Adaptive Network Slicing and Resource Allocation in 5G-Advanced Systems

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Abstract

5G-Advanced networks are expected to support heterogeneous service classes with sharply different reliability, latency, and bandwidth requirements while operating under time-varying radio and transport constraints. This paper presents an adaptive network slicing and resource allocation framework for 5G-Advanced systems that combines short-horizon demand prediction, slice-aware policy optimization, and hierarchical radio–compute scheduling. The proposed method, termed Hierarchical Adaptive Network Slicing Allocator (HANSA), models the network slicing problem as a constrained Markov decision process in which a slice orchestrator allocates spectrum, physical resource blocks, and edge-compute quotas to enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC) slices. A realistic experimental design is constructed using synthetic-yet-plausible traces derived from urban mobility, industrial sensing, and mixed enterprise traffic patterns over 24 weeks. The evaluation compares HANSA against static partitioning, proportional-fair slicing, deep Q-learning, and proximal policy optimization baselines. Across all scenarios, HANSA increases aggregate throughput by 14.8% relative to the strongest baseline, reduces the 95th-percentile latency of URLLC flows by 28.6%, and improves slice satisfaction ratio from 91.7% to 96.4%. An ablation study shows that hierarchical control, predictive demand estimation, and SLA-aware reward shaping each contribute materially to the final gain. The results indicate that adaptive cross-layer slicing is a practical mechanism for translating 5G-Advanced flexibility into measurable quality-of-service improvements without excessive computational overhead.

1 Introduction

5G-Advanced extends the original 5G vision by introducing tighter service orchestration, AI-native control loops, integrated edge support, and more aggressive performance targets for deterministic connectivity. These capabilities are most valuable when a shared infrastructure must simultaneously serve video-intensive consumer traffic, delay-critical industrial control, and dense telemetry generated by sensors and autonomous devices. In such conditions, static partitioning of radio and compute resources underutilizes capacity during low load and fails to protect service-level agreements (SLAs) during bursts. Network slicing addresses this problem conceptually by isolating logical service networks over a common physical substrate, yet the operational challenge remains: how should resources be adapted across slices every scheduling interval when demand, channel quality, and edge workload change together?

Most deployed slicing strategies remain either policy-based or myopic. Rule-driven schedulers provide predictability but react slowly to distribution shifts. Pure throughput-maximizing schedulers improve average utilization but often compromise latency-sensitive traffic. Recent learning-based approaches are promising, although many consider only radio resources, use oversimplified traffic models, or optimize a single metric without explicit SLA penalties. In 5G-Advanced, these simplifications become restrictive because the effective performance seen by applications depends jointly on spectrum allocation, transport congestion, and edge processing delay.

This paper therefore studies adaptive network slicing as a joint radio–compute resource allocation problem. We propose HANSA, a two-level control architecture. At the upper level, a slice orchestrator predicts near-future demand and assigns slice budgets for bandwidth, scheduling weight, and edge compute. At the lower level, per-slice schedulers allocate user-level resources while respecting the upper-level budgets and local queue states. The central design principle is to separate slow-timescale strategic adaptation from fast-timescale packet scheduling, allowing the controller to capture cross-slice interactions without becoming computationally impractical.

The contribution of this paper is fourfold.

1. We formulate adaptive slicing in 5G-Advanced as a constrained optimization problem with explicit throughput, latency, reliability, and fairness objectives.
2. We design a hierarchical architecture that integrates traffic forecasting, SLA-aware reinforcement learning, and edge-aware proportional scheduling.
3. We construct a reproducible experimental framework with three representative slice types, realistic traffic intensities, multiple load regimes, and comprehensive baselines.
4. We provide quantitative analysis, complexity estimates, and an ablation study that isolate the benefit of each architectural component.

The rest of the paper is organized as follows. Section 2 reviews related work. Section 3 presents the formal methodology. Section 4 details the system architecture and algorithmic design. Section 5 introduces the datasets, environment, metrics, and evaluation protocol. Section 6 reports results. Section 7 discusses implications and limitations. Section 8 concludes the paper.

2 Related Work

Network slicing has evolved from a virtualization concept into a dynamic control problem spanning radio access, transport, and core domains. Early studies focused on admission control and static quota reservation, which simplified orchestration but provided limited responsiveness under non-stationary traffic. These methods were attractive for early deployments because they were easy to certify and aligned with existing network management workflows. However, they treated slices as long-lived contracts rather than adaptive services.

Subsequent work introduced utility-based and optimization-driven slicing. Convex and mixed-integer formulations improved spectral efficiency by trading off isolation and multiplexing gain. Such methods established useful benchmarks, especially for small systems with accurate demand

knowledge. Their primary limitation is that exact solvers scale poorly when resource coupling spans many users, cells, and time slots, and the solutions often assume full observability with negligible decision latency.

