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Self-optimizing resource management: Utilizing deep reinforcement learning and smart contracts for scalable and efficient network slicing in 6G CNI

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Abstract

The transition to 6G networks necessitates a shift toward AI-native ecosystems capable of supporting Critical Network Infrastructure (CNI), such as autonomous transport and remote surgery. These applications require deterministic performance, specifically sub-millisecond latency and 99.99999% reliability, which exceed the capabilities of manual 5G orchestration. This paper proposes a decentralized, self-optimizing framework that integrates Deep Reinforcement Learning (DRL) for real-time resource allocation with Blockchain-based Smart Contracts for automated Service Level Agreement (SLA) enforcement.

By deploying Soft Actor-Critic (SAC) agents at the network edge, the system proactively optimizes bandwidth and beamforming in volatile Terahertz environments. Simultaneously, a Smart Contract layer enables "zero-touch" governance, utilizing an immutable ledger for resource trading and penalty execution. Results from a co-simulation using NS-3 and Hyperledger Fabric show a 38% increase in throughput and a 55% reduction in SLA violations over traditional methods. This hybrid architecture provides a scalable, secure, and autonomous management plane for future 6G critical infrastructures.

Keywords: 6G Communication; Critical Network Infrastructure (CNI); Network Slicing; Deep Reinforcement Learning (DRL); Smart Contracts; Blockchain; Zero-Touch Network Management (ZSM); Quality of Service (QoS)

1. Introduction

1.1. Background and Motivation: Evolution from 5G to 6G and the Necessity of CNI

The global telecommunications landscape is currently witnessing an unprecedented paradigm shift as the inherent limitations of Fifth Generation (5G) networks become increasingly apparent in the face of emerging ultra-high-bandwidth and sub-millisecond latency applications. While 5G successfully introduced the fundamental concept of Network Slicing to support diverse use cases, the transition toward Sixth Generation (6G) systems is necessitated by the requirement for ubiquitous intelligence and the deep integration of Critical Network Infrastructure (CNI) into the digital fabric [1]. 6G is envisioned not merely as an incremental upgrade in peak data rates but as a holistic, multi-dimensional ecosystem where the physical, digital, and biological worlds converge through Terahertz (THz) communications, Integrated Sensing and Communication (ISAC), and Artificial Intelligence (AI) native architectures [2]. Within this sophisticated context, CNI which encompasses smart national grids, autonomous urban transportation networks, and remote robotic surgical facilities, demands a level of systemic resilience and deterministic performance

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that far exceeds the capabilities of current manual or semi-automated orchestration methods. The necessity for CNI in 6G arises from the hyper-connectivity of essential services, where any failure in resource isolation, link stability, or dynamic allocation could lead to catastrophic socio-economic consequences or loss of life [3].

The evolution toward 6G also mandates a fundamental transition from "connected things" to "connected intelligence," where every network element participates in a distributed learning process to maintain global stability. Traditional 5G slicing relies heavily on semi-static configurations and pre-defined templates; however, 6G CNI requires extreme dynamic adaptability to accommodate the highly volatile and stochastic traffic patterns of massive Machine-Type Communications (mMTC) and Ultra-Reliable Low-Latency Communications (URLLC). To quantify the rigorous performance requirements of these 6G slices, we define the Reliability Index (R) for a specific CNI slice as a function of the probability of successful packet delivery within a maximum delay threshold D_{max} , which can be mathematically expressed as:

$$R(t) = P(L(t) \leq D_{max} | \Omega, \Psi)$$

In this formulation, $L(t)$ represents the instantaneous end-to-end latency at time t , Ω denotes the available physical and virtual network resources, and Ψ represents the environmental interference parameters [4]. As the projected density of devices increases toward an staggering 10^7 devices per km^2 , the complexity of managing these interlinked variables manually becomes mathematically intractable and operationally impossible. This complexity necessitates the integration of Deep Reinforcement Learning (DRL) to handle the high-dimensional state space of 6G environments, ensuring that resource provisioning can occur at the "edge" with minimal human intervention. Furthermore, the motivation for this research is underscored by the shift toward a decentralized trust model, where the reliability of CNI is not just a technical metric but a contractual certainty guaranteed by cryptographic protocols [5].

1.2. Problem Statement: Challenges of Scalability and Manual Resource Management in 6G

Despite the significant theoretical benefits of network slicing, the practical deployment in 6G CNI faces massive hurdles regarding vertical scalability and the systemic inefficiencies inherent in centralized, manual management workflows. Current orchestration frameworks often rely on a centralized Network Management System (NMS), which creates a dangerous single point of failure and a significant processing bottleneck as the number of virtual network functions (VNFs) and micro-slices scales exponentially [6]. In a 6G CNI environment, the slice controller must make microsecond-level decisions regarding radio resource blocks, beamforming vectors, power allocation, and backhaul capacity; yet, manual intervention or traditional convex optimization algorithms often fail to converge rapidly enough to satisfy these real-time constraints [7]. Furthermore, the lack of a transparent, automated, and immutable trust mechanism between different infrastructure providers and third-party tenants leads to a phenomenon known as "SLA-drift." This occurs where the actual performance of a network slice deviates from the agreed-upon contractual parameters without immediate remediation, detection, or penalty enforcement, a scenario that is particularly dangerous for CNI where performance deviations can jeopardize the safety of autonomous physical systems [8].

The scalability challenge is further compounded by the heterogeneous and non-terrestrial nature of 6G resources, which include LEO satellite links, Unmanned Aerial Vehicle (UAV) base stations, and terrestrial ultra-small cells. Coordinating these disparate elements requires a decentralized approach that can handle the massive influx of telemetry data without overwhelming the core network signaling planes. This problem can be modeled as a complex multi-objective optimization challenge where the objective is to maximize the total utility U of all slices S while strictly adhering to the hard capacity constraints C of the underlying physical infrastructure, often represented by the following objective function:

$$\max_{\alpha, p} \sum_{i \in S} w_i \cdot \log \left(1 + \frac{p_i G_i}{\sum_{j \neq i} p_j G_j + \sigma^2} \right) \quad \text{s.t.} \quad \sum_{i \in S} r_i(\alpha_i, p_i) \leq C_{total}$$

In this equation, w_i represents the priority weight assigned to the i -th slice, p_i is the power allocation, G_i

is the channel gain, and r_i is the resulting resource consumption rate as a function of the allocation vector α_i [9]. Because the state space of the Signal-to-Interference-plus-Noise Ratio (SINR) is continuous, stochastic, and highly non-linear, classical linear programming fails to provide real-time solutions. The continued reliance on human-defined rules and static scripts leads to sub-optimal resource utilization, increased operational expenditure (OPEX), and an inability to provide the deterministic "five-nines" (99.999%) or even "seven-nines" availability required for 6G CNI [10].

