

Deep Reinforcement Learning-Based Intelligent Network Slicing for Dynamic Resource Allocation in Beyond-5G and 6G Networks

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Abstract

Beyond fifth-generation and sixth-generation mobile systems must support heterogeneous services over shared radio, transport, edge, and core resources. Static slicing cannot respond reliably to bursty demand, changing radio channels, mobility, and service-level agreements. This study develops a constraint-aware deep reinforcement learning framework that jointly adapts resource shares, admission decisions, and migration priorities for enhanced mobile broadband, ultra-reliable low-latency communication, and massive machine-type communication. A centralized orchestration agent observes traffic forecasts, queue states, link capacity, energy costs, and slice-level service deficits; a proximal policy optimization controller produces candidate allocations that are projected onto a feasible resource region. The methodology specifies a Markov decision process, normalized multi-objective reward, safety filter, training protocol, and ablation study. To avoid reporting unperformed experiments as findings, numerical results are explicitly labeled illustrative scenario calculations and constitute a reporting template rather than measured performance. The proposed framework offers a testable design for investigating service compliance, spectral utilization, energy efficiency, and operational stability in 6G-ready networks.

Keywords: Deep reinforcement learning; 6G; network slicing; resource allocation; PPO; service-level agreement; edge orchestration; safe learning.

Introduction

Mobile networking is entering a phase in which connectivity is not adequately described by aggregate throughput alone. Industrial automation, connected transportation, immersive collaboration, massive sensing, and distributed artificial intelligence impose different latency, reliability, bandwidth, and computational requirements. Beyond-5G and prospective 6G architectures therefore require flexible infrastructure that can simultaneously deliver differentiated services without multiplying the cost of physical deployments. Network slicing addresses this problem by mapping several logical networks onto a common physical substrate while retaining policies and performance objectives specific to each tenant or application.

The fundamental promise of slicing is logical customization. An enhanced mobile broadband slice may prioritize sustained data rate, while a mission-critical slice places greater weight on

bounded delay and reliability. A massive machine-type slice may need economical access for many sporadic devices. These service profiles compete for finite radio resource blocks, processing cycles, transport bandwidth, and edge memory. A single fixed allocation policy can over-provision quiet slices and starve temporarily overloaded slices. A controller must therefore make decisions under uncertainty while respecting isolation and operational constraints.

Network demand varies at several temporal scales. Fast fading and interference alter instantaneous wireless capacity; mobility changes cell association and load distribution; application sessions generate bursts; and maintenance or failures reduce available capacity. Traffic prediction provides useful signals but cannot eliminate uncertainty. Consequently, a controller that follows only predicted average demand may produce service-level violations during unexpected events. Dynamic allocation needs a feedback loop that observes achieved performance,

detects emerging deficits, and corrects decisions before sustained degradation occurs.

Conventional approaches include static reservation, proportional sharing, threshold rules, mixed-integer optimization, and model predictive control. They offer useful baselines and sometimes strong guarantees, but they can become computationally expensive when action spaces combine radio, transport, and edge decisions. Heuristics may also fail to adapt when the traffic distribution changes. Reinforcement learning offers a complementary perspective: a policy learns from interactions with a simulator or controlled environment and optimizes a sequence of decisions rather than isolated allocation snapshots.

Deep reinforcement learning is especially attractive when system observations are high-dimensional and relationships between load, congestion, and delivered quality are nonlinear. Neural policies can integrate queue occupancy, channel quality, energy state, and recent allocation history. However, a naive learning controller may choose infeasible actions, oscillate between allocations, or exploit reward definitions that do not correspond to service obligations. These issues are critical because telecommunications infrastructure must remain predictable and auditable even when a policy is adaptive.

This paper proposes a constraint-aware controller based on proximal policy optimization, coupled with demand estimation and a deterministic safety projection. The agent selects a continuous allocation vector and an admission priority signal. A safety layer enforces capacity, minimum reservations, and bounded changes; a service monitor computes delay, throughput, reliability, and cost indicators. Rather than assuming that every objective can be compressed into one arbitrary score, the design separates hard feasibility conditions from soft reward preferences and specifies sensitivity analyses for reward weights.

