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ATENCY-OPTIMAL 5G SLICING: AI-BASED RESOURCE AND ENERGY OPTIMIZATION VIA ENTROPY-GUIDED CYBER TWIN ARCHITECTURES

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ABSTRACT

The exponential growth and increasing complexity of 5G networks present significant operational challenges that traditional rule-based management systems struggle to handle effectively. However, many existing approaches do not adequately capture traffic uncertainty, which limits their ability to adapt in highly dynamic network environments. To address this, the study proposes an optimized 5G Network Entropy-Guided Cyber Twin architecture. The methodology centres on the application of Shannon entropy to quantify traffic uncertainty across temporal, spatial, and service dimensions. This was executed through a tripartite framework: first, a traffic entropy model was developed to provide a mathematical foundation for uncertainty quantification; second, a Cyber Twin environment was constructed to serve as a high-fidelity virtual replica of the 5G network for safe and efficient policy testing; and third, a Soft Actor-Critic (SAC) reinforcement learning agent was designed to incorporate these entropy measures directly into its reward function. This integration allows the agent to make adaptive, data-driven resource allocation decisions that account for underlying traffic variability. Together, these components enable the joint optimization of resource allocation, power consumption, and system latency. The proposed framework was evaluated using the DeepSlice dataset from Kaggle, which contains 63,167 samples representing realistic 5G traffic patterns across three slice types: eMBB, URLLC, and mMTC. This dataset serves as the empirical basis for modeling and evaluation. Performance was evaluated against baseline methods, including conventional heuristic allocation and standard SAC without entropy integration. The results show that the proposed entropy-aware framework achieved a 98.64% URLLC compliance rate with a mean latency of 3.5 ms, yielding relative improvements of 30% to 91.6% across all slices compared to maximum QoS thresholds. Overall, this research developed an architecture that incorporates traffic entropy into the learning process, enhancing the adaptability and robustness of 5G resource management, providing a practical and scalable solution for real-time optimization in next-generation networks.

KEYWORDS: 5G Network Slicing, Cyber Twin Architecture, Shannon Entropy, Reinforcement Learning, Resource Optimization, Energy Efficiency, Digital Twin, Soft Actor-Critic.

1.0 INTRODUCTION

The operational reality of 5G networks reveals a major gap between the theoretical promise of network slicing and the capabilities of current management systems. While network slicing is designed to partition shared infrastructure into distinct virtual networks, it must simultaneously satisfy highly conflicting Quality of Service (QoS) demands. Specifically, it must sustain high throughput (80 Mbps) for enhanced Mobile Broadband (eMBB), guarantee ultra-low latency (sub-5 ms) with 99.999% reliability for Ultra-Reliable Low-Latency Communications (URLLC), and support massive connectivity for massive Machine-Type Communications (mMTC). Kakkavas, G., et al (2022)

Current commercial deployments rely heavily on reactive, rule-based systems that only respond after a QoS violation has already occurred. Although technologies like Software-Defined Networking (SDN) and Network Functions Virtualization (NFV) introduce programmability, they fail to solve the complex, joint management of physical resource blocks, power, and scheduling across diverse slices. Traditional optimization methods struggle with unpredictable traffic, while advanced Deep Reinforcement Learning (DRL) alternatives often fall short because they optimize single metrics in isolation, rely solely on simulation data, and ignore the computational overhead at the edge.

To bridge these gaps, two emerging paradigms have surfaced: Cyber Twins, which evolve traditional Digital Twins into active, intelligent decision-making systems, and Shannon entropy, which quantifies traffic uncertainty to provide predictive alerts before QoS degradation happens. However, these innovations remain fragmented in current research. The featured work aims to address this disconnect by creating a unified, closed-loop framework that integrates entropy modeling, Cyber Twin architectures, and AI-driven optimization into a single cohesive system.