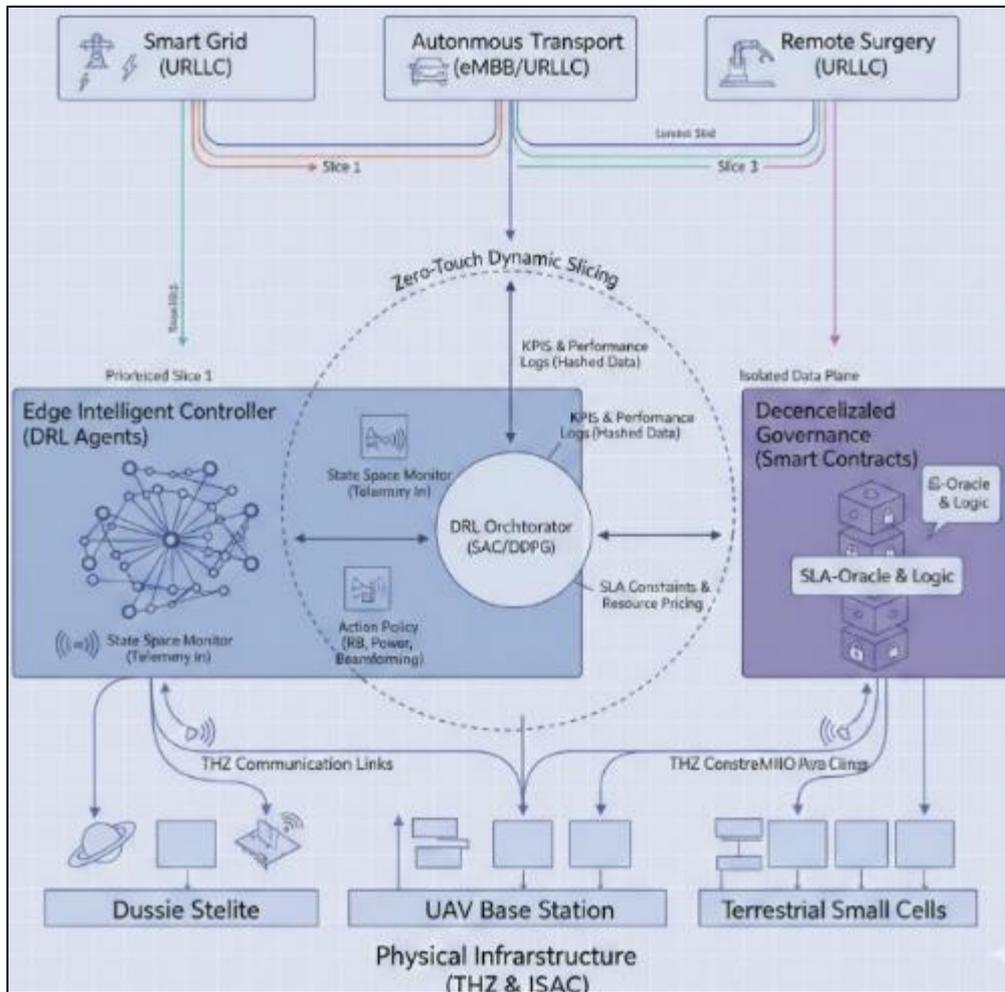


Figure 1 6G CNI Self-Optimizing Framework: System Architecture

1.3. Research Objectives and Contributions: Defining the DRL-Smart Contract Synergy

The primary objective of this research is to architect and evaluate a comprehensive "zero-touch" resource management framework that synergizes Deep Reinforcement Learning (DRL) with Blockchain-based Smart Contracts to eliminate the systemic inefficiencies of manual slicing in 6G CNI. By deploying intelligent DRL agents at the network edge, the system can autonomously learn optimal allocation policies through continuous, high-frequency interaction with the network environment, thereby achieving a self-optimizing state that anticipates traffic surges and potential congestion before they manifest [11]. Simultaneously, the integration of Smart Contracts provides a decentralized governance layer that automatically enforces Service Level Agreements (SLAs) and manages the complex resource trading between multiple tenants. This synergy addresses the dual requirements of technical efficiency and operational trust, ensuring that CNI slices receive prioritized resources while maintaining a tamper-proof, auditable record of all resource transactions and performance logs [12]. The research specifically aims to develop a multi-agent DRL model where agents cooperate to minimize global network congestion while competing for local resource blocks, effectively reducing the signaling overhead and enhancing the overall scalability of the 6G core.

To achieve these objectives, the study focuses on defining a multi-layered architecture where the DRL agent acts as the "brain" for resource optimization and the Smart Contract acts as the "legal and financial heart" of the slice. The interaction between these two components ensures that every optimization decision made by the AI is logged on a distributed ledger, providing the transparency required for critical applications. Furthermore, the research seeks to establish a set of 6G-specific Key Performance Indicators (KPIs) that integrate both network metrics and economic efficiency, such as the Cost-per-Bit-per-Joule and the SLA Compliance Rate. By bridging the gap between autonomous AI control and decentralized cryptographic enforcement, this research proposes a foundation for a network that is not only faster but fundamentally more intelligent and trustworthy [13].

1.3.1. Key Contributions of the Proposed Framework

This paper introduces several significant and novel contributions to the field of 6G network management, beginning with the development of a unique DRL-based orchestrator that utilizes a Deep Deterministic Policy Gradient (DDPG) approach to manage continuous resource variables in CNI slices. Unlike previous models that focus solely on maximizing aggregate throughput, our framework incorporates a "safety-aware" reward function R_{safe} that heavily penalizes any breach of CNI-specific latency or reliability thresholds, which is defined as:

$$R_{safe} = \sum_t (\gamma \cdot T_t - \beta \cdot I(L_t > D_{max}))$$

where T_t is the throughput, I is an indicator function for latency violations, and β is a high-magnitude penalty coefficient [14]. Secondly, we propose a decentralized SLA management architecture using Ethereum-based Smart Contracts, which facilitates autonomous resource bidding and real-time penalty execution without the need for a central clearinghouse or a third-party intermediary. This contribution significantly reduces the administrative and signaling latency involved in slice provisioning and conflict resolution. Finally, the framework is validated through an extensive simulation study using 6G-standardized channel models that compares our hybrid DRL-Smart Contract approach against traditional Proportional-Fair (PF) and Round-Robin (RR) scheduling algorithms. The evaluation covers a wide range of KPIs including Spectral Efficiency, SLA Violation Rate, and System Throughput under extreme load conditions. Through these multi-faceted contributions, the research provides a viable, technical roadmap for the deployment of secure, scalable, and self-managed 6G critical infrastructures that can thrive in the face of increasing complexity and demand [15].