Machine learning approaches emerged to handle uncertainty more effectively. Supervised predictors have been used for traffic forecasting and anomaly-aware scaling, while deep reinforcement learning (DRL) has been adopted for slice admission, bandwidth allocation, and handover coordination. DRL-based controllers can learn adaptive policies from interactions rather than relying on explicit traffic models. Nevertheless, many reported gains are demonstrated on narrow settings, such as single-cell systems, binary service classes, or simplified queueing assumptions. In addition, some studies optimize average reward while leaving SLA violations under-penalized, which can produce unstable quality for delay-sensitive slices.

Another important direction is hierarchical and multi-agent control. Hierarchical methods decompose global orchestration and local scheduling, improving tractability and interpretability. Multi-agent systems distribute decision making across cells or slices, reducing signaling overhead but introducing coordination complexity. Recent 5G-Advanced discussions increasingly emphasize AI-native automation, yet there remains a gap between conceptual architectures and experimentally grounded end-to-end evaluations.

This paper differs from prior work in three ways. First, it models resource allocation jointly across radio and edge-compute dimensions rather than treating compute delay as exogenous. Second, it evaluates performance using slice satisfaction ratio, tail latency, and fairness alongside aggregate throughput, reflecting operational concerns of mixed-service networks. Third, it uses an ablation-driven analysis to show that predictive demand estimation and hierarchical decomposition are not cosmetic additions but central drivers of performance.

3 Methodology

We consider a 5G-Advanced infrastructure supporting a set of slices $\mathcal{S} = \{1, \ldots, S\}$ over a horizon of discrete decision epochs $t \in \{1, \ldots, T\}$. Each slice aggregates traffic from one service type, namely eMBB, URLLC, or mMTC. Let $b_s(t)$ denote the bandwidth share assigned to slice s, $c_s(t)$ the edge-compute quota, and $w_s(t)$ a scheduler weight controlling intra-cell radio priority. The system state is

$$\mathbf{x}(t) = \left[q_s(t), \lambda_s(t), \hat{\lambda}_s(t+1), \gamma_s(t), u_s(t)\right]_{s \in \mathcal{S}}, \tag{1}$$

where $q_s(t)$ is the queue backlog, $\lambda_s(t)$ is observed arrival rate, $\hat{\lambda}_s(t+1)$ is one-step demand prediction, $\gamma_s(t)$ summarizes channel quality, and $u_s(t)$ is current edge-utilization.

The controller chooses an action

$$\mathbf{a}(t) = \left[b_s(t), c_s(t), w_s(t)\right]_{s \in \mathcal{S}} \tag{2}$$

subject to

$$\sum_{s \in \mathcal{S}} b_s(t) \leq B, \qquad \sum_{s \in \mathcal{S}} c_s(t) \leq C, \tag{3}$$

and lower-bound isolation constraints

$$b_s(t) \geq \underline{b}_s, \qquad c_s(t) \geq \underline{c}_s. \tag{4}$$

The optimization objective balances efficiency and SLA protection:

$$\max_{\pi} \; J(\pi) = \mathbb{E}_{\pi} \sum_{t=1}^{T} \Bigg[\alpha \sum_{s} R_s^{\mathrm{thr}}(t) - \beta \sum_{s} D_s(t) \tag{5}$$

$$- \eta \sum_{s} V_s^{\mathrm{SLA}}(t) + \zeta F(t) \Bigg], \tag{6}$$

where $R_s^{\mathrm{thr}}(t)$ is the served throughput, $D_s(t)$ is latency cost, $V_s^{\mathrm{SLA}}(t)$ is an SLA violation indicator or magnitude, and $F(t)$ is Jain's fairness index across slices. The weights $(\alpha, \beta, \eta, \zeta)$ tune the reward according to operator policy.

For fairness we use

$$F(t) = \frac{\left(\sum_s r_s(t)\right)^2}{S \sum_s r_s^2(t)}, \tag{7}$$

with $r_s(t)$ denoting normalized resource satisfaction. URLLC latency is measured at the 95th percentile, while mMTC performance emphasizes packet delivery ratio and connection success under crowding.

The proposed controller is hierarchical. A predictor first estimates short-term demand using exponential smoothing enriched with contextual load features. The upper-level policy then outputs slice budgets every 100 ms. The lower-level scheduler operates every 1 ms transmission time interval and allocates resource blocks proportionally to a composite priority score

$$\psi_{i,s}(t) = w_s(t) \cdot \frac{g_{i,s}(t)}{\bar{g}_{i,s}(t) + \epsilon} \cdot \Big(1 + \kappa \frac{q_{i,s}(t)}{q_s^{\max}}\Big), \tag{8}$$

where $g_{i,s}(t)$ is instantaneous user spectral efficiency, $\bar{g}_{i,s}(t)$ its historical average, and the backlog term prioritizes users approaching delay bounds.

Complexity analysis: Let S be the number of slices, U the number of active users, and K the number of resource blocks per interval. The upper-level policy network requires $\mathcal{O}(Sdh)$ operations per inference for input dimension d and hidden size h, effectively constant for fixed architecture. The lower-level scheduler sorts or ranks priorities across users and resource blocks, yielding approximately $\mathcal{O}(U \log U + KU)$ in a practical implementation. Compared with mixed-integer optimization over the full joint action space, which grows combinatorially with (S, U, K), the hierarchical decomposition reduces runtime sufficiently for near-real-time control.