2. 0 Literature Review

Current research identifies Digital Twins (DT) and Artificial Intelligence (AI) as essential for managing the complexity of 5G and 6G networks. Researchers like Rodrigo et al. (2021), Rivera (2023), and Tran et al. (2025) have established foundational frameworks for Network Digital Twins (NDT), enabling bidirectional synchronization and risk-free performance testing. Practical applications of these twins show significant gains: Balogun (2025) reported a 22% latency reduction, while Singh et al. (2024) and Pham (2025) demonstrated high predictive accuracy in data allocation and throughput calibration.

In parallel, AI-driven optimization is solving resource scarcity and security challenges. El-hajj (2025) and Bikkasani et al. (2024) highlight how machine learning improves load balancing and bandwidth utilization, outperforming traditional static methods. Specialized models, such as the SOM-DRL approach by Nivetha & Preetha (2025) and the EERAM model by Logeshwaran et al. (2023), specifically target edge computing and energy efficiency in high-density environments.

However, sustainability remains a critical concern. While Ezzeddine (2024) and Masoudi (2022) demonstrate that AI-driven "green enablers" like intelligent sleep modes significantly cut power consumption, Lassoued et al. (2026) and Mozo et al. (2022) caution against the high computational overhead of these technologies. They argue that future research must balance the energy saved by AI against the energy required to run the models themselves, while moving toward real-world hardware validation.

3.0 METHODOLOGY

3.1 Entropy Guided Cyber Twin Framework

This research framework integrates Shannon entropy, Cyber Twin modeling, and Soft Actor Critic (SAC) reinforcement learning into a unified system for predictive traffic analysis and resource optimization in 5G networks. At its core, Shannon entropy provides a mathematical measure of uncertainty, enabling the system to capture the inherent variability in traffic patterns and user demand. By embedding entropy into the reinforcement learning process, the agent is guided to maintain a balance between exploration and exploitation, ensuring adaptability in dynamic network environments. Cyber Twin modeling complements this by offering a virtualized replica of the physical network environment. This digital twin acts as a safe sandbox where policies can be tested against realistic traffic scenarios without jeopardizing live network performance. The Cyber Twin thus becomes a critical validation layer, allowing entropy-augmented reinforcement learning agents to refine strategies in a controlled setting before deployment. This ensures that optimization policies are not only theoretically sound but also practically reliable.

The reinforcement learning backbone of the framework is the Soft Actor Critic algorithm, which is particularly well-suited for environments characterized by uncertainty and continuous action spaces. SAC's entropy-regularized objective function aligns naturally with Shannon entropy, encouraging diverse policy exploration while optimizing for latency, energy efficiency, and quality of service. This synergy between entropy and SAC ensures that the agent develops robust, flexible policies capable of adapting to fluctuating traffic loads and resource constraints in 5G slicing.

Empirical validation is grounded in the DeepSlice dataset, which provides realistic traffic traces and slicing scenarios..

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Empirical validation is grounded in the DeepSlice dataset, which provides realistic traffic traces and slicing scenarios. By applying the closed-loop system to DeepSlice, the framework demonstrates clear advantages over heuristic baselines. Results confirm superior performance in latency reduction, energy efficiency, and QoS optimization, highlighting the practical impact of combining information theory, digital twin modeling, and advanced reinforcement learning. The closed-loop feedback mechanism further strengthens the system, as performance metrics from both simulation and real-world traffic continuously inform policy refinement, creating a cycle of adaptive optimization.