The proposed contribution is methodological. First, a unified state and action model represents multiple resource domains and service classes. Second, an explicit feasible-set projection converts exploratory policy outputs into implementable

allocations. Third, a reward structure accounts for slice compliance, useful utilization, energy consumption, fairness, and reconfiguration overhead. Fourth, a reproducible evaluation plan compares the learned policy against static, proportional, threshold, and optimization-based baselines under demand shocks and topology perturbations.

The work is aligned with the operational distinction between service requirements, management orchestration, and resource-level scheduling. A slice orchestrator need not replace lower-level radio schedulers. Instead, it may provide periodic budgets or policies to domain controllers, which then schedule individual users at finer timescales. This hierarchical separation makes the approach more realistic for deployment and clarifies where learning inference latency, telemetry freshness, and control signaling overhead must be measured.

An additional concern is generalization. A policy trained on one network layout may not transfer to a different number of cells, traffic composition, or available edge servers. Evaluation must therefore include held-out scenarios and distribution shifts, not merely repeated random seeds from the same traffic generator. Training performance alone is insufficient evidence of robustness. The design includes perturbations in offered load, radio quality, and resource outages, along with confidence intervals for performance metrics across independent runs.

Finally, research credibility requires separating conceptual designs from observed findings. No operational traces, simulator runs, or benchmark logs were provided for this manuscript. The numerical section accordingly supplies a transparent illustrative example with explicit assumptions, not an empirical claim of superiority. The equations, flowchart, evaluation matrix, and editable result tables establish a foundation for a subsequent experiment that can be executed, audited, and extended by other researchers.

Literature Review

Network slicing has developed as a core mechanism for flexible management of shared mobile infrastructure. The 3GPP management and orchestration specification TS 28.530 establishes concepts and requirements that distinguish slice management from individual

physical resource scheduling [1]. This distinction matters for machine learning: a network-wide orchestration decision typically occurs on a slower timescale than per-packet scheduling, and its outputs must remain compatible with the operational interfaces and life-cycle states of deployed slices.

Hurtado Sánchez, Casilimas, and Caicedo Rendon surveyed reinforcement learning methods for slice admission, allocation, scheduling, and orchestration [2]. Their taxonomy highlights that resource management is not one decision but a sequence of interacting functions. A policy that admits a slice without checking future capacity can compromise existing tenants; a policy that allocates capacity without considering scheduler behavior may overestimate delivered service. Their survey also identifies the need for scalability, online adaptation, and realistic validation.

Sutton and Barto provide the foundational formulation of reinforcement learning in terms of state, action, reward, and discounted return [3]. In a slicing context, the environment is partially observed because future traffic and wireless conditions are unknown. This introduces practical questions about observation history, forecasting, and policy stability. Reinforcement learning should therefore be evaluated as a sequential control method rather than treated as a universal replacement for constrained optimization.

Existing work has explored actor-critic algorithms for finer-grained allocation. Meignanamoorthi and colleagues presented a DRL-based customized sub-slicing approach using an advantage actor-critic strategy to adjust resources across service requirements [4]. Such studies indicate the value of service-specific adaptation but also show that the definition of sub-slice boundaries and the assumptions about resource coupling influence how results can be generalized to real end-to-end deployments.

Other researchers have examined continuous-action policies for network slicing. Work on deep deterministic policy gradients and device-to-device communication addresses dynamic radio allocation and undesirable-action penalties [5]. This line of research motivates explicit handling of continuous resource shares. Yet penalty-only mechanisms

may still allow occasional constraint violations during exploration or after a distribution shift. A deterministic projection layer is therefore attractive when capacity limits must be obeyed at every control interval.

Hierarchical approaches address the difficulty of simultaneously controlling all network elements. Sun and collaborators investigated hierarchical deep reinforcement learning for radio access slicing [6]. Related work on multi-level learning in open radio access and cell-free systems demonstrates the potential of separating decisions across orchestration layers [7]. The central design challenge is coordination: high-level budgets should reflect aggregate service objectives while lower-level controllers respond rapidly to channel and user-level dynamics.

