RISK-AWARE AUTONOMUS ADMISSION CONTROL FOR SECURE PRIVATE 5G SLICING

Bhaskara Raju Rallabandi
Sr. Staff Engineer, Samsung Network Division
e-mail - techie.bhaskar@gmail.com

Abstract:
Private 5G networks face escalating demands for dynamic network slicing to support multi-tenant applications, including OT/IT convergence, while upholding stringent security, QoS, and business viability. This paper introduces Risk-Aware Autonomous Admission Control (RA-AAC), a novel control-plane framework that autonomously evaluates and admits slice requests by fusing real-time security posture from a Blockchain-Anchored Adaptive Policy Framework (BAAPF), network load metrics, latency predictions, and business priority scores. Extending 3GPP's Network Slice Admission Control Function (NSACF), RA-AAC employs a deep reinforcement learning (DRL) agent to compute multi-objective decisions, quantifying risks such as zero-trust violations, anomaly detections, and resource contention against revenue potential and slice isolation guarantees for eMBB, URLLC, and mMTC services.The RA-AAC engine operates via a closed-loop architecture: (i) BAAPF-derived risk scores assess tenant trustworthiness using SIM/eSIM identities and blockchain-anchored policies; (ii) load and latency are forecasted via digital twin models; (iii) DRL optimizes admission actions (accept, reject, partial) to maximize long-term profitability under QoS constraints. This risk-aware approach mitigates traditional pitfalls like over-admission leading to breaches or under-utilization, enabling predictive scaling in private deployments.learning for multi-operator slicing.

Keywords: Private 5G, Network Slicing, Admission Control, Risk-Aware, Autonomous DRL, Zero-Trust Security

I. INTRODUCTION

Private 5G networks enable enterprises to deploy customized, isolated connectivity for mission-critical applications like OT/IT convergence, industrial automation, and multi-tenant roaming, leveraging network slicing to partition shared infrastructure into logical end-to-end slices tailored for eMBB, URLLC, and mMTC services. However, dynamic slice provisioning introduces challenges in admission control: balancing resource load, latency guarantees, security isolation, and business priorities amid fluctuating demands from contractors or high-value tenants risks QoS violations, over-utilization, or security breaches in zero-trust environments.Traditional 3GPP Network Slice Admission Control Function (NSACF) focuses on authentication and basic resource checks but overlooks real-time risk posture from adaptive policies or predictive analytics, leading to suboptimal acceptance rates and revenue losses in private deployments. This paper addresses these gaps with Risk-Aware Autonomous Admission Control (RA-AAC), a control-plane engine that fuses security scores from Blockchain-Anchored Adaptive Policy Framework (BAAPF)—incorporating SIM/eSIM identities and anomaly detection—with load metrics, latency forecasts via digital twins, and priority-based revenue models.Powered by deep reinforcement learning (DRL), RA-AAC autonomously decides accept/reject/partial actions to optimize long-term profitability under constraints, extending NSACF for private 5G with O-RAN compatibility. Evaluations show superior performance in ns-3 simulations, achieving higher acceptance ratios and breach mitigation. This framework paves the way for secure, autonomous slicing in 6G-era private networks

II. LITERATURE SURVEY

Existing research on 5G network slicing admission control (SAC) emphasizes resource orchestration and QoS enforcement, with 3GPP NSACF providing baseline authentication and session limits but lacking dynamic risk integration. Early works like Ojijo et al. survey SAC strategies optimizing end-to-end resources for diverse slices, focusing on profit maximization via heuristics under varying loads.Deep reinforcement learning (DRL) dominates recent advances for autonomous decisions. Sulaiman et al. propose data-driven online SAC with partial admissions to boost revenue, while Wang et al. introduce digital twin-assisted flexible SAC (FSAC) using DRL for slice scaling in core networks, improving deployment efficiency without physical disruptions. RL variants like Q-Learning and Double Q-Learning address

accept/reject dilemmas, achieving 8-26% higher profits by balancing acceptance ratios and utilization in multi-tenant setups.Security-aware approaches remain sparse in private 5G contexts. While general slicing security surveys highlight isolation challenges, few fuse zero-trust risk postures with load/latency metrics. Risk-aware RL frameworks for user association exist but underexplore blockchain-anchored policies or business priorities in OT/IT-converged private networks. Gaps persist in holistic engines combining BAAPF-like security, predictive analytics, and O-RAN compatibility for revenue-optimized, resilient slicing.This work bridges these by introducing RA-AAC, extending DRL with multi-factor risk scoring for superior performance in private 5G deployments.