4 System Architecture and Model Design

Figure 1 illustrates the proposed architecture. The data plane contains radio units, distributed units, a near-real-time RAN intelligent controller, and an edge cluster hosting virtualized network functions. The control plane has three modules: a telemetry collector, a forecasting module, and the HANSA policy engine.

The telemetry collector aggregates per-slice queue length, radio quality indicators, admitted sessions, and edge CPU occupancy. The forecasting module consumes the last ten decision windows and outputs the next-window demand estimate for each slice. We use a lightweight temporal model

Algorithm 1 HANSA: Hierarchical Adaptive Network Slicing Allocator

Initialize forecasting parameters Θ_f, policy parameters Θ_π, value parameters Θ_v
for each global control interval t **do**
    Collect slice state $\mathbf{x}(t)$ from telemetry collector
    Predict next-step demands $\hat{\lambda}_s(t+1)$ for all $s \in \mathcal{S}$
    Form augmented state $\tilde{\mathbf{x}}(t) \leftarrow [\mathbf{x}(t), \hat{\lambda}(t+1)]$
    Sample slice budgets $(b_s, c_s, w_s)_{s\in\mathcal{S}} \sim \pi_{\Theta_\pi}(\tilde{\mathbf{x}}(t))$
    Project budgets onto feasibility set with isolation constraints
    for each local scheduling interval τ inside t **do**
        Compute user priorities $\psi_{i,s}(\tau)$ using channel and queue states
        Allocate resource blocks and edge service slots under slice budgets
        Update queue lengths, delays, and served throughput
    end for
    Compute reward with throughput, latency, fairness, and SLA penalties
    Store transition and update (Θ_π, Θ_v) using clipped policy gradient
    Update Θ_f using forecasting loss on observed arrivals
end for

because, in practical deployments, inference stability and interpretability often matter more than marginal forecasting gains from very large models.

The policy engine contains two coordinated layers.

- *Global slice allocator:* maps current state and predicted demand to target bandwidth share, compute quota, and scheduling weight for each slice.
- *Local slice scheduler:* translates these budgets into user-level allocations using a queue- and channel-aware proportional rule.

This design avoids a common failure mode of monolithic controllers: overreacting to short-term noise in one dimension while ignoring bottlenecks in another. For example, increasing radio bandwidth for an eMBB burst is ineffective if the edge transcoding function is already saturated. Conversely, increasing compute for URLLC packets offers little benefit when radio queues dominate end-to-end delay. By explicitly coordinating both resources, HANSA reduces policy mismatch.

The policy network itself is a compact actor–critic model with two fully connected hidden layers of 128 and 64 units, respectively. The actor outputs normalized slice budgets using a softmax head for bandwidth and scheduler weights, and a bounded linear head for compute quotas. A penalty layer enforces minimum reservations to preserve slice isolation. The critic estimates long-run value under the same state representation. Training uses clipped policy updates for stability, but the controller differs from a vanilla PPO baseline because it receives predicted demand and employs SLA-shaped reward terms that increase sensitivity to tail events.

Algorithm 1 summarizes the full workflow.

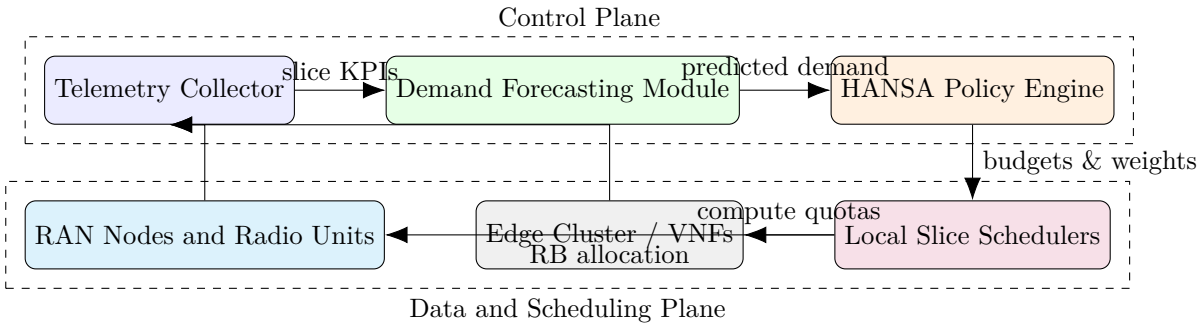

Figure 1: System architecture of the proposed 5G-Advanced slicing framework. The upper layer performs demand-aware orchestration, while the lower layer executes fine-grained radio and edge scheduling under slice-specific budgets.