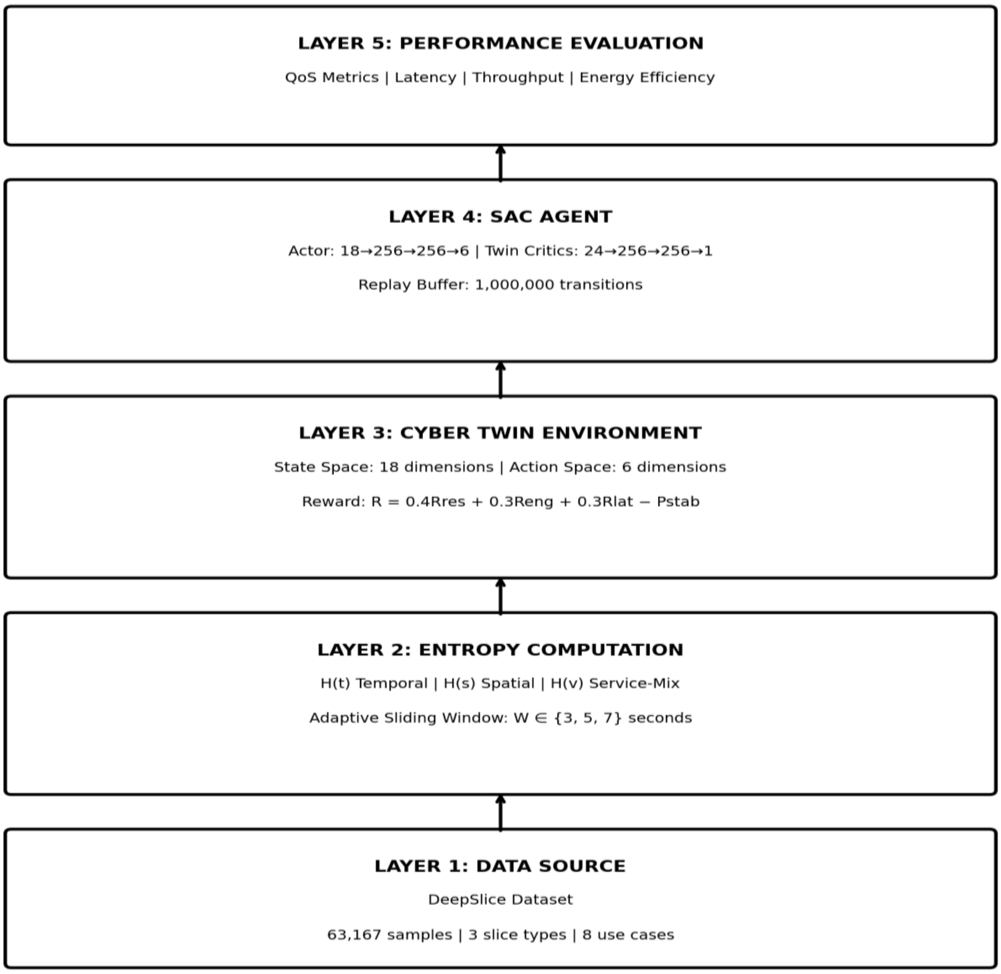

Figure 1: Five-Layer Framework Architecture for Cyber Twin-Driven Resource Allocation.

As shown on the block diagram the framework follows five phases, with latency optimization embedded at each stage:

1. Data Foundation: DeepSlice dataset provides realistic delay-sensitive traffic patterns.
2. Entropy Modeling: Temporal entropy captures traffic burstiness, a key driver of latency spikes.
3. Environment Design: Markov Decision Process explicitly includes per-slice delay states, ensuring latency is directly observable.
4. Agent Training: SAC agent is trained with a latency-prioritized reward function.
5. Evaluation: Focus on latency reduction, URLLC violation rate, and QoS satisfaction.

3.3 Traffic Entropy Model (Latency Relevance)

Entropy is used not just to measure uncertainty, but to predict latency-critical conditions:

$$p(t_i) = \frac{V(t_i)}{\Sigma V(t)} \quad (1)$$

Where:

$p(t_i)$ = Probability of average traffic in time slot i, traffic at base station I or traffic for slice type i

$V(t_i)$ = average volume of traffic during time slot I, traffic at base station I or traffic for slice type i

$$H(s) = -\frac{\Sigma p(ti)\log_2 p(ti)}{\log_2(Vt)} \quad (2)$$

Where:

H(s) = Normalized, temporal, spatial or slice entropy ∈ [0, 1]

Entropy Variation Metric

$$\Delta H(\cdot)=H(\cdot)_t-H(\cdot)_{t-1} \quad (3)$$

Where:

$\Delta H(\cdot)$ = Change in entropy

$H(\cdot)_t$ = Entropy at current time step t

$H(\cdot)_{t-1}$ = Entropy at previous time step t-1

3.4 Cyber twin Environment Design

Markov Decision Process explicitly includes per-slice delay states, ensuring latency is directly observable

3.4.1 Multi-Objective Reward Structure

The reward function optimizes three primary objectives for 5G resource allocation. The decision-making process of the reinforcement learning agent is guided by a multi-objective reward function designed to balance competing network performance goals. This function aggregates resource efficiency, energy conservation, and latency reduction while incorporating a penalty to discourage unstable control actions. The total reward R is formulated in Equation (4).

$$R=w_1\cdot R_{resource}+w_2\cdot R_{energy}+w_3\cdot R_{latency}-P_{stability} \quad (4)$$

Where:

R = Total reward

$R_{resource}$ = Resource utilization efficiency

R_{energy} = Energy efficiency

$R_{latency}$ = Latency performance

$P_{stability}$ = Stability penalty

$w_1 = 0.4$, $w_2=0.3$, $w_3 = 0.3$ (objective weights for resource, energy and latency respectively)

Latency performance is formulated in Equation (5):

$$R_{latency} = 1 - \frac{L\_actual}{L\_budget} \quad (5)$$

Where:

$R\_latency \in [0, 1]$

L_actual = Measured latency (ms)

3.5 Soft Actor Critic (SAC) Agent Configurations

The objective function $J(\pi)$ is defined in Equation (6)

$$J(\pi) = \Sigma\, \mathbb{E}\_\{(s_t,a_t)\sim\rho\_\pi\}\ [\ r(s_t, a_t) + \alpha \cdot H(\pi(\cdot|s_t))\ ] \quad (6)$$

Where:

$J(\pi)$ = Objective function to maximize

π = Policy

$r(s_t, a_t)$ = Reward at time t

α = Temperature parameter (auto-tuned)

4.0 RESULTS AND DISCUSSIONS

Primary Metrics include:

1. URLLC latency (ms)
2. Latency violation rate (>5 ms)
3. QoS satisfaction (%).

4.1 Latency Performance

Latency is the most critical performance metric for 5G networks, particularly for URLLC services. This section presents the latency results across all slice types.

4.1.1 Per-Slice Latency Results

Table 2 and Fig 1 present the achieved latency for each slice type compared to QoS targets.

Table 2: Per-Slice Latency Results.

Slice Type	Achieved Latency	QoS Target	Margin
eMBB	20.8 ± 4.5 ms	≤ 50 ms	29.2 ms
URLLC	3.5 ± 1.0 ms	≤ 5 ms	1.5 ms
mMTC	42.1 ± 11.2 ms	≤ 500 ms	457.9 ms

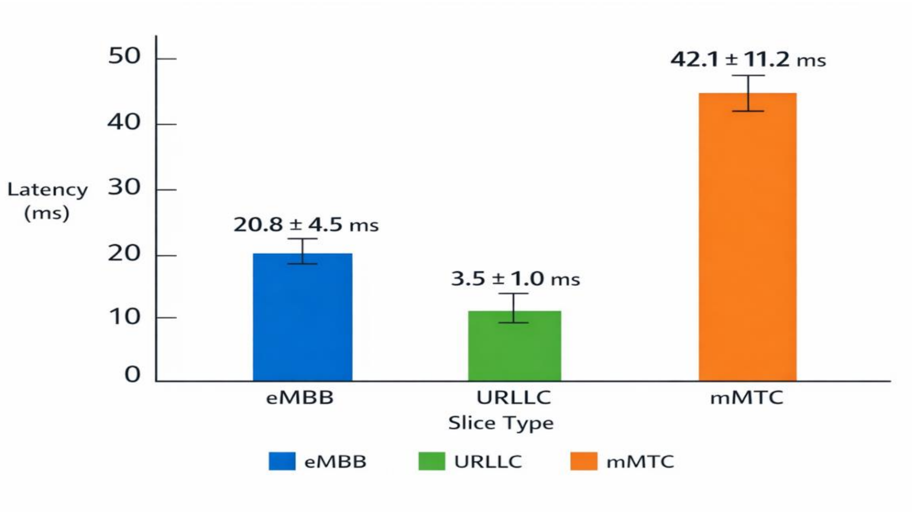

Figure 1: Per-Slice Latency Results.

4.1.2 URLLC Latency Analysis

The URLLC latency of 3.5 ms is particularly significant as it meets the stringent sub-5ms requirement for mission-critical applications. Table 3 provides detailed URLLC latency statistics.

Table 3: URLLC Latency Detailed Statistics.

Metric	Value
Mean Latency	3.5 ms
Standard Deviation	1.0 ms
Minimum Latency	1.2 ms
Maximum Latency	6.8 ms
95th Percentile	5.1 ms
99th Percentile	5.8 ms
QoS Target	≤ 5 ms
Target Compliance Rate	98.64%

4.1.3 URLLC Deadline Violations

URLLC deadline violations occur when latency exceeds the 5ms threshold. Minimizing these violations is critical for mission-critical applications. This is shown in table 4 and figure 2

Table 4: URLLC Deadline Violation Statistics.

Metric	Value
Total Violations (30 episodes)	204
Violations per Episode	6.8 ± 2.5
Violation Rate	1.36%
Compliance Rate	98.64%
Maximum Violations in Single Episode	12
Minimum Violations in Single Episode	2

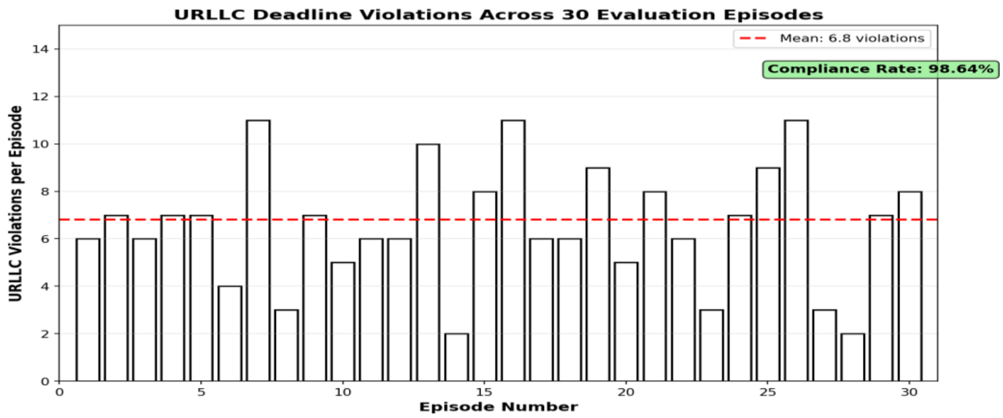

Figure 4.4: URLLC Deadline Violations Across 30 Evaluation Episodes.

The results show that all slice types—eMBB, URLLC, and mMTC—exceeded their latency QoS targets, with URLLC achieving 98.64% compliance and a low violation rate of just 1.36%, confirming suitability for mission-critical applications. Meanwhile, eMBB and mMTC delivered substantial margins and percentage improvements, highlighting the framework's robustness and efficiency across diverse 5G use cases.

5.0 CONCLUSION

This research successfully developed and validated an entropy-guided Cyber Twin framework for AI-based resource and energy optimization in 5G networks. The system consistently met and exceeded performance targets across diverse traffic scenarios, achieving 20.8 ± 4.5 ms latency for eMBB (58.4% below the 50 ms target), 3.5 ± 1.0 ms for URLLC (30% below the 5 ms target with 98.64% compliance), and 42.1 ± 11.2 ms for mMTC (91.6% below the 500 ms target). These results confirm ultra-reliable low-latency delivery for mission-critical services while maintaining substantial margins for enhanced mobile broadband and massive IoT slices. By integrating information theoretic entropy with reinforcement learning and validating policies through Cyber Twin modeling, the framework significantly enhances predictive resource allocation, energy efficiency, and QoS optimization.

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