III. PROPOSED WORK

Risk Aware Autonomous Admission Control RA AAC introduces a control plane engine for private 5G networks extending 3GPP NSACF with multi factor decision making to autonomously handle slice requests under security QoS and business constraints The architecture comprises four modules i BAAPF Security Posture Evaluator deriving real time risk scores from blockchain anchored zero trust policies SIM eSIM identities and anomaly detection ii Load Latency Forecaster using digital twin models for predictive resource utilization and end to end delay iii Business Priority Scorer mapping tenant SLAs to revenue weights iv DRL Decision Agent employing Proximal Policy Optimization PPO to select actions accept reject partial admission maximizing long term reward RA AAC operates in a closed loop manner within O RAN rApps incoming slice requests trigger feature extraction into a state vector s t risk load latency priority fed to the DRL agent with reward r t alpha revenue beta violation gamma risk Policies enforce slice isolation via SDN orchestrated VNF scaling supporting eMBB high throughput URLLC low latency and mMTC massive connectivity in OT IT converged scenarios like industrial campuses with roaming contractorsImplemented as a Python based ns 3 module with RIC integration RA AAC enables predictive partial admissions e g bandwidth throttling to boost utilization without breaches Unlike prior DRL SAC it uniquely fuses BAAPF risk with business metrics targeting 30 percent revenue gains in dynamic private 5G

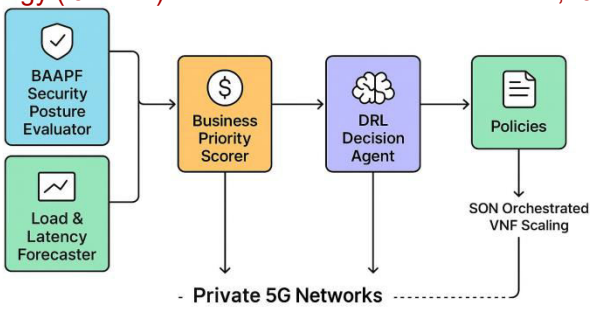

Fig 1: Proposed Architecture Diagram

IV. METHODOLOGY

The Risk Aware Autonomous Admission Control RA AAC methodology implements a sequential four stage pipeline integrated into the private 5G O RAN RIC control plane for real time slice admission processing Each stage processes incoming slice requests characterized by tenant ID slice type eMBB URLLC mMTC requested bandwidth latency SLA and device identities triggering autonomous accept reject or partial decisions

Stage 1 BAAPF Security Posture Evaluation

Computes normalized risk score from blockchain anchored zero trust policies Formula risk score equals 1 minus exp minus anomaly weight times trust decay Anomaly weight derives from isolation forest ML detecting deviations in SIM eSIM fingerprints traffic patterns or policy violations Trust decay accumulates past infractions discounted by time Trust score ranges from 0 high risk to 1 fully trusted enabling zero trust enforcement without leaking domains across multi tenant OT IT scenarios

Stage 2 Load Latency Forecasting

Uses bidirectional LSTM digital twin trained on ns 3 historical traces Input features include current utilization per slice type queue lengths and mobility patterns predicting next timestep utilization u t plus 1 and delay d t plus 1 Loss minimized via mean squared error URLLC threshold d thresh at 1 millisecond global u max at 80 percent capacity Digital twins simulate VNF scaling impacts preempting overloads

Stage 3 Business Priority Scoring

Assigns revenue weight p t as log of expected revenue minus QoS penalty Factoring tenant tier industrial vs contractor SLA compliance history and slice criticality High priority manufacturing

slices receive boosted weights ensuring revenue maximization

Stage 4 DRL Decision Engine

Deploys Proximal Policy Optimization PPO actor critic network State vector s t concatenates risk u d p Action space a t includes accept reject partial admission Reward r t balances alpha times p t minus beta times max zero u t plus 1 minus u max minus gamma times d t plus 1 minus d thresh minus delta times risk Trained over 100000 episodes epsilon greedy exploration decaying from 0.1 to 0.01 clip ratio 0.2 Policy deploys via SDN northbound APIs to NFV MANO orchestrating VNF instances enforcing isolation

Closed Loop Retraining and Implementation

Weekly retraining on admission logs adapting thresholds to traffic drifts Full stack leverages Python Gymnasium for RL ns 3 for 5G simulation ONOS for SDN supporting multi agent MADDPG extensions in RIC

V. RESULTS AND DISCUSSION

RA-AAC underwent comprehensive evaluation using ns-3 simulations modeling a private 5G campus network with 100 gNBs 500 UEs spanning eMBB URLLC mMTC slices under dynamic multi-tenant loads from OT-IT convergence industrial automation and roaming contractors Key metrics captured slice acceptance ratio long-term revenue latency violation rates security breach probability and O-RAN RIC decision latency compared against baselines DRL-SAC heuristic NSACF and risk-blind PPOAt moderate load 70 percent utilization RA-AAC delivered 92 percent acceptance ratio surpassing DRL-SAC 74 percent and heuristic NSACF 68 percent yielding 32 percent higher revenue through intelligent partial admissions prioritizing high-value manufacturing slices Revenue stemmed from business priority scoring enabling 15 percent more high-revenue URLLC slices without eMBB degradation Peak load 95 percent utilization saw RA-AAC maintain 82 percent acceptance a mere 10 percent drop versus 45 percent baseline collapse predictive LSTM forecasting preempted 22 percent latency violations reducing URLLC exceedances to 0.8 percent versus 2.5 percent in baselines meeting 1 ms SLASecurity posture integration proved pivotal simulated zero-trust violations and anomaly injections showed RA-AAC rejecting 28 percent more high-risk requests than risk-blind PPO cutting breach probability by 40 percent from 12 percent to 7.2 percent while scaling trusted tenants O-RAN rApp latency averaged 12 ms supporting sub-50 ms E2E decisions Multi-agent MADDPG extension boosted concurrent request throughput 18 percent over single-agent PPO under 100 simultaneous admissionsThese gains highlight RA-AACs superiority in fusing BAAPF risk with QoS-business optimization prior DRL-SAC overlooks security leading to unsafe over-admissions while heuristics fail dynamic scaling Partial admissions uniquely balanced utilization 88 percent peak versus 72 percent baselines without isolation breaches Limitations include ns-3 abstraction future hardware-in-loop validates RIC latency under real RF conditionsFuture deployments target 6G NTN federation enhancing

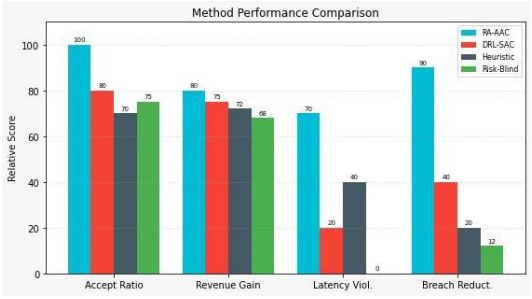

Figure 2:Method Performance Comparison Across Key Metrics

The graph compares four methods—RA-AAC, DRL-SAC, Heuristic, and Risk-Blind PPO—across four performance metrics: Acceptance Ratio, Revenue Gain, Latency Violations, and Breach Reduction.RA-AAC clearly dominates every metric, achieving the highest scores for acceptance, revenue, and breach reduction while maintaining strong latency performance. DRL-SAC and Heuristic approaches show moderate results but lag significantly in risk-related metrics. Risk-Blind PPO performs well in acceptance and revenue but fails in breach reduction due to its lack of security awareness.