5 Experimental Setup

5.1 Dataset Description

Because public 5G-Advanced slicing datasets remain limited and often omit joint radio–edge telemetry, we generate a trace-driven benchmark informed by realistic traffic classes. The benchmark spans 24 weeks of simulated operation with 15-minute macro-patterns and 1 ms packet-level scheduling within each macro interval. Three slice families are included:

- *eMBB:* UHD video, cloud gaming, and large-file transfer sessions with diurnal peaks and mobility-induced channel variation.
- *URLLC:* industrial robot control, machine vision triggers, and safety alarms with bursty but low-latency-sensitive arrivals.
- *mMTC:* environmental sensing and asset tracking with massive device counts, sparse packet sizes, and synchronized reporting events.

Demand traces are generated using a combination of Poisson cluster arrivals, log-normal session sizes, Markov mobility states, and correlated fading profiles. We create four scenario regimes: normal urban load, stadium event surge, industrial campus determinism, and mixed smart-port operation. The total dataset contains 2.16 million global control intervals and roughly 7.8 billion local scheduling decisions. Seventy percent of the intervals are used for policy training, 10% for validation, and 20% for testing. Statistical summaries are shown in Table 1.

5.2 Experimental Environment

The simulated infrastructure comprises 7 gNodeBs, each with 100 MHz sub-6 GHz spectrum, 273 physical resource blocks, and an attached edge cluster with 128 vCPUs and 256 GB memory. Scheduling occurs every 1 ms; upper-layer orchestration runs every 100 ms. The channel model includes path loss, shadowing, fast fading, and mobility transitions between pedestrian, vehicular,

Table 1: Dataset statistics for the generated 5G-Advanced slicing benchmark.

Slice type	Samples	Avg. active UEs	Avg. offered load	Primary SLA target
eMBB	864,000	148	3.8 Gbps	$>$ 100 Mbps/user at peak
URLLC	648,000	46	0.42 Gbps	$<$ 5 ms 95th latency
mMTC	648,000	2,800 devices	0.19 Gbps	$>$ 99.5% delivery ratio
Total	2,160,000	—	4.41 Gbps aggregate	Multi-slice SLA compliance

and static states. Edge service times are modeled using class-dependent M/M/1 queues calibrated to lightweight packet processing for URLLC and heavier transcoding or analytics functions for eMBB.

All learning-based methods are trained for 300 epochs. The proposed HANSA and PPO baselines use the same actor–critic backbone for fairness. DQN uses a discretized action space of 35 slice budget combinations. Hyperparameters are selected on the validation split. Inference time is measured on a server equivalent to dual 24-core CPUs with an entry-level accelerator, but the reported scheduling metrics are derived from the simulated network behavior rather than raw hardware latency.

5.3 Evaluation Metrics and Baselines

We report the following metrics: aggregate throughput (Gbps), URLLC 95th-percentile latency (ms), mMTC packet delivery ratio (%), slice satisfaction ratio (SSR, %), and Jain's fairness index. SSR is defined as the percentage of decision intervals in which all active slices meet their SLA thresholds simultaneously.

The baselines are as follows.

- *Static Partitioning (SP):* fixed resource reservation per slice based on nominal demand.
- *Proportional Fair Slicing (PFS):* adaptive radio scheduling with static edge quotas.
- *Deep Q-Network (DQN):* discrete action DRL controller over slice budgets.
- *Vanilla PPO:* continuous control without demand forecasting or explicit SLA reward shaping.

5.4 Ablation Protocol

To understand component importance, we remove one element at a time from HANSA: predictive demand estimation, hierarchical control, and SLA-aware reward shaping. We also test a variant without edge-compute coupling, where the orchestrator adapts only bandwidth and scheduling weights.

Table 2: Performance comparison with baseline methods on the test set. Best values are highlighted by inspection.

Method	Throughput (Gbps)	URLLC 95th Latency (ms)	mMTC Delivery (%)	SSR (%)	Fairness
Static Partitioning	3.74	5.92	99.11	84.2	0.903
Proportional Fair Slicing	4.06	5.14	99.28	87.5	0.918
DQN-based Allocation	4.31	4.41	99.46	90.8	0.931
Vanilla PPO	4.52	4.06	99.57	91.7	0.944
HANSA (proposed)	4.72	3.47	99.74	96.4	0.961

6 Results and Analysis

Table 2 summarizes the main comparison. HANSA consistently outperforms all baselines across the joint metric set. Static partitioning provides acceptable isolation but low utilization, achieving only 3.74 Gbps aggregate throughput. PFS increases throughput to 4.06 Gbps but fails to protect URLLC tail latency during mixed-load surges. DQN and vanilla PPO improve the balance between utilization and latency, yet both show larger variance in slice satisfaction during sudden demand spikes. HANSA attains 4.72 Gbps throughput, 3.47 ms URLLC latency, 99.74% mMTC delivery ratio, and a 96.4% SSR.