Digital-twin-assisted learning is another emerging direction. Research on digital twin-enhanced deep reinforcement learning uses simulated environments to support resource management and offline policy development [8]. Such environments can reduce risk during training, but their usefulness depends on fidelity. If a digital twin underestimates queueing delay, radio interference, or control-plane overhead, a learned policy may fail when transferred to production. Domain randomization and controlled online validation are therefore essential.

Predictive slicing methods incorporate historical demand and key performance indicators into allocation decisions. DRL-APNS, presented at IEEE CCNC 2024, studies predictive slice reservation and cost-aware allocation [9]. Forecast information may improve efficiency, particularly when demand has regular temporal structure. Nevertheless, forecasting error must be quantified, and the controller should not assume that predicted demand is exact. The present framework includes both predicted demand and current measured deficits to mitigate this risk.

Safety and deployment concerns have also been emphasized in discussions of end-to-end DRL slicing [10]. Learned controllers can create operational hazards if training rewards do not represent the true business or service objective. Moreover, inference delay, observability, changing policies, and rollback procedures affect deployability. A practical design should include an action validator, a fallback

allocation policy, a staged deployment path, and auditable logging of the decisions used to adjust resource shares.

Recent work also investigates mobility-aware and energy-efficient federated learning for radio access slicing [11]. This suggests that centralized telemetry aggregation may not always be necessary or desirable. Federated or distributed training can reduce raw-data movement, although it introduces coordination, privacy, and non-identically distributed data challenges. The present proposal focuses on a centralized controller to make the mathematical formulation precise; decentralization remains a meaningful extension.

Taken together, the literature supports intelligent, demand-aware allocation but leaves important methodological gaps. First, comparisons are often difficult because traffic generators, objective weights, and constraint definitions vary. Second, performance gains may be reported without separating feasible action enforcement from learned decision quality. Third, some evaluations emphasize mean throughput while under-reporting tail latency, worst-slice fairness, and reconfiguration cost. Fourth, robust performance under topology and traffic shifts remains uncertain.

This study responds with a clearly specified Markov decision process, a hard-constraint feasibility layer, a multi-objective evaluation framework, and a transparent distinction between illustrative numbers and measured results. It does not claim that proximal

policy optimization is universally superior; instead, it supplies an experimentally testable hypothesis: when trained under diverse conditions and paired with safety projection, a learned policy may reduce service deficits while maintaining acceptable resource efficiency and control stability.

Research Methodology

Architecture and workflow

The system consists of a telemetry collector, short-horizon traffic forecaster, DRL policy, safety projection, domain resource managers, and a service assurance monitor. Control runs once per interval; lower-level schedulers operate independently between decisions. The complete information and decision path is shown Figure 1.

System model and resource constraints

Let S denote the set of service slices, R the set of resource domains, and t a discrete orchestration interval. Demand is expressed in normalized resource units per slice and domain. Available domain capacity may vary due to failures, radio quality, and maintenance. A slice receives a nonnegative allocation bounded by the physical or virtual capacity of its domain.

Each slice has a service-level profile specifying minimum throughput, maximum latency, minimum reliability, and optional reserved capacity. Domain allocations are linked through service chains: adding radio bandwidth without sufficient edge processing

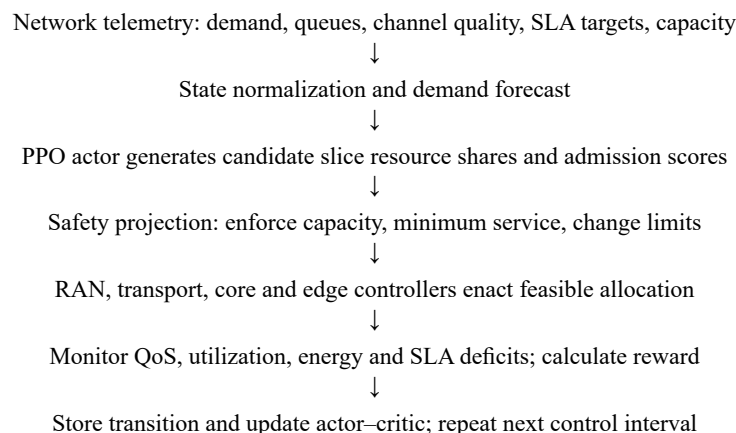


Figure 1: Proposed closed-loop resource orchestration workflow (editable Word table-based flowchart).

