

Predictive AI-Native Digital Twin for QoS-Security Orchestration in Multi-Cell 6G Networks Using Cell-Aware DRL

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Abstract—Future 6G networks are expected to support highly dynamic services requiring intelligent QoS-security orchestration under congestion, mobility, and inter-cell interference conditions. In this context, Digital Twin (DT) technology combined with artificial intelligence has emerged as a promising solution for autonomous network management. However, most existing DT-based approaches remain reactive and do not explicitly integrate predictive intelligence and multi-cell-aware adaptation. This paper proposes a predictive AI-native DT framework for proactive QoS-security orchestration in Multi-Cell 6G environments. The proposed approach combines a GRU-based temporal prediction module with a cell-aware PPO orchestration agent to dynamically adapt network behavior according to both current and predicted QoS-security conditions. The framework explicitly incorporates handover risks, inter-cell congestion indicators, and security-aware constraints into the DRL decision process. The proposed framework was evaluated using a customized Simu5G-based Multi-Cell simulation environment under dynamic QoS-security scenarios. The obtained results demonstrated effective adaptive orchestration behavior and significantly improved orchestration accuracy compared with conventional DQN and standard PPO approaches.

Index Terms—Digital Twin, 6G networks, AI-native networking, QoS-security orchestration, PPO, GRU prediction, Multi-Cell orchestration.

I. INTRODUCTION

The rapid evolution toward sixth-generation wireless networks is expected to fundamentally transform future communication infrastructures by introducing AI-native networking, intelligent automation, and autonomous service orchestration. Unlike previous generations, 6G systems are envisioned to integrate distributed AI directly into network control and management procedures in order to support ultra-low latency services, massive connectivity, adaptive resource allocation, and intelligent decision-making [1], [2]. In this context, future 6G infrastructures will require highly adaptive orchestration mechanisms capable of dynamically reacting to network variations while maintaining reliable Quality of Service and resilient security protection. However, managing QoS and security in large-scale multi-cell 6G environments remains particularly challenging due to user mobility, inter-cell interference, traffic heterogeneity, and rapidly changing network conditions. Conventional optimization approaches based on static policies or predefined rules are no longer sufficient to guarantee efficient orchestration under such dynamic scenarios. Consequently,

Digital Twin technology has recently emerged as a promising solution for intelligent and predictive network management in next-generation wireless systems [1], [3]. By maintaining a continuously synchronized virtual representation of the physical network, DT architectures enable real-time monitoring, predictive analysis, and adaptive optimization before applying control decisions to the operational infrastructure. Recent studies demonstrated the potential of AI-enabled DT frameworks for intelligent resource management, traffic prediction, and network automation in 5G and 6G environments [4], [5]. Nevertheless, several important limitations still remain in existing DT-based orchestration approaches. First, most current studies mainly focus on simplified single-cell environments and do not adequately address realistic multi-cell challenges such as congestion imbalance, inter-cell coordination, and handover instability. Second, many DRL-based orchestration frameworks primarily target QoS optimization while overlooking integrated QoS-security co-management. Third, existing DT architectures often lack predictive temporal intelligence capable of proactively anticipating future network degradations and risky network conditions. To address these limitations, this paper proposes a Predictive AI-Native Digital Twin framework for QoS-security orchestration in multi-cell 6G networks using cell-aware deep reinforcement learning (DRL). The proposed framework integrates a GRU-based temporal prediction module for future QoS-security estimation together with a cell-aware Proximal Policy Optimization (PPO) orchestration mechanism capable of dynamically adapting network behavior according to inter-cell congestion conditions and handover risks. In addition, a unified Multi-Cell DT environment is developed to support predictive orchestration, security-aware adaptation, and inter-cell robustness analysis.