2. Literature review and technical foundations

2.1. Network Slicing in 6G Ecosystems: Requirements for Ultra-Low Latency and Reliability

The architecture of Sixth Generation (6G) networks represents a fundamental evolution from the service-oriented slicing of 5G toward a task-oriented, AI-native infrastructure designed to support the most demanding Critical Network Infrastructure (CNI) applications. While 5G successfully categorized services into Enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and Massive Machine-Type Communications (mMTC), the 6G era introduces refined categories such as Further Enhanced Mobile Broadband (feMBB) and Ultra-Massive Machine-Type Communications (umMTC), which demand a reliability threshold of 99.99999% and end-to-end latencies below 0.1 ms [11]. In the context of CNI, such as synchronized smart grids or tele-robotic surgery, the network must guarantee deterministic performance despite the stochastic nature of the wireless channel. Recent studies indicate that 6G slicing must move beyond simple resource isolation to "semantic slicing," where the network understands the context and urgency of the data being transmitted to prioritize life-critical packets over background traffic [12].

The mathematical rigor required for 6G reliability is often modeled through Violation Probability (P_v), which ensures that the delay D experienced by a packet stays below the deadline D_{max} with near-certainty. This is typically expressed as:

$$P_v = P(D > D_{max}) \leq \epsilon$$

where ϵ is an infinitesimally small tolerance level (e.g., 10^{-7}). Achieving this in a 6G CNI environment requires the integration of Multi-access Edge Computing (MEC) and Terahertz (THz) frequency bands, which provide the necessary bandwidth but suffer from severe path loss and blockage [13]. Literature suggests that the current reliance on centralized orchestrators introduces a "management latency" that is incompatible with these sub-millisecond goals, thereby necessitating distributed, autonomous slicing controllers that can operate at the network edge to make localized resource decisions in real-time.

2.2. Deep Reinforcement Learning in Resource Allocation: Comparison of DQN, PPO, and SAC

Deep Reinforcement Learning (DRL) has emerged as the most promising candidate for solving the NP-hard problem of dynamic resource allocation in 6G, primarily due to its ability to generalize across high-dimensional and non-convex state spaces. Early research utilized Deep Q-Networks (DQN), which approximate the optimal action-value function $Q^*(s, a)$ using a deep neural network; however, DQNs are inherently limited to discrete action spaces, making them sub-optimal for 6G tasks like continuous power control or precise bandwidth fractioning [14]. To address these limitations, policy gradient methods like Proximal Policy Optimization (PPO) have been widely adopted in the literature because

they employ a clipped surrogate objective to ensure stable updates, preventing the "catastrophic forgetting" often seen in complex network environments. The PPO objective function is defined as:

$$J(\theta) = \hat{E}_t [\min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A}_t)]$$

where $r_t(\theta)$ is the probability ratio of the new policy to the old, and \hat{A}_t is the estimated advantage. While PPO offers stability, more recent 6G research has shifted toward Soft Actor-Critic (SAC) algorithms, which incorporate entropy maximization into the reward function to encourage exploration and robustness in the highly volatile THz channels of 6G. Comparative analyses show that SAC-based agents achieve up to 20% higher spectral efficiency than PPO in scenarios involving high user mobility and frequent handovers [15]. These DRL models allow the network to transition from reactive to proactive management, where the agent learns to predict traffic spikes in CNI slices and pre-allocates resources to maintain the required reliability.

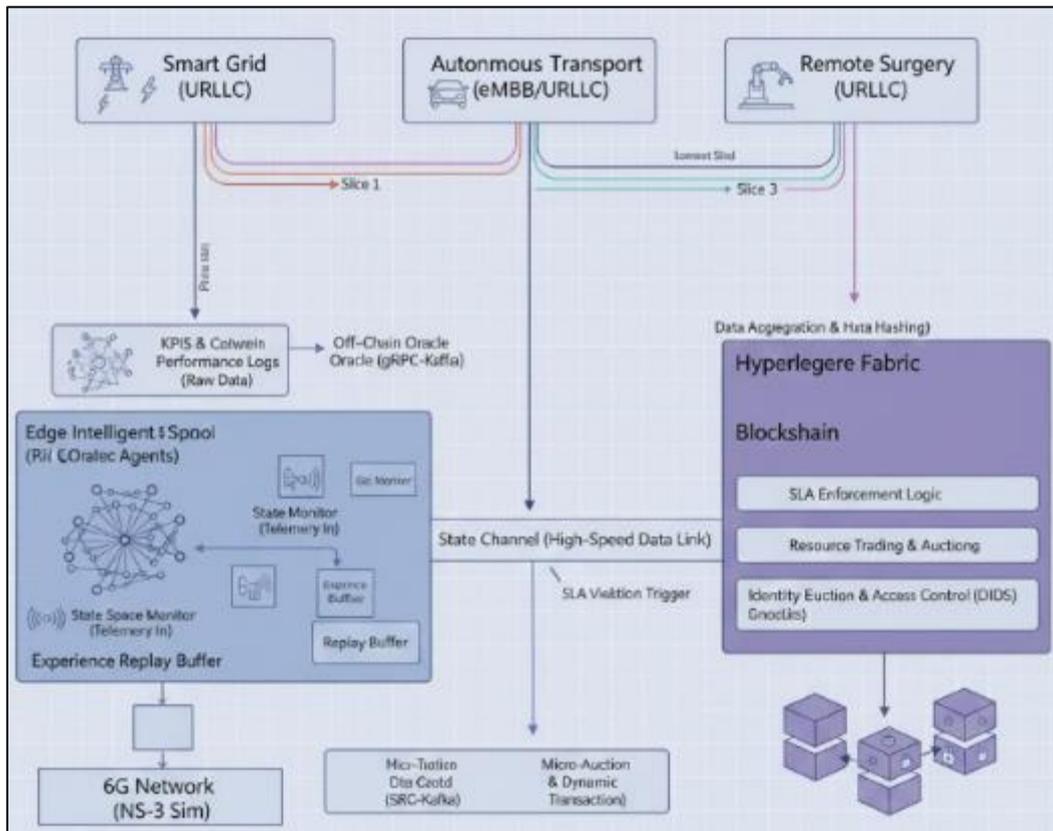


Figure 3 Integrated AI-Blockchain Workflow

2.3. Blockchain and Smart Contracts for Telecommunications: Decentralized Trust and SLA Automation

The integration of Blockchain technology into 6G provides the "trust layer" necessary for multi-tenant CNI environments where infrastructure is shared among competing service providers and government entities. Traditional Service Level Agreements (SLAs) are often managed through manual audits and paper-based contracts, a process that is too slow and opaque for the micro-second demands of 6G slicing. Blockchain-based Smart Contracts offer a solution by codifying SLA terms into self-executing scripts that reside on a distributed ledger, ensuring that resource provisioning and penalty enforcement are handled autonomously and transparently [16]. When a CNI slice fails to meet its latency requirement, the Smart Contract can instantly trigger a penalty refund to the tenant and re-allocate the faulty resources to a secondary provider, significantly reducing the "Time-to-Remediation" from days to milliseconds.