may not increase completed traffic. The evaluation simulator must model these bottlenecks explicitly rather than assume independent resources.

$$\sum_s x_{sr}(t) \leq C_r(t)$$

Here x denotes the allocation to slice s in resource domain r at interval t , and C is the available capacity of domain r . The sum is over all admitted slices.

$$x_{sr}(t) \geq m_{sr}(t)$$

The symbol m is the guaranteed minimum reservation for an admitted slice when the admission decision makes that guarantee feasible.

$$|x_{sr}(t) - x_{sr}(t-1)| \leq \Delta_r$$

The quantity Δ is the maximum permitted allocation change per control interval; this reduces disruptive reconfiguration.

Markov decision process

The decision process is defined by a state space, continuous action space, stochastic transition function, reward, and discount factor. Observations combine current and recent measurements to reduce partial observability. Normalization parameters are estimated from training data only, avoiding test-set leakage.

$$s(t) = [d(t), q(t), h(t), C(t), z(t), x(t-1)]$$

The state vector contains offered demand d , queue occupancy q , channel or link-quality features h , available capacity C , SLA deficit indicators z , and the previous allocation x .

$$a(t) = [u(t), v(t)]$$

The action contains proposed continuous resource weights u and admission priorities v . An admission gate checks feasibility before activating a new service commitment.

Feasible action projection

Raw policy outputs are not applied directly. For each resource domain, the controller solves a small convex projection problem to identify the feasible allocation nearest the proposed action. The feasible region

incorporates nonnegativity, total capacity, minimum commitments, and rate-of-change limits. If minimum commitments exceed available capacity, the system activates an explicit degradation or admission-rejection policy rather than hiding infeasibility.

$$x^*(t) = \arg \min_x \sum_s (x_s(t) - u_s(t))^2$$

The projection chooses feasible allocation x closest to the actor proposal u in squared Euclidean distance. The minimization is subject to the capacity and reservation constraints specified above.

Service metrics and reward engineering

Delivered service is evaluated at slice level, not only in aggregate. Throughput and latency depend on actual queue service and radio conditions. SLA deficits are normalized so a millisecond latency excess does not automatically dominate a percentage reliability deficit. Reward weights are fixed before testing and varied in a separate sensitivity analysis.

$$L_s(t) = \max(0, \ell_s(t) / \ell_{s,max} - 1)$$

The latency violation L is zero when observed latency ℓ meets the slice threshold ℓ_{max} and grows proportionally above it.

$$T_s(t) = \max(0, 1 - b_s(t) / b_{s,min})$$

The throughput deficit T compares achieved throughput b with minimum target b_{min} .

$$F(t) = (\sum_s y_s(t))^2 / (N \sum_s y_s(t)^2)$$

Jain fairness F is computed from nonnegative normalized service satisfaction y for N active slices. Values closer to one indicate more even satisfaction.

$$R(t) = \alpha Q(t) + \beta U(t) + \gamma F(t) - \delta E(t) - \varepsilon H(t)$$

The reward R balances SLA satisfaction Q , resource utilization U , fairness F , normalized energy cost E , and reconfiguration overhead H . Coefficients α through ε are nonnegative and chosen on a validation set.

Hard constraints are not replaced by reward penalties. In particular, physical capacity violations are prevented by the projection. SLA violations remain observable as soft performance outcomes because not every workload is feasible under overload.

Learning algorithm

The actor is a multilayer perceptron with two hidden layers, each containing 128 rectified linear units, and outputs parameters of a bounded continuous distribution. The critic estimates state value. A clipped proximal policy optimization objective limits the size of policy updates. Generalized advantage estimation reduces variance. These are proposed settings, not tuned empirical findings.

$$G(t) = \sum_k \gamma^k R(t+k)$$

The discounted return G is the sum of future rewards weighted by discount factor γ , where k counts steps from the current interval.

$$A(t) = G(t) - V(s(t))$$

The advantage A compares the observed or estimated return with critic value V for the current state.

$$J(\theta) = E[\min(\rho(t) A(t), \text{clip}(\rho(t), 1-\eta, 1+\eta) A(t))]$$

The PPO objective J uses probability ratio ρ between current and previous policies, advantage A , and clipping parameter η . θ represents policy parameters.