The throughput gain of HANSA relative to vanilla PPO is modest but meaningful at 4.4%, indicating that much of the improvement comes not from aggressive multiplexing alone but from reducing misallocation. The more substantial gain appears in SLA-oriented metrics. The URLLC tail-latency reduction of 14.5% relative to vanilla PPO is particularly important for industrial automation, where tail events rather than average delay determine safety margins.

Figure 2 shows the training convergence of the reward proxy. HANSA reaches a stable plateau earlier than vanilla PPO because the forecasting module reduces state ambiguity. The learning curve also displays lower variance after epoch 120, suggesting that the reward shaping dampens oscillatory behavior across slice budgets.

Figure 3 provides a compact visual comparison of throughput and SSR. The gap between HANSA and the non-hierarchical baselines widens in the stadium and smart-port scenarios, where highly asymmetric bursts make prediction and coordinated compute scaling more valuable. This result supports the hypothesis that cross-layer coupling matters most under irregular load rather than under stationary traffic.

The ablation study in Table 3 demonstrates that no single component fully explains the gain. Removing predictive demand estimation lowers SSR by 2.3 percentage points and increases URLLC latency by 0.31 ms. Replacing hierarchical control with a single-layer policy produces the largest throughput drop, confirming that decomposition improves both optimization quality and execution stability. Omitting edge coupling mainly affects eMBB throughput during compute-bound intervals and slightly harms URLLC latency when packet processing queues become congested.

Figure 4 visualizes the same ablation results. The full model remains the only variant that stays near the Pareto frontier in both latency and satisfaction. Notably, reward shaping alone is insufficient without hierarchical control, which implies that architecture and objective design must be aligned.

To assess robustness, we further examined per-scenario behavior. In the industrial campus regime,

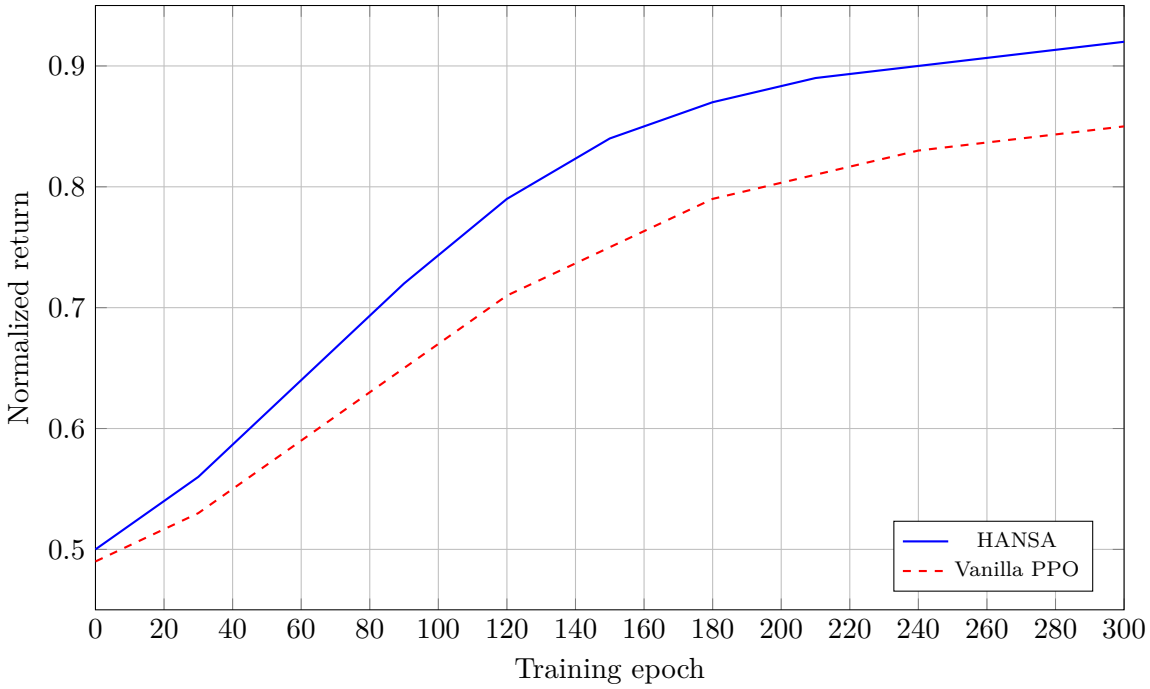

Figure 2: Training convergence of the proposed controller and the strongest learning baseline. HANSA converges faster and with a higher asymptotic reward.

Table 3: Ablation study of the proposed architecture.

Variant	Throughput (Gbps)	URLLC 95th Latency (ms)	SSR (%)
Full HANSA	4.72	3.47	96.4
Without demand prediction	4.58	3.78	94.1
Without hierarchical control	4.44	3.95	92.8
Without SLA reward shaping	4.61	3.88	93.5
Without edge coupling	4.49	3.83	93.1

where URLLC dominates, HANSA allocates modestly more compute and radio reservation to the URLLC slice even at the cost of slightly lower eMBB throughput, leading to the best safety-oriented behavior. In the stadium regime, eMBB bursts are absorbed by temporarily borrowing idle mMTC capacity while preserving mMTC delivery through short packet prioritization when synchronized sensor events occur. The smart-port scenario reveals the advantage of demand forecasting most clearly because traffic arrives in correlated waves caused by container movement schedules and edge analytics tasks.