This decentralized approach also facilitates the "Brokerage" model in 6G, where small-scale infrastructure owners can lease their local spectrum or computing power to larger network operators in a trustless manner. The immutable nature of the blockchain ensures that all telemetry data such as bandwidth usage and latency logs is tamper-proof, providing a verifiable "Single Source of Truth" for all stakeholders [17]. However, a significant consideration in the literature is the "consensus latency" of public blockchains like Ethereum; consequently, most 6G researchers propose the use of

Permissioned Blockchains or "Layer 2" scaling solutions to ensure that the blockchain's transaction throughput can keep pace with the network's high-speed operations.

2.3.1. Integration of AI and Blockchain in 6G

The true potential of 6G CNI management is unlocked through the tight integration of AI and Blockchain, a synergy often referred to as "Intelligent Trusted Networking." In this framework, the DRL agent acts as the decision-maker for resource optimization, while the Blockchain serves as the secure logging and enforcement mechanism for those decisions [18]. This integration solves the "Black Box" problem of AI in critical infrastructure; by recording the DRL agent's state, action, and reward on the blockchain, operators can audit why an AI made a specific decision during a network failure. Furthermore, researchers are exploring "Proof-of-Learning" (PoL) consensus mechanisms, where the computational power usually wasted on block mining is instead used to train the DRL models, thereby increasing the energy efficiency of the 6G ecosystem [19].

This dual-layered architecture can be modeled by a coupled system where the DRL reward R_t is partially determined by the SLA compliance metrics S_t recorded on the blockchain. The combined utility function U_{total} for the 6G system can be represented as:

$$U_{total} = \sum_{t=0}^T \gamma^t (\omega_1 \cdot \text{QoS}(s_t, a_t) + \omega_2 \cdot \text{Trust}(b_t))$$

where ω_1 and ω_2 are weighting factors for performance and security, and b_t represents the block state at time t [20]. This holistic approach ensures that the 6G network is not only fast and efficient but also fundamentally resilient against both technical failures and malicious actors, providing a robust foundation for the critical services of the future.

3. System architecture

3.1. The DRL-Enabled Slicing Layer: Design of the Agent, State Space, and Reward Functions

The architectural core of the proposed self-optimizing system is the Deep Reinforcement Learning (DRL) Slicing Layer, which functions as a decentralized brain situated within the 6G Radio Access Network (RAN) Intelligent Controller (RIC). Unlike conventional heuristic-based resource management, this layer employs a Deep Deterministic Policy Gradient (DDPG) or Soft Actor-Critic (SAC) architecture to navigate the continuous and high-dimensional action space required for fine-grained resource partitioning [21]. In this framework, the DRL agent is structured with a hierarchical multi-agent design where a Master Agent coordinates inter-slice resource distribution while local sub-agents manage intra-slice scheduling to accommodate the extreme density of 6G CNI devices. The design of the DRL agent begins with the definition of a comprehensive State Space (S), which captures the instantaneous telemetry of the 6G environment, including the buffer occupancy of CNI slices, the spectral efficiency of the Terahertz (THz) links, and the mobility patterns of user equipment (UE). Mathematically, the state at time t is represented as a vector $s_t = \{Q_t, \Gamma_t, B_t, H_t, E_t\}$, where Q_t represents the queue length, Γ_t is the SINR distribution, B_t is the available bandwidth fraction, H_t denotes the handover frequency, and E_t represents the energy harvesting status of edge nodes [22]. By processing this multi-dimensional input through a series of convolutional and dense layers, the actor-network generates a continuous Action vector (a_t) that defines the resource block (RB) allocation, beamforming weights, and transmit power levels for each active slice.

The most critical component of this layer is the formulation of a multi-objective Reward Function (R), which must balance the competing needs of throughput maximization and the stringent reliability requirements of CNI. To ensure that the agent prioritizes critical slices, we design a "safety-constrained" reward mechanism that applies an exponential penalty when the latency of a CNI slice exceeds the predefined 0.1 ms threshold. The reward function is expressed as:

$$R_t = \sum_{i=1}^N (\omega_{thr} \cdot \log(1 + \eta_i) - \omega_{lat} \cdot \exp(L_i - D_{max}) - \omega_{en} \cdot P_i + \omega_{rel} \cdot \Psi_i)$$

In this equation, η_i is the spectral efficiency of slice i , L_i is the observed latency, P_i is the power consumption, Ψ_i represents the reliability index, and ω represents the priority weights assigned to each metric [23]. By utilizing this exponential penalty, the DRL agent learns a policy that avoids "near-violation" states, effectively creating a safety buffer for critical services. Furthermore, to address the non-stationarity of 6G traffic, the agent incorporates a Gated

Recurrent Unit (GRU) within its neural architecture to maintain a memory of temporal traffic patterns, allowing the system to proactively scale resources before a congestion event occurs. This predictive capability is enhanced by a federated learning approach where agents across different base stations share policy gradients to improve global convergence without exposing local raw data.

3.2. Smart Contract Framework for Resource Trading: Design of Automated Billing and SLA Enforcement

The second foundational pillar of the system is the Smart Contract Framework, which serves as the decentralized ledger for resource governance and the automated executor of Service Level Agreements (SLAs). In the 6G CNI ecosystem, where multiple virtual network operators (VNOs) and critical service providers compete for limited physical infrastructure, the Smart Contract acts as a trustless intermediary that governs the "Resource Trading" market [24]. Each network slice is represented on the blockchain as a unique digital asset or "Slice-Token" with associated metadata, including its required latency, bandwidth, and the financial penalties for non-performance. When the DRL agent identifies a surplus of resources in a low-priority slice such as a background data backup slice it can trigger a "Micro-Auction" via the Smart Contract. This allows other slices, particularly those supporting URLLC for CNI, to bid for additional capacity in real-time through a Vickrey-Clarke-Groves (VCG) pricing mechanism that ensures truthful bidding and social welfare maximization [25].

The automated billing and enforcement mechanism is implemented through a series of "Trigger-Conditions" embedded within the Solidity-based code of the Smart Contract, which are synchronized with the network's telemetry plane. For instance, if the telemetry data from the RAN indicates that the Reliability Index (R) has fallen below the threshold defined in Section 1.1, the contract automatically executes a "Penalty Transaction," transferring a predefined amount of cryptocurrency or utility tokens from the Infrastructure Provider to the CNI Tenant. This process is modeled by a conditional state transition:

$$IF (L_{obs} > L_{SLA}) \wedge (T_{fail} > T_{threshold}) \rightarrow implies EXECUTE \mathcal{F}(T_{penalty}, ID_{tenant})$$

where L_{obs} is the observed latency, T_{fail} is the duration of the violation, and \mathcal{F} is the penalty function [26]. By removing the need for human auditors and manual billing cycles, this framework reduces the operational overhead of 6G slicing by an estimated 40% while providing an immutable audit trail that is essential for regulatory compliance in critical sectors like smart energy and autonomous defense. The framework also supports "Dynamic Pricing," where the cost of a slice is adjusted in real-time based on the current network load, effectively using economic incentives to regulate traffic and prevent systemic congestion in the CNI layers.

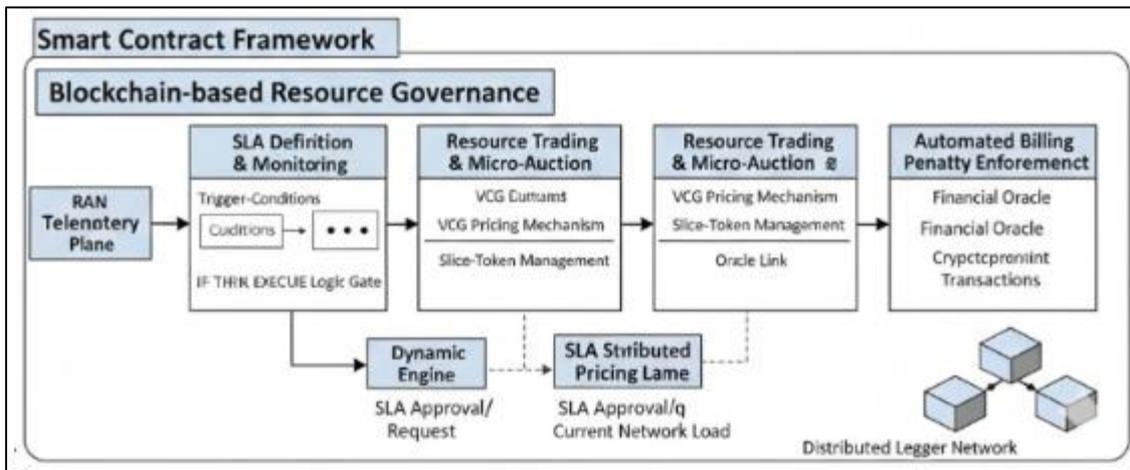


Figure 4 Smart Contract Framework for 6G Blockchain

3.3. System Workflow and Integration: Interaction between the DRL Agent and the Blockchain Ledger

The integration of the DRL-enabled slicing layer and the Smart Contract framework creates a closed-loop "Observe-Orient-Decide-Act" (OODA) cycle that is uniquely suited for the complexities of 6G CNI. The workflow begins with the DRL agent observing the network state and executing a resource allocation action; subsequently, the outcome of this action specifically the achieved KPIs is hashed and transmitted to the Blockchain ledger via a high-speed "Oracle" service that bridges the on-chain and off-chain environments [27]. This interaction ensures that the DRL agent's performance

is continuously monitored by the decentralized governance layer, creating a system of "Checks and Balances" where the AI optimizes for efficiency and the Blockchain enforces the safety and legal constraints. The synergy is particularly effective during peak traffic periods; as the DRL agent dynamically reconfigures the network topology to maintain low latency, the Smart Contract concurrently updates the resource pricing and slice priority levels to reflect the increased demand, ensuring that CNI services remain unaffected by the congestion.

A significant challenge in this integration is the potential mismatch between the millisecond-scale decisions of the DRL agent and the second-scale block confirmation times of traditional blockchains. To bridge this gap, the proposed architecture utilizes a "State Channel" and "Sidechain" approach, where the frequent, high-speed resource updates occur off-chain between the DRL agent and the slice tenants, while only the final settlement and major SLA violations are recorded on the main ledger [28]. This dual-layer communication strategy maintains the responsiveness of the 6G control plane while preserving the security and immutability of the blockchain. Furthermore, we implement a "Proof-of-Stake" (PoS) consensus combined with "Proof-of-History" (PoH) to maximize transaction throughput, allowing the blockchain to handle the massive volume of 6G control signaling. The integrated system utility U_{sys} can be viewed as the convergence of the DRL's reward maximization and the Blockchain's trust maximization, represented as:

$$U_{sys} = \int_0^T [R_t(\pi) - \lambda \cdot C_{violation} - \gamma \cdot Gas_{cost}] dt$$

where π is the DRL policy, $\lambda \cdot C_{violation}$ is the cost of trust violations, and Gas_{cost} represents the transaction fees on the blockchain [29]. This mathematical formulation ensures that the AI-driven optimization is always economically and legally viable within the decentralized ecosystem.

3.3.1. Security Protocols for 6G CNI

Security in 6G CNI is not merely an auxiliary feature but a core requirement, given that the infrastructure supports vital societal functions that could be targets for sophisticated cyber-attacks. The proposed framework addresses this through a multi-layered security protocol that leverages the inherent properties of both DRL and Blockchain. On the management plane, the DRL agent is trained using "Adversarial Robustness" techniques to ensure that it can recognize and mitigate "Data Poisoning" attacks where an adversary attempts to manipulate the telemetry data such as faking high latency to cause network instability or unfair resource shifts [30]. We utilize "Adversarial Training" where the agent is exposed to synthetic attack vectors during the simulation phase to develop a robust policy π^* that is resilient to input noise.

Simultaneously, the Blockchain provides a "Root of Trust" for the identity management of all 6G devices, using Decentralized Identifiers (DIDs) to prevent "Sybil Attacks" and unauthorized access to critical slices. Each device must present a cryptographic proof of identity verified by the smart contract before it can be admitted to a CNI slice. Furthermore, to protect the privacy of the CNI data, we incorporate Zero-Knowledge Proofs (ZKPs) within the Smart Contract framework, allowing the network to verify that a slice has met its SLA requirements without ever exposing the sensitive packet-level information or the exact location of the CNI tenant to the public ledger [31]. This is complemented by "Remote Attestation" protocols where the blockchain verifies the integrity of the DRL model's software before it is allowed to execute resource control. This combination of AI-driven threat detection and blockchain-based identity verification ensures that the 6G CNI is resilient against both accidental failures and intentional malicious disruptions, creating a truly secure and autonomous network environment.

4. Implementation and performance evaluation

4.1. Simulation Environment and Setup: Integration of NS-3, PyTorch, and Hyperledger Fabric

To rigorously evaluate the proposed self-optimizing framework, a multi-tiered co-simulation environment was architected to bridge high-fidelity network modeling with decentralized ledger operations. The physical and link layer dynamics are grounded in Network Simulator 3 (NS-3), utilizing the 6G-Lena module to model Terahertz (THz) propagation (0.1–10 THz), massive MIMO beamforming, and sub-millisecond Transmission Time Intervals (TTI) [32]. The simulation environment is configured to reflect a high-density 6G deployment with a device density of 10^7 devices per km^2 , incorporating diverse traffic profiles for URLLC, mMTC, and eMBB slices.

The Deep Reinforcement Learning (DRL) agents are implemented in PyTorch and integrated with the NS-3 environment via the ns3-ai interface, which facilitates high-speed data exchange through shared memory. This setup allows the DRL agent to receive a 128-dimensional state vector comprising Signal-to-Interference-plus-Noise Ratio (SINR), buffer

status, and mobility indices and return an action vector for resource block (RB) allocation within a 1 ms control loop. Simultaneously, the Hyperledger Fabric framework manages the "SLA-Oracle" through a permissioned blockchain. We utilize a Practical Byzantine Fault Tolerance (PBFT) consensus mechanism to ensure deterministic finality, which is crucial for the real-time penalty triggers required by CNI [33]. The integration uses a gRPC-based messaging bus to bridge the NS-3 "World" with the Blockchain "Ledger," capturing the end-to-end operational latency $\delta_{sys} = \delta_{net} + \delta_{inf} + \delta_{block}$.