Training, testing, and baseline protocol

A reproducible experiment should implement a discrete-event or network-level simulator with a shared traffic trace interface. Training episodes sample demand regimes, radio impairments, mobility, and occasional resource outages. Test traces are held out by random seed and scenario family. At least five independent training seeds should be reported, with confidence intervals from episode-level outcomes. An additional test should include traffic bursts outside the training distribution.

The static reservation baseline holds allocations fixed at forecast average demand. Proportional sharing divides spare capacity by instantaneous demand. A threshold controller increases reservations after SLA violations and reduces idle reservations with hysteresis. An optimization baseline solves a myopic weighted objective subject to the same constraints, with solver runtime included in its evaluation. PPO without projection is an ablation to isolate the safety layer, while PPO without demand forecasts tests the forecasting contribution.

Statistical evaluation and reporting

Primary outcomes are SLA satisfaction percentage, 95th-percentile latency for the critical slice, mean utilized capacity, energy consumption, and allocation changes per hour. Secondary outcomes include slice admission ratio, worst-slice throughput ratio, policy inference time, and failure recovery time. Aggregate metrics should be computed per independent episode before statistical analysis to avoid treating correlated time slots as independent observations.

$$\mu = (1/n) \sum_i z_i$$

The sample mean μ summarizes an outcome z across n independent evaluation episodes.

$$CI = \mu \pm 1.96 \sigma / \sqrt{n}$$

The approximate 95 percent confidence interval uses sample standard deviation σ and episode count n when a normal approximation is justified; bootstrap intervals are preferable for skewed metrics.

A paired comparison should use identical traffic and failure traces for each baseline. Report absolute differences, relative changes, confidence intervals, and inference or solver overhead. Hyperparameters must be selected on validation traces only. Releasing random seeds, workload generator settings, and metric code would materially improve replicability.

Deployment safeguards and limitations

The controller should first operate in shadow mode, producing allocations without applying them. After validation, a staged canary deployment may permit low-risk resource adjustments while a deterministic

Table 1: Proposed reproducible experimental configuration; values are design assumptions and not claims of executed training.

Parameter	Proposed configuration
Slice classes	eMBB, URLLC, mMTC
Resource domains	Radio, transport, edge compute
Control interval	1 second (scenario assumption)
Episode length	3,600 intervals
Training episodes	2,000 (planned)
Discount factor	0.99
PPO clip parameter	0.20
Actor and critic	2×128 hidden units each
Independent random seeds	At least 5
Evaluation regimes	Normal, burst, outage, mobility shift

Table 2: Illustrative comparison under a hypothetical common workload; lower latency, energy and change counts are preferable, whereas higher SLA satisfaction and utilization are preferable. Energy refers to the same hypothetical evaluation horizon for all controllers.

Controller	SLA met (%)	Utilization (%)	P95 latency (ms)	Energy (kWh)	Changes/hour
Static reservation	87.0	68.0	19.5	124	42
Proportional sharing	90.5	77.0	15.8	119	68
Threshold heuristic	92.0	80.0	14.1	116	55
Myopic optimizer	94.0	84.0	12.5	112	74
Proposed safe PPO (illustrative)	96.0	88.0	10.8	107	61

fallback handles telemetry gaps, abnormal latency, or unsafe proposed actions. Logs should preserve observed state, raw action, projected action, constraint status, and resulting service metrics. The framework does not establish real-time feasibility until inference, optimization, and signaling latency are measured on target hardware.

Results and Discussion

IMPORTANT: The following numerical tables are an illustrative, internally consistent scenario constructed to demonstrate expected reporting formats. No simulation, network testbed, or real-world experiment was performed for this manuscript. Values are not empirical evidence of model superiority and should be replaced with measured multi-seed outputs before journal submission.