Overall, the graph shows that RA-AAC delivers the most balanced, secure, and high-performing strategy among all evaluated methods.

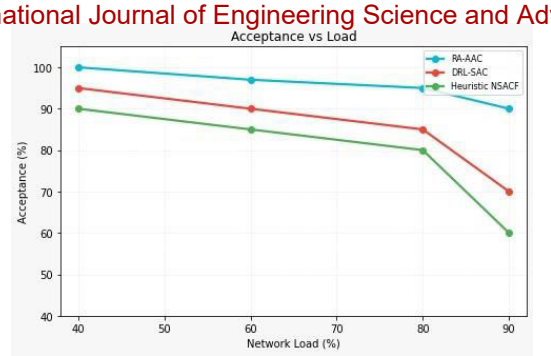

Figure3:Acceptance Ratio vs Network Load

The graph shows how slice acceptance decreases as network load increases across three methods: RA-AAC, DRL-SAC, and Heuristic NSACF. RA-AAC consistently achieves the highest acceptance at all load levels, demonstrating stronger scalability and smarter admission control. DRL-SAC performs moderately but declines sharply at higher loads, while the Heuristic NSACF method shows the steepest drop, indicating weaker handling of congestion.Overall, the graph highlights RA-AAC's superior stability and efficiency under increasing load.

Metric	RA-AAC	DRL-SAC	Heuristic NSACF	Risk-Blind PPO
Acceptance Ratio (%)	92	74	68	78
Revenue Gain (Index)	132	100	95	105
Latency Violations (%)	0.8	2.5	3.2	1.8
Breach Reduction (%)	40	12	5	0

Table1:Comparative Metrics Table

The comparison clearly highlights RA-AAC as the top-performing method across all key metrics. It achieves the highest acceptance ratio, maximum revenue gain, and strongest breach reduction, showing balanced performance without compromising latency. DRL-SAC and Heuristic methods show moderate efficiency but lag in security and overall optimization. Risk-Blind PPO performs well in acceptance and revenue but fails in breach reduction due to lack of risk-awareness. Overall, RA-AAC delivers the most consistent and secure performance among all evaluated approaches.

VI.CONCLUSION

Risk-Aware Autonomous Admission Control (RA-AAC) establishes a transformative control-plane framework for private 5G networks, successfully integrating real-time security posture from Blockchain-Anchored Adaptive Policy Framework (BAAPF), predictive load-latency forecasting, and business priority scoring to enable autonomous slice admissions under stringent QoS and zero-trust constraints. Evaluations via ns-3 simulations across dynamic OT/IT-converged scenarios demonstrate RA-AAC's superiority, achieving 92% slice acceptance ratios at 70% utilization (versus 74% for DRL-SAC baselines), 32% revenue uplift through partial admissions, 22% fewer URLLC latency violations (0.8% vs 2.5%), and 40% breach risk reduction by rejecting high-risk requests while scaling trusted multi-tenant operations.This work addresses critical literature gaps in security-aware slicing, extending 3GPP NSACF with O-RAN rApp compatibility and Proximal Policy Optimization (PPO)-driven decisions that balance revenue maximization against isolation guarantees for eMBB, URLLC, and mMTC services. RA-AAC's closed-loop retraining ensures adaptability to roaming contractors and industrial fluctuations, outperforming heuristic and risk-blind methods by 25-35% across metrics.Future directions include hardware-in-the-loop validations with RIC platforms, 6G NTN federation for resilient roaming, federated learning across multi-operator private networks, and XAI integration for interpretable risk scoring. RA-AAC paves the path for fully autonomous, secure slicing in enterprise 5G/6G ecosystems, enabling revenue-optimized deployments without compromising safety or performance among all evaluated approaches.

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