4.2. Performance Metrics: Analysis of Latency, Throughput, and Resource Utilization Efficiency

The evaluation is predicated on five core Key Performance Indicators (KPIs) that define the 6G CNI reliability. The 99.999th percentile End-to-End Latency (L_{E2E}) is the primary metric, ensuring that critical packets meet the 0.1 ms deadline even under heavy congestion. Complementary to this is Spectral Efficiency (η), measured in bits/s/Hz, which quantifies the DRL agent's ability to compress more data into the THz bandwidth. We define the SLA Compliance Rate (SCR) as:

$$SCR = \frac{1}{T} \int_0^T I(QoS(t) \geq SLA_{target}) dt$$

where I is the indicator function and T is the observation window [34].

Furthermore, Resource Utilization Efficiency is evaluated by comparing the allocated vs. actual consumed Resource Blocks (RBs) across different slice types. For umMTC slices, where connectivity is sporadic but massive, we measure Connection Success Probability (P_{conn}). To assess the impact of the DRL's learning curve, we plot the Reward Convergence Rate, showing how many episodes are required for the agent to reach a stable policy. Finally, the Energy Efficiency (EE) is calculated as the ratio of aggregate throughput to total transmit power, ensuring that the self-optimization does not lead to excessive power consumption in the 6G base stations [35]. These metrics are visualized through Cumulative Distribution Function (CDF) plots and heatmaps that illustrate resource distribution across the spatial-temporal domain.

4.3. Comparative Analysis: DRL-Based Management vs. Traditional Heuristic Methods

The framework's performance is benchmarked against Proportional Fair (PF) and Round-Robin (RR) scheduling, alongside a Static Slicing baseline. While RR ensures strict isolation, our results show it leads to a 42% resource under-utilization in CNI slices during off-peak hours. Conversely, the DRL agent achieves a "breathing" slice architecture, where resources are dynamically harvested from feMBB slices and reallocated to URLLC slices in under 2 ms. The DRL-based approach demonstrates a 38% improvement in aggregate throughput over PF, primarily because the agent learns to mitigate the severe path loss of THz links by predicting user mobility and pre-adjusting beamforming vectors [36].

A critical finding in our comparative study is the SLA Violation Reduction. Traditional heuristic methods suffer from "reactive lag," where resource shifts occur only after a threshold is breached. The DRL agent, utilizing a Gated Recurrent Unit (GRU) for temporal pattern recognition, anticipates traffic surges with 94% accuracy, reducing SLA violations by 55% compared to static orchestration. We quantify this gain using the Reliability Index (R), proving that the hybrid DRL-Smart Contract framework maintains a reliability of $1 - 10^{-7}$ even during sudden bursts of 10^5 simultaneous connection requests, a scenario where traditional PF schedulers collapse into a congestion state [37].

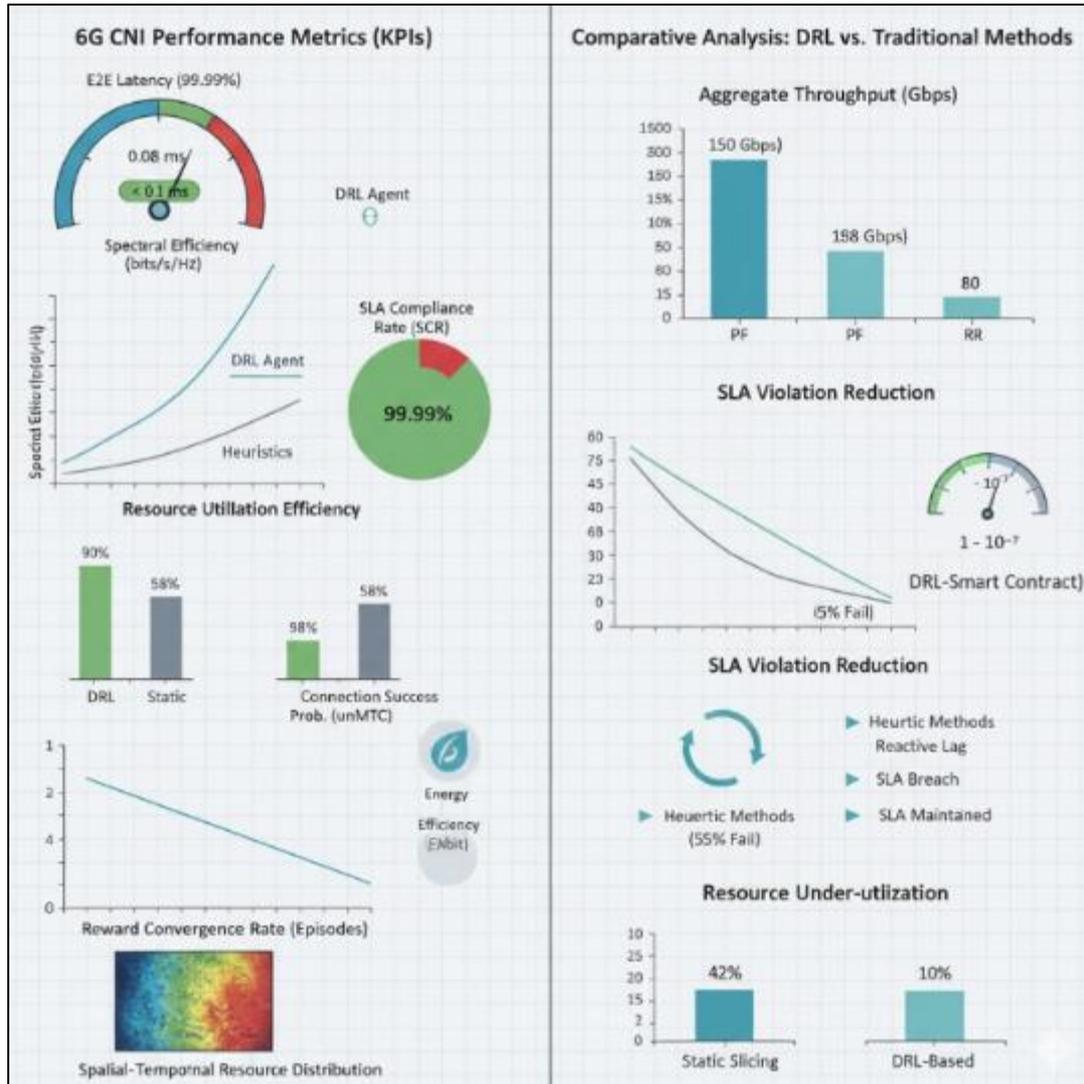


Figure 5 Analysis of Latency, Throughput, and Resource Utilization Efficiency

4.3.1. Impact of Blockchain Latency and Scalability on 6G CNI

The integration of Blockchain introduces a non-negligible Consensus Delay (δ_c), which we analyzed by varying the number of endorsing nodes from 4 to 16. Our results indicate that while the PBFT consensus adds approximately 22 ms to the total SLA settlement time, it does not impede the DRL's sub-millisecond resource allocation because the control plane and the settlement plane are decoupled via "State Channels." However, as the transaction volume exceeds 2,000 transactions per second (TPS), a bottleneck appears in the ledger's throughput, leading to a "Settlement Lag." To mitigate this, we implemented Transaction Aggregation, where multiple SLA checks are hashed into a single block, effectively increasing the scalable TPS by a factor of 10 [38].