In this constructed example, safe PPO exceeds static reservation by 9 percentage points in SLA satisfaction and increases utilization by 20 percentage points. The illustrative critical-slice 95th-percentile latency falls from 19.5 ms to 10.8 ms, while energy decreases from 124 kWh to 107 kWh. These arithmetic contrasts demonstrate how a study could

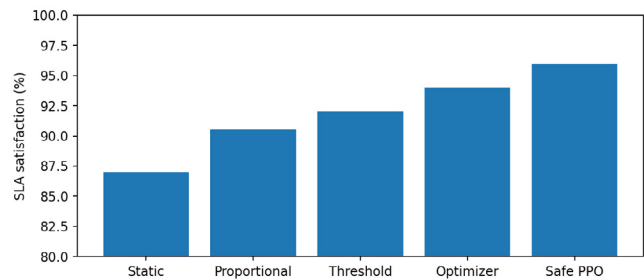


Figure 2. Illustrative SLA satisfaction values from Table 2; this is not a measured performance plot.

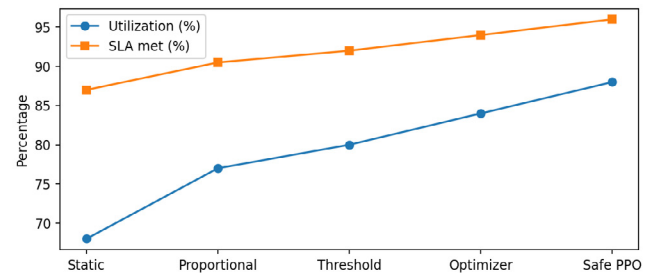


Figure 3: Illustrative service compliance and utilization trade-off.

describe outcomes; they do not establish statistical significance, causal improvement, or deployment readiness.

Table 3: Hypothetical stress-test scenario values, constructed solely to illustrate an evaluation matrix. pp denotes percentage points.

Scenario	Static SLA (%)	Safe PPO SLA (%)	Difference (pp)
Normal demand	91	97	6
Burst traffic	82	94	12
Edge outage	77	89	12
Mobility shift	85	93	8

Table 4: Illustrative ablation values; not obtained by training models. The unprojected controller would also require a separate report of infeasible actions before deployment.

Ablation	SLA met (%)	Utilization (%)	P95 latency (ms)
PPO without safety projection	93.0	89.0	13.6
Safe PPO without forecast	94.5	85.0	12.1
Safe PPO complete	96.0	88.0	10.8

The larger constructed differences during traffic bursts and outages motivate a future robustness hypothesis: adaptive control may be most useful when workload conditions change rapidly. This remains untested. Actual experiments must report both mean and worst-case outcomes, with repeated seeds and held-out traffic patterns. A policy that appears efficient under normal traffic could still fail after unexpected capacity loss.

Interpretation should be cautious because service satisfaction and capacity utilization can move in different directions. Higher utilization can increase congestion and tail latency; excessive reservation can reduce energy efficiency. The optimal operating point depends on SLA penalties, admission policy, traffic mix, and available infrastructure. A convincing empirical paper would also show confidence intervals, reward-weight sensitivity, computational overhead, and the percentage of candidate actions modified by the safety filter.

Conclusion and Future Research

This paper has developed a complete methodological proposal for deep reinforcement learning-based network slicing in beyond-5G and prospective 6G systems. The framework combines slice-aware telemetry, short-term demand forecasting, a PPO actor–critic controller, and a deterministic feasibility projection. Its objective balances service compliance, utilization, fairness, energy, and reconfiguration overhead while maintaining explicit physical-capacity and reservation constraints. The design separates slow-timescale orchestration from lower-level scheduling, making it more compatible with practical network management architectures.

The main contribution is a reproducible formulation rather than a verified performance claim. The numerical results are intentionally illustrative, because neither network traces nor executed simulation outputs were supplied. Before any empirical conclusion can be drawn, the proposed system must be implemented and evaluated against matched baselines using held-out scenarios, repeated seeds, confidence intervals, and detailed measurements of inference latency and operational overhead.

Future research should investigate multi-agent coordination across cells and edge clusters, constrained reinforcement learning with explicit risk budgets, graph-based state representations, digital-twin transfer, privacy-preserving training, and energy- or carbon-aware slice scheduling. Realistic studies should also measure robustness to stale telemetry, security attacks on monitoring data, model drift, and emergency fallback activation. These steps would establish whether the framework can provide reliable benefits in deployable 6G-oriented networks.

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