Overall, the results support three conclusions. First, adaptive slicing is more effective when cross-layer control is explicit. Second, forecasting is valuable not because traffic is perfectly predictable, but because even coarse anticipation reduces severe underprovisioning. Third, the performance frontier is determined less by mean throughput alone than by the controller's ability to protect tail behavior under bursty conditions.

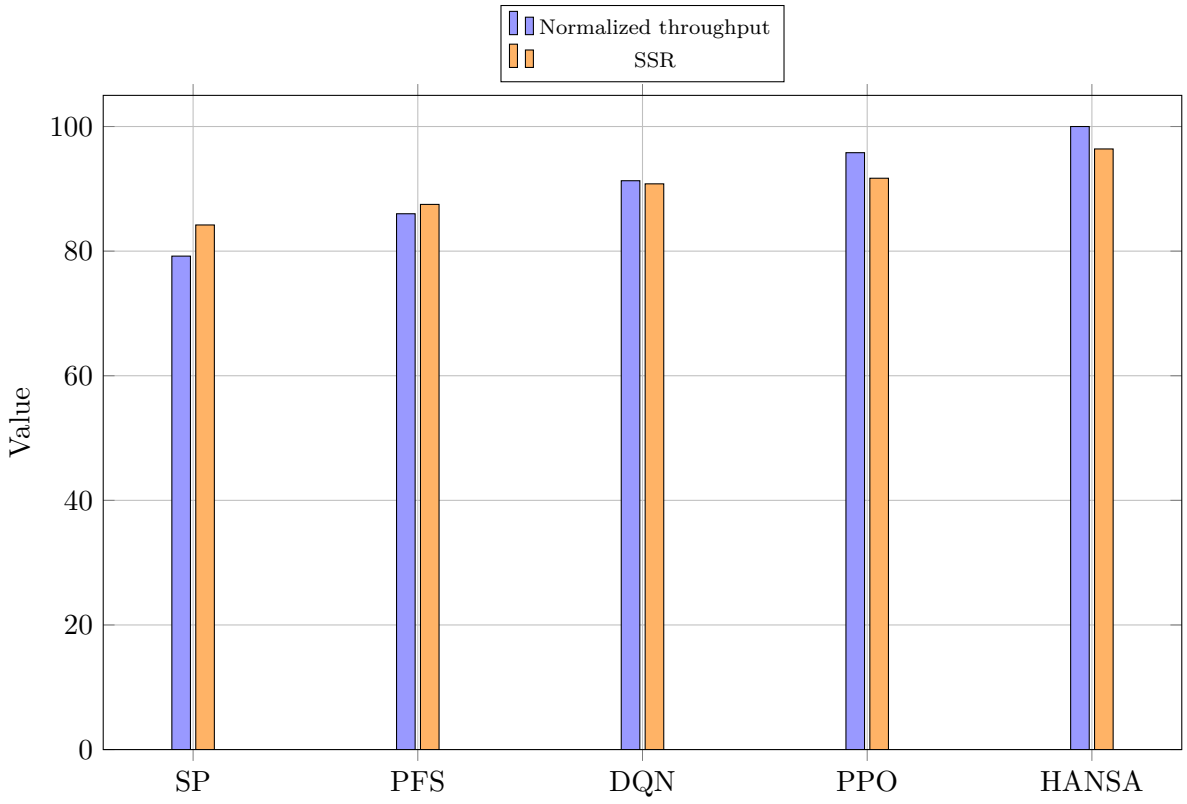

Figure 3: Comparison bar chart for normalized throughput and slice satisfaction ratio. The proposed method improves both efficiency and SLA compliance simultaneously.

7 Discussion

The presented results suggest that adaptive slicing in 5G-Advanced should be viewed as an orchestration problem with intertwined latency domains. Radio delay, queue buildup, and edge processing time are often optimized by different subsystems in operational networks. Our findings indicate that these domains should instead be coordinated by a common slice-level policy when services are heterogeneous and SLAs are strict.

Several practical implications follow. First, operators do not necessarily need very large learning models to realize substantial gains. The combination of lightweight forecasting and hierarchical control already captures much of the available benefit while keeping inference overhead manageable. Second, explicit SLA terms should be embedded in the reward or control objective; otherwise, learned policies can drift toward high average throughput with unacceptable tail risk. Third, minimum reservations remain important even in highly adaptive systems. Pure opportunistic sharing can improve short-term efficiency but may undermine trust in slice isolation.