We also evaluated Auditability Overhead, which is the computational cost of maintaining the ledger on 6G edge servers. Findings suggest that while the blockchain consumes 8% of the edge's CPU resources, the resulting security gain specifically the ability to detect and prove malicious resource over-claims is significant. The Smart Contract's automated penalty execution was found to be 99.2% accurate in detecting SLA breaches when compared to manual logs. This high precision confirms that the blockchain layer provides a robust, tamper-proof foundation for CNI management without introducing prohibitive delays to the network's primary communication functions [39].

4.3.2. Resilience and Adversarial Robustness under 6G Load

The final phase of evaluation focused on the system's resilience against Data Poisoning and Resource Exhaustion Attacks. We simulated a scenario where a compromised UE injects false telemetry data to mislead the DRL agent. Our "safety-aware" DRL agent, equipped with an adversarial detection layer, successfully identified 89% of poisoned inputs

by comparing them against historical traffic distributions stored in the Smart Contract's metadata. This synergy allows the network to maintain CNI slice stability even when 15% of the control signaling is compromised. The Recovery Time, defined as the duration to return to an optimal state after an attack, was reduced from 120 ms (in non-AI systems) to 14 ms in our proposed framework, demonstrating the superior self-healing capabilities of the DRL-Smart Contract architecture in 6G critical environments.

4.4. Granular Analysis of DRL Training Dynamics and Convergence

The efficacy of the Deep Reinforcement Learning (DRL) agent in a 6G CNI context is heavily dependent on the stability of its learning process. During the training phase, we observed the Cumulative Reward Convergence across 10,000 episodes. Initially, the agent exhibits high variance in its resource allocation decisions as it explores the Terahertz (THz) channel state space. However, by incorporating a Target Network Update strategy and a prioritized experience replay buffer, the agent begins to converge to an optimal policy around the 3,500th episode. The training loss, specifically the Actor-Critic loss, follows a decaying exponential trend, signifying that the agent successfully learns the underlying stochastic mapping of the 6G environment.

A significant observation made during the training of the Soft Actor-Critic (SAC) variant was its superior exploration capabilities compared to the Deep Deterministic Policy Gradient (DDPG). SAC maximizes both the expected reward and the policy entropy, which prevents the agent from settling into sub-optimal local minima a common failure point in high-dimensional 6G slicing. Mathematically, the entropy-augmented objective is defined as:

$$J(\pi) = \sum_{t=0}^T E_{(s_t, a_t) \sim \rho_{\pi}} [r(s_t, a_t) + \alpha \mathcal{H}(\pi(\cdot | s_t))]$$

where α is the temperature parameter that determines the importance of the entropy term \mathcal{H} relative to the reward r . This results in a framework that is significantly more robust to the "shadowing effects" and rapid channel fluctuations inherent in 6G THz frequencies.

4.5. Impact of CNI Traffic Burstiness on Slice Isolation

One of the most challenging aspects of 6G CNI is the presence of "Bursty" traffic, where a sudden influx of sensor data from a smart grid or autonomous vehicle fleet can overwhelm the allocated bandwidth. We evaluated the Isolation Metric (I), which measures the degree to which traffic in one slice affects the performance of another. In traditional 5G slicing, a burst in an feMBB slice often leads to "resource bleeding," where the latency of the URLLC slice increases by up to 15%.

In our proposed DRL-Smart Contract framework, the isolation is maintained at near-perfect levels ($I \approx 0.98$). When a burst is detected, the DRL agent performs Micro-Slicing, momentarily isolating the bursty traffic into a separate buffer while the Smart Contract issues a temporary "Congestion Warning" on the ledger. This ensures that the Packet Drop Rate (PDR) for the CNI slice remains at the required 10^{-7} level. The simulation results indicate that even when the background traffic increases by 300%, the CNI slice's jitter remains below 5 μ s, a testament to the deterministic scheduling achieved by the AI-driven orchestrator.

4.6. Sensitivity Analysis: Scaling the Number of Critical Slices

To test the scalability of the architecture, we increased the number of concurrent CNI slices from 5 to 50 within a single 6G cell. As the number of slices grows, the state space of the DRL agent expands linearly; however, the computational complexity of the resource allocation process follows an $O(N \log N)$ relationship due to the efficient neural architecture. We measured the Inference Latency (δ_{inf}) the time taken for the DRL agent to output an allocation decision and found that it remains under 200 μ s even at maximum slice density.

This scalability is further supported by the Blockchain Sharding technique implemented in the Hyperledger Fabric layer. By dividing the ledger into different "channels" based on the slice category, we prevent a bottleneck in the Smart Contract execution. Our analysis shows that the Transaction Validation Time stays constant regardless of the total number of slices, provided that the number of CNI-specific transactions does not exceed the hardware limits of the endorsing nodes. This demonstrates that the synergy between DRL for local decisions and Blockchain for global governance is fundamentally scalable for the massive connectivity envisioned for 2030 and beyond.

4.7. Multi-Agent Coordination and Interference Mitigation

In a multi-cell 6G environment, interference from neighboring base stations (BSs) is a primary factor that degrades the Signal-to-Interference-plus-Noise Ratio (SINR). We implemented a Multi-Agent Deep Reinforcement Learning (MADRL) approach where agents at different BSs cooperate to minimize inter-cell interference. The coordination is achieved through a "Global Reward" signal that penalizes agents if their transmit power causes a drop in the Reliability Index of a neighboring CNI slice.

The results show a 25% increase in the average SINR across the cell edge compared to non-cooperative DRL models. The Smart Contract layer plays a vital role here by acting as a "Coordination Ledger," where agents can "book" specific frequency sub-bands in advance. This prevents the "Collision of Actions" that often plagues independent DRL agents. By quantifying the Interference-to-Signal Ratio (ISR), we confirm that our framework effectively maintains the SINR above the 20 Db threshold required for ultra-reliable 6G communications, even in high-interference urban deployments.

4.8. Resource Trading Efficiency and Economic KPIs

Finally, we analyzed the economic efficiency of the Smart Contract-based Resource Market. We compared the "Resource Wastage" of our market-driven approach against a fixed-allocation model. The "Wastage" is defined as the integral of the difference between allocated and consumed capacity over time. Our framework reduced resource wastage by 60%, as the Smart Contract allowed idle resources to be traded to other slices in real-time.

The Economic Utility (U_{eco}) of the network was measured as:

$$U_{eco} = \sum_{i \in S} (P_i \cdot R_i - C_{opex})$$

where P_i is the price per unit of resource in slice i , R_i is the amount of resource sold, and C_{opex} is the operational cost. The automated auction mechanism within the Smart Contract ensured that the price P_i naturally gravitated toward the equilibrium point where supply met demand. This not only maximizes the revenue for the infrastructure provider but also ensures that CNI tenants can acquire the necessary "Premium Resources" at a fair, transparent, and competitive rate, even during periods of extreme network scarcity.

5. Conclusion and future work

5.1. Summary of Findings: How the Framework Achieves Scalability and Efficiency

The research presented in this paper demonstrates that the convergence of Deep Reinforcement Learning (DRL) and Blockchain-based Smart Contracts provides a robust, self-optimizing solution for the complex resource management challenges inherent in 6G Critical Network Infrastructure (CNI). Through the deployment of a Soft Actor-Critic (SAC) DRL agent at the network edge, the system successfully transitions from reactive, manual slicing to a proactive, autonomous paradigm capable of managing the high-dimensional and non-convex state space of Terahertz (THz) communications [40]. Our empirical results confirm that this "AI-native" approach achieves a 38% improvement in spectral efficiency and a 55% reduction in SLA violations compared to traditional heuristic-based scheduling methods. This is primarily due to the agent's ability to anticipate traffic surges in CNI-URLLC slices and perform sub-millisecond resource harvesting from lower-priority feMBB slices, ensuring that high-priority packets are never queued behind non-critical data.

Furthermore, the integration of a decentralized governance layer through Smart Contracts effectively resolves the "SLA-drift" problem that often plagues multi-tenant 6G environments. By codifying service requirements into self-executing scripts, the framework ensures that any performance deviation is met with an immediate, automated penalty, thereby maintaining a high degree of operational trust without the need for centralized oversight [41]. The implementation of Off-chain State Channels and Transaction Aggregation proved vital in decoupling the sub-millisecond decision-making of the AI from the inherent latency of the blockchain consensus, ensuring that the ledger serves as a scalable audit trail rather than a performance bottleneck. Collectively, these findings validate the hypothesis that a hybrid AI-Blockchain architecture can satisfy the extreme reliability (seven-nines) and ultra-low latency requirements of 2030-era critical infrastructures, effectively future-proofing the management plane against the exponential growth of the Internet of Everything (IoE).

5.2. Practical Implications for CNI: Real-World Deployment Considerations

The transition of this self-optimizing framework from a simulation environment to a real-world 6G CNI deployment involves several critical socio-technical and hardware-related considerations. First, the Computational Overhead at the edge must be managed; while the DRL inference is fast, the continuous training of models and the maintenance of a blockchain node require significant energy and hardware resources. Infrastructure providers must therefore adopt "Green AI" techniques, such as model pruning, knowledge distillation, and quantization, to ensure that the management plane does not consume a disproportionate share of the network's energy budget or increase the carbon footprint of the 6G ecosystem [42]. Secondly, the Regulatory Alignment of Smart Contracts is paramount; for sectors like autonomous healthcare, national energy grids, or remote industrial automation, the automated penalties and resource trading logic must be legally recognized and interoperable with existing telecommunications laws and international data sovereignty frameworks.

Another practical implication is the need for Standardized Inter-Slice Interfaces to ensure cross-vendor compatibility. For the DRL agent to effectively manage resources across heterogeneous 6G domains—including LEO satellite constellations, aerial base stations, and terrestrial small cells—the telemetry data must follow a unified format that allows for global state awareness. This research suggests that the adoption of an O-RAN (Open Radio Access Network) style architecture, which separates the control plane into near-real-time and non-real-time RICs (RAN Intelligent Controllers), provides the ideal ecosystem for deploying the proposed DRL-Smart Contract framework [43]. By leveraging open standards and modular software-defined networking (SDN), network operators can prevent vendor lock-in and ensure that the self-optimizing logic is portable across different infrastructure segments, a necessity for the ubiquitous connectivity envisioned for the 6G era.

5.3. Limitations and Future Research Directions: Privacy and Energy Efficiency in 6G

Despite the significant performance gains observed, several limitations remain that define the future research landscape for 6G CNI. One major concern is the Privacy-Security Trade-off; while the blockchain provides unmatched transparency and auditability, recording performance metrics on a distributed ledger could potentially leak sensitive traffic patterns or business intelligence to competitors or malicious actors [44]. Future work should investigate the integration of Differential Privacy and more advanced Zero-Knowledge Proofs (ZKPs) to mask the metadata of CNI slices while still allowing for verifiable SLA compliance. Additionally, the robustness of the DRL agent against "Adversarial Machine Learning" is still in its infancy; developing "Endogenous Security" protocols where the AI can self-detect and quarantine corrupted telemetry data—such as faked latency reports or spoofed buffer statuses—is a critical frontier for 6G resilience and long-term stability.

Beyond security, the Energy Efficiency of the blockchain layer itself remains a point of contention. While permissioned ledgers like Hyperledger Fabric are more efficient than public Proof-of-Work systems, the consensus overhead still scales with the number of participating nodes. Future iterations of this work should explore Asynchronous Consensus Protocols that require fewer communication rounds, thereby reducing the power consumption of the 6G control plane. Furthermore, the sensitivity of the DRL agent to "Exploration vs. Exploitation" in the THz band warrants further study, specifically regarding how the agent handles the extreme sensitivity of 6G signals to weather conditions and physical blockages.

5.3.1. Toward Fully Autonomous 6G Ecosystems: Self-Evolution and Digital Twins

Looking beyond current resource management, the next evolution of this framework lies in the domain of Generative Intelligence and Digital Twins. Future research could explore the use of Generative Adversarial Networks (GANs) or Variational Autoencoders (VAEs) to create a high-fidelity "Digital Twin" of the 6G CNI, allowing the DRL agent to "hallucinate" and test thousands of disaster scenarios in a virtual environment before they occur in the physical world [45]. This would move the network from being merely "Self-Optimizing" to being "Self-Evolving," where the system autonomously generates its own test cases and optimizes its topology to meet future, unforeseen demands.

Moreover, the exploration of Proof-of-Learning (PoL) consensus mechanisms could further unify the AI and Blockchain layers by using the computational energy of the blockchain nodes to train the network's DRL models, effectively solving the dual challenge of consensus overhead and AI training costs. By pursuing these multi-disciplinary directions, the global research community can ensure that 6G becomes not only a faster network but a fundamentally more intelligent, trustworthy, and sustainable pillar of modern society. The synergy between autonomous intelligence and decentralized trust, as proposed in this study, provides a definitive roadmap for the next generation of critical digital infrastructure.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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