensure system continuity for critical slices following a failure event.

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