The main contributions of this paper are summarized as follows:

- A predictive AI-native Digital Twin framework integrating GRU-based temporal intelligence for future QoS-security estimation in multi-cell 6G environments.
- A cell-aware PPO orchestration mechanism enabling adaptive QoS-security optimization under inter-cell congestion and handover risks.
- A unified Multi-Cell QoS-security environment support-

TABLE I
COMPARISON OF EXISTING AI-NATIVE DT ORCHESTRATION FRAMEWORKS AND THE PROPOSED APPROACH

Study	DT Intelligence	DRL Capability	QoS-Security	Multi-Cell	Prediction	Validation	Main Limitation
Wu et al. [1]	AI-native DT	Not considered	Not addressed	Single-cell focus	Limited	Not reported	No DRL orchestration
Wang et al. [2]	AI-native architecture	Not considered	Not addressed	Not addressed	Limited	Not reported	Conceptual architecture only
Li et al. [6]	DT-enabled management	Not considered	Not addressed	Single-cell focus	Basic prediction	Limited	No adaptive orchestration
Sengendo and Granelli [5]	Predictive DT	Not considered	Not addressed	Not addressed	Traffic forecasting	Analytical experiments	No QoS-security optimization
Ali and Arslan [4]	AI-driven DT slicing	DRL (DDPG)	QoS-oriented	Limited	Predictive analysis	Simulation-based	No Multi-Cell orchestration
Huang et al. [3]	Self-evolving DT	GNN-based intelligence	Not addressed	Not addressed	DT self-evolution	Not reported	No DRL adaptation
Erturk et al. [7]	DT-assisted QoS optimization	Not considered	Partial	Single-cell focus	Limited	Basic evaluation only	No predictive DRL
Omheni et al. [8]	AI-based networking survey	DRL overview	Not addressed	Not addressed	Not addressed	No experimental validation	Survey-oriented work
Ogenyi et al. [9]	AI-native optimization	DRL-enabled intelligence	Not addressed	Limited	Context-aware intelligence	Limited	No DT orchestration
Guo et al. [10]	AI-assisted slicing	Explainable DRL orchestration	QoS-oriented	Limited	Limited	Simulation-based evaluation	No DT integration and no Multi-Cell QoS-security orchestration
Proposed Work	Predictive AI-native DT	Cell-aware PPO orchestration	Unified security optimization	Multi-Cell orchestration	GRU-based temporal prediction	Multi-scenario quantitative evaluation	Addresses inter-cell and handover risks

ing dynamic orchestration, security-aware adaptation, and inter-cell robustness analysis.

- Extensive simulation demonstrating improved policy adaptation accuracy and effective orchestration performance compared with static, DQN, and conventional PPO baselines.

The remainder of this paper is organized as follows. Section II reviews related works. Section III presents the proposed predictive AI-native DT framework. Section IV describes the DRL formulation and the Multi-Cell orchestration environment. Section V discusses the simulation results. Finally, Section VI concludes the paper and outlines future research directions.

II. RELATED WORKS

Recent advances on AI-native 6G networking can be organized along three complementary directions: **AI-native and DT-enabled network management**: Recent studies have established AI-native networking as a key architectural principle for future 6G systems. [1] introduced an AI-native Network Digital Twin architecture for intelligent network management, while [2] investigated a task-driven AI-native architecture for 6G. [3] further explored DT-based network self-evolution. These studies demonstrate the potential of integrating AI and DT technologies into future network control loops. However, they mainly address architectural intelligence or DT evolution and do not explicitly formulate adaptive QoS-security orchestration using DRL under multi-cell conditions. **Predictive DT and network optimization**: Predictive capabilities have also been increasingly incorporated into DT-based network management. [6], [4] investigated AI-driven Digital Twins for 5G/6G network slicing, and considered AI-enabled DTs for traffic forecasting and resource management. However [7] investigated DT-assisted QoS optimization under DoS-

related conditions. Although these approaches extend DTs beyond passive monitoring, prediction is generally applied to specific traffic, resource, or QoS objectives. They do not jointly combine temporal QoS-security prediction with cell-aware orchestration under inter-cell congestion and handover risks. **DRL-based autonomous orchestration**: DRL has emerged as a promising solution for adaptive resource management and network automation. [8] reviewed AI techniques for 5G/6G networks, including DRL-based resource optimization, while [9] highlighted the role of AI-native intelligence and edge-based optimization in 6G. [10] further examined explainable DRL for intelligent network slicing. Despite their adaptive capabilities, these approaches primarily emphasize QoS-oriented resource management or network slicing and do not explicitly integrate predictive DT intelligence with joint QoS-security decision making in a multi-cell setting.