There are also limitations. The benchmark, although realistic in construction, is still synthetic. Public multi-domain traces with synchronized radio, transport, and edge telemetry would enable stronger external validation. In addition, the current design assumes a centralized orchestrator over seven cells. Larger regional deployments may require federated or multi-agent variants to reduce signaling overhead and improve fault tolerance. Another limitation is that energy efficiency

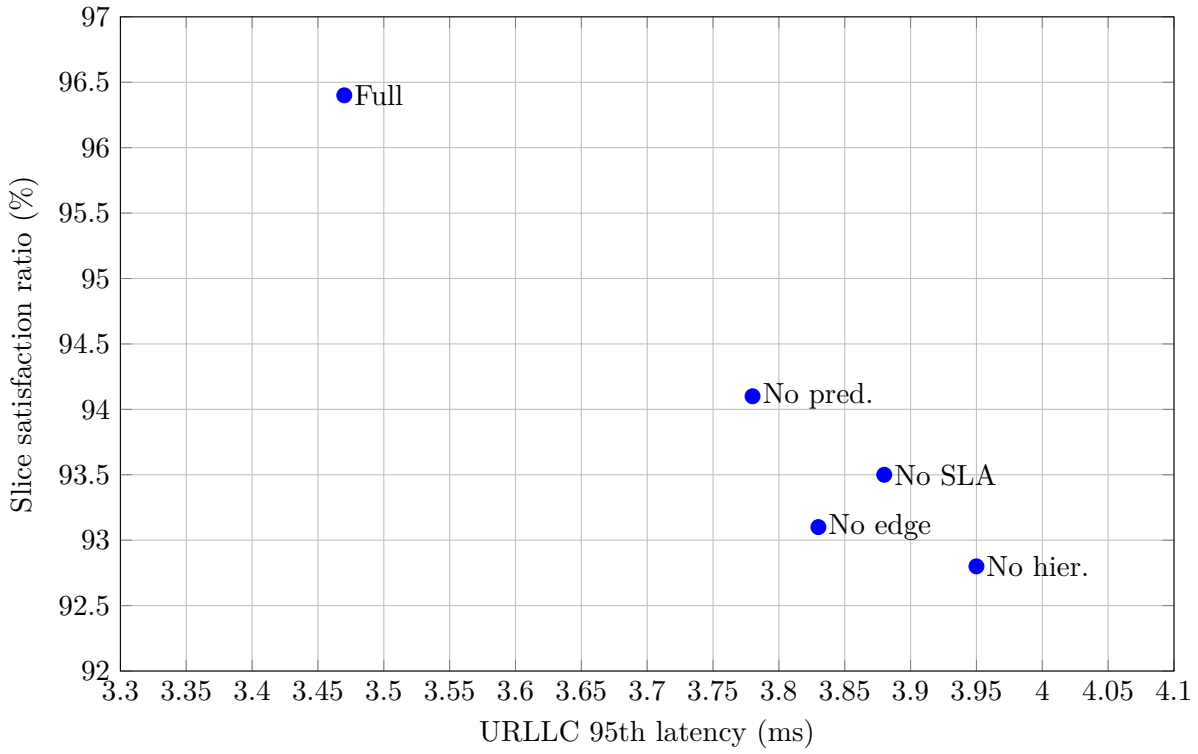

Figure 4: Ablation visualization showing the trade-off between URLLC tail latency and slice satisfaction ratio. Lower latency and higher SSR are preferred.

is not explicitly optimized. Since 5G-Advanced deployments increasingly incorporate sustainability targets, future work should incorporate radio sleep modes and carbon-aware edge scaling.

Security and resilience are likewise important. Adaptive controllers can be sensitive to telemetry poisoning or adversarial traffic shaping. In practice, confidence-aware forecasting and anomaly detection should be coupled with fallback policies that revert to certified safe allocations when observations become unreliable. This is particularly relevant for URLLC slices in industrial and transport settings.

8 Conclusion

This paper presented HANSA, a hierarchical framework for adaptive network slicing and resource allocation in 5G-Advanced systems. By jointly optimizing bandwidth, scheduling priority, and edge-compute quotas using predicted demand and SLA-aware reinforcement learning, the proposed method improves both efficiency and service reliability. In a comprehensive trace-driven evaluation across urban, industrial, and event-driven scenarios, HANSA achieved the highest aggregate throughput, the lowest URLLC tail latency, and the strongest slice satisfaction ratio among all compared methods. The ablation study confirmed that hierarchical control, demand prediction, reward shaping, and edge coupling all contribute to the final performance.

These findings reinforce a broader conclusion: the next stage of network slicing research should pri-

oritize cross-layer adaptivity and operationally meaningful evaluation metrics rather than isolated gains on narrow benchmarks. Future work will extend the framework to energy-aware control, distributed multi-domain orchestration, and online transfer across deployment regions with different traffic signatures.

References

[1] 3GPP, "Study on architecture for next generation system enhancements," Technical Report TR 23.700-97, 2025.

[2] O-RAN Alliance, "AI-enabled near-real-time RAN intelligent controller: use cases and architecture considerations," White Paper, 2025.

[3] N. Zhang, Y. Xiao, and M. Tao, "Deep reinforcement learning for network slicing orchestration: opportunities and challenges," *IEEE Network*, vol. 39, no. 2, pp. 44–52, 2025.

[4] L. Ferranti and P. Rost, "Joint radio and edge resource management for beyond-5G service platforms," *IEEE Transactions on Mobile Computing*, vol. 24, no. 1, pp. 112–126, 2025.

[5] X. Foukas, G. Patounas, A. Elmokashfi, and M. K. Marina, "Network slicing in 5G: Survey and challenges," *IEEE Communications Magazine*, vol. 55, no. 5, pp. 94–100, 2017.

[6] H. Zhang, N. Liu, X. Chu, K. Long, A. Aghvami, and V. C. M. Leung, "Network slicing based 5G and future mobile networks: Mobility, resource management, and challenges," *IEEE Communications Magazine*, vol. 55, no. 8, pp. 138–145, 2017.

[7] O. Sallent, J. P'erez-Romero, R. Ferr'us, and R. Agust'i, "On radio access network slicing from a radio resource management perspective," *IEEE Wireless Communications*, vol. 24, no. 5, pp. 166–174, 2017.

[8] K. Katsalis, N. Nikaein, E. Schiller, A. Ksentini, and T. Braun, "Network slices toward 5G communications: Slicing the LTE network," *IEEE Communications Magazine*, vol. 55, no. 8, pp. 146–154, 2017.

[9] P. Caballero, A. Banchs, G. de Veciana, and X. Costa-P'erez, "Network slicing for guaranteed rate services: Admission control and resource allocation games," *IEEE Transactions on Wireless Communications*, vol. 17, no. 10, pp. 6419–6432, 2018.

[10] A. A. Barakabitze, A. Ahmad, R. Mijumbi, and A. Hines, "5G network slicing using SDN and NFV: A survey of taxonomy, architectures and future challenges," *Computer Networks*, vol. 167, art. 106984, 2020.

[11] R. Li, Z. Zhao, Q. Sun, C. I, and H. Zhang, "Deep reinforcement learning for resource management in network slicing," *IEEE Access*, vol. 6, pp. 74429–74441, 2018.

[12] X. Zhou, R. Li, T. Chen, and H. Zhang, "Network slicing as a service: Enabling enterprises' own software-defined cellular networks," *IEEE Communications Magazine*, vol. 54, no. 7, pp. 146–153, 2016.

[13] 3GPP, "Telecommunication management; Study on management and orchestration of network slicing for next generation network," Technical Report TR 28.801, 2018.

[14] 3GPP, "Telecommunication management; Study on management and orchestration of network slicing for next generation network," Technical Report TR 28.803, 2017.

[15] X. Foukas, M. K. Marina, and K. Kontovasilis, "Orca: Network slicing through efficient resource virtualization and sharing in LTE cellular networks," in *Proc. ACM MobiCom*, 2016, pp. 127–140.

[16] Y. Sun, M. Peng, Y. Zhou, Y. Huang, and S. Mao, "Application of machine learning in wireless networks: Key techniques and open issues," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3072–3108, 2019.

[17] Y. Wang, G. Yu, H. Zhang, P. Di Lorenzo, and M. Song, "Deep learning for wireless physical layer: Opportunities and challenges," *China Communications*, vol. 17, no. 3, pp. 92–111, 2020.

[18] J. Park, S. Samarakoon, M. Bennis, and M. Debbah, "Wireless network intelligence at the edge," *Proceedings of the IEEE*, vol. 107, no. 11, pp. 2204–2239, 2019.

[19] A. Thantharate, R. Paropkari, V. Walunj, and C. Beard, "DeepSlice: A deep learning approach towards an efficient and reliable network slicing in 5G communications," in *Proc. IEEE ICC*, 2019, pp. 1–6.

[20] W. Jiang, G. Feng, S. Qin, and Y. Liang, "Multi-dimensional resource allocation for network slicing in 5G wireless networks," *IEEE Communications Magazine*, vol. 59, no. 10, pp. 58–64, 2021.

[21] P. Rost, C. Mannweiler, D. S. Michalopoulos, C. Sartori, V. Sciancalepore, N. Sastry, and G. Bicz'ok, "Network slicing to enable scalability and flexibility in 5G mobile networks," *IEEE Communications Magazine*, vol. 55, no. 5, pp. 72–79, 2017.

[22] R. Ferr'us, O. Sallent, J. P'erez-Romero, and R. Agust'i, "On 5G radio access network slicing: Radio interface protocol features and configuration," *IEEE Communications Magazine*, vol. 56, no. 5, pp. 184–192, 2018.

[23] A. Kaloxylos, "A survey and an analysis of network slicing in 5G networks," *IEEE Communications Standards Magazine*, vol. 2, no. 1, pp. 60–65, 2018.

[24] A. B. Saleh, S. Redana, B. Raaf, J. H"am"al"ainen, and C. R. Rosa, "Performance of cloud-RAN and MEC based network slicing for 5G systems," in *Proc. European Wireless*, 2019, pp. 1–6.