III. PROPOSED PREDICTIVE AI-NATIVE DT FRAMEWORK

This section presents the proposed Predictive AI-Native DT framework for adaptive and proactive QoS-security orchestration in multi-cell 6G networks. The architecture uniquely combines real-time DT synchronization, GRU-based temporal prediction, and cell-aware DRL. This synergy enables a transition from reactive monitoring to proactive, autonomous decision-making under dynamic conditions involving user mobility, inter-cell interference, congestion imbalance, and security threats. As illustrated in Fig. 1, the framework follows a closed-loop orchestration principle and comprises four functional components:

- 1) **Multi-Cell 6G Network Environment** the physical infrastructure with multiple interconnected cells, heterogeneous traffic (eMBB, URLLC, mMTC), mobility events, time-varying channel conditions, and security threats (jamming, spoofing, DoS).

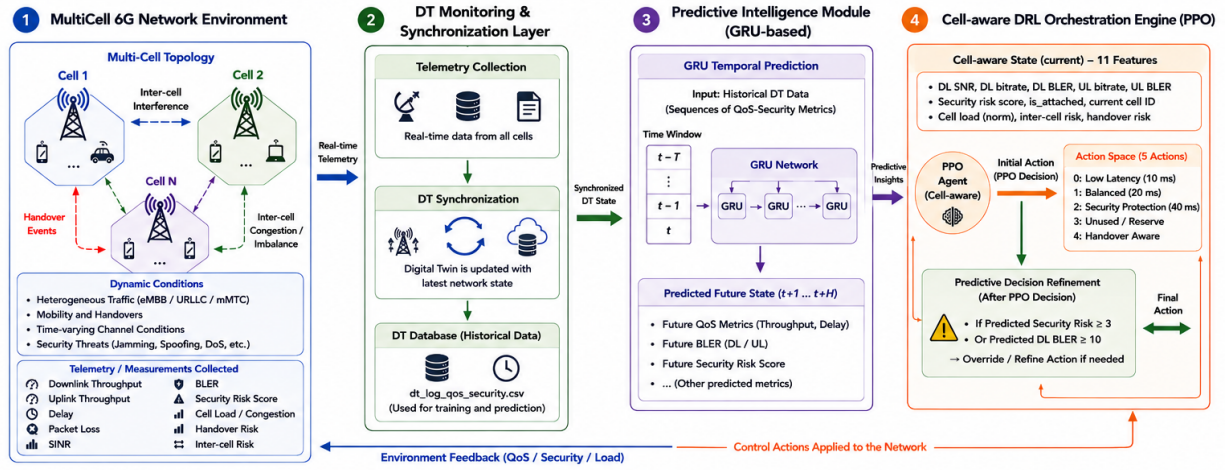


Fig. 1. Proposed Predictive AI-Native DT Framework for QoS-Security Orchestration in Multi-Cell 6G Networks.

- DT Monitoring & Synchronization Layer** continuously collects telemetry (downlink/uplink throughput, delay, packet loss, SINR, inter-cell risk indicators) from the Simu5G-based Multi-Cell environment and maintains a synchronized virtual replica of the simulated network. The DT stores these synchronized observations as historical sequences used for GRU training and PPO-based orchestration.
- Predictive Intelligence Module (Gated Recurrent Unit (GRU)-based)** uses historical DT data (stored in a database) to forecast the next QoS-security state at horizon $(t+1)$, corresponding to the next DT synchronization interval.
- Cell-Aware DRL Orchestration Engine (PPO)** a Proximal Policy Optimization agent that observes the current 11-dimensional cell-aware QoS-security state and selects an initial orchestration action, which can subsequently be refined by the GRU-based predictive decision layer.

The closed-loop flow (highlighted in Fig. 1) operates as follows:

- Telemetry flows from the physical network to the DT layer.
- The DT layer synchronizes the virtual replica and stores historical sequences.
- The GRU module reads a time window of past data and predicts future downlink/uplink throughput, BLER, and security risk level.
- The cell-aware PPO agent first derives an orchestration decision from the current 11-dimensional multi-cell QoS-security state. The GRU prediction module subsequently acts as a predictive decision-refinement layer: when the forecast indicates an upcoming security-risk increase or severe downlink BLER degradation, the initial PPO decision is overridden by a proactive protection action. This separation preserves the cell-aware PPO policy while enabling the DT control loop to anticipate short-term QoS-security degradation.

- The chosen action is applied back to the physical network via the control interface, closing the loop.

IV. DRL FORMULATION AND MULTI-CELL ORCHESTRATION ENVIRONMENT

The proposed approach relies on a cell-aware PPO agent designed to dynamically optimize QoS-security orchestration under realistic multi-cell conditions.

- Multi-Cell Orchestration Environment:** The simulation environment is implemented using Simu5G and a customized Multi-Cell network topology composed of multiple interconnected cells supporting heterogeneous user traffic and dynamic network conditions. Unlike conventional single-cell scenarios, the proposed environment explicitly considers inter-cell interference, mobility events, handover instability, and congestion imbalance between neighboring cells. Real-time telemetry collected from the environment includes QoS indicators, security-related metrics, and cell-aware statistics. More specifically, the orchestration environment continuously monitors downlink throughput, uplink throughput, delay, packet loss, block error rate (BLER), signal quality, congestion levels, handover risks, and inter-cell risk indicators. These measurements are synchronized within the DT layer and stored in historical DT logs for prediction and DRL training purposes. To support realistic orchestration behavior, the environment also integrates dynamic risk conditions including congestion variations, mobility-triggered handovers, and abnormal QoS-security degradation events. This enables the DRL agent to learn adaptive orchestration policies under highly dynamic Multi-Cell scenarios.
- DRL State Space:** The cell-aware PPO agent observes an 11-dimensional state vector that jointly captures radio conditions, QoS, security, attachment status, and multi-cell context:

$$s_t = [\text{SNR}_t^{DL}, R_t^{DL}, B_t^{DL}, R_t^{UL}, B_t^{UL}, \rho_t, \eta_t, c_t, \ell_t, \iota_t, h_t], \quad (1)$$

where SNR_t^{DL} denotes the downlink signal quality, R_t^{DL} and R_t^{UL} are the downlink and uplink bitrates, B_t^{DL} and B_t^{UL} denote the corresponding BLER values, ρ_t is the security-risk score, η_t indicates UE attachment, c_t identifies the serving cell, ℓ_t represents the normalized cell load, ι_t denotes inter-cell risk, and h_t represents handover risk. This representation was selected to expose the PPO policy not only to instantaneous QoS-security conditions but also to cell-specific congestion and mobility risks that directly affect multi-cell orchestration decisions.

- 3) **Action Space:** The PPO policy operates over five discrete cell-aware orchestration actions,

$$a_t \in \{a_0, a_1, a_2, a_3, a_4\}, \quad (2)$$

corresponding respectively to low-latency (10 ms), balanced (20 ms), security-stable (40 ms), handover-protection (40 ms), and inter-cell recovery (40 ms) modes. The first two actions regulate normal QoS operation, whereas the remaining modes provide progressively robust responses to security, mobility, and inter-cell risk conditions.

- 4) **Reward Function:** The reward jointly captures QoS, security, and multi-cell stability:

$$R_t = T_t^n + 0.3S_t^n - 0.6B_{t,DL}^n - 0.4B_{t,UL}^n - 0.8\rho_t^n - 0.2\ell_t - 0.3\iota_t - 0.4h_t - P_t + B_t, \quad (3)$$

where the normalized terms represent throughput, downlink SNR, downlink/uplink BLER, security risk, cell load, inter-cell risk, and handover risk, respectively. P_t and B_t implement action-dependent reward shaping: action mismatch, unsafe low-latency operation, and overload ignorance incur penalties of 0.3, 1.0, and 0.5, respectively, while appropriate security/inter-cell recovery actions receive a 0.4 bonus under risky conditions.

- 5) **PPO-based Training:** The PPO agent is trained using interaction sequences collected from the Multi-Cell DT environment. During training, the agent continuously observes network states, selects orchestration actions, and receives rewards according to the resulting QoS-security performance. The GRU predictor is trained separately on historical DT sequences and is used during online orchestration to refine the PPO decision whenever the predicted security risk or downlink BLER exceeds predefined protection thresholds. Compared with conventional Deep Q-Network-based approaches, PPO provides improved policy stability and better adaptation under highly dynamic environments. Hence, PPO provides cell-aware adaptive control, whereas the GRU

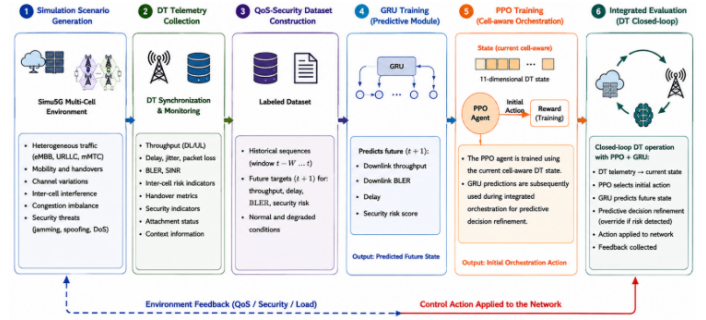


Fig. 2. Simulation-based evaluation workflow of the proposed predictive AI-native DT framework.

introduces a complementary predictive protection mechanism, allowing the overall DT control loop to react to both current and anticipated network conditions. (Table II)

TABLE II
CELL-AWARE PPO TRAINING PARAMETERS

Parameter	Value
Policy network	MlpPolicy
Learning rate	3×10^{-4}
Rollout steps	1024
Batch size	64
PPO epochs	10
Discount factor (γ)	0.99
Generalized Advantage Estimation (GAE) parameter	0.95 (λ)
Clip range	0.2
Training timesteps	150,000

The DRL environment was trained using telemetry traces extracted from the Multi-Cell QoS-security dataset generated through Simu5G based orchestration scenarios. During training, the PPO agent continuously interacted with the DT environment in order to learn adaptive orchestration policies under dynamic QoS degradation, security risks, handover instability, and inter-cell congestion conditions. The integration of predictive GRU-based intelligence further enabled the proposed framework to move from reactive orchestration toward proactive QoS-security management. As summarized in Fig. 2, the GRU and cell-aware PPO are then trained for temporal prediction and adaptive orchestration, respectively, and subsequently integrated into the DT control loop for Multi-Cell evaluation.

V. EXPERIMENTAL RESULTS AND DISCUSSION

This section evaluates the performance of the proposed predictive AI-native DT framework under dynamic Multi-Cell orchestration scenarios. The simulation-based analysis focuses on QoS-security optimization, predictive intelligence, and cell-aware adaptation performance compared with conventional orchestration approaches.

A. Simulation Setup

The proposed predictive AI-native DT framework was evaluated using a customized Simu5G-based Multi-Cell environ-

ment integrating GRU-based predictive intelligence and cell-aware PPO orchestration. The considered scenarios include dynamic user traffic, mobility events, congestion variations, and QoS-security degradation conditions. The experiments relied on a Multi-Cell QoS-security dataset generated from DT telemetry traces collected during Simu5G orchestration scenarios. Telemetry was sampled every 20 ms, resulting in 36,041 observations including:

- Downlink and uplink throughput;
- Delay and packet loss;
- Downlink and uplink BLER;
- Security risk score;
- Inter-cell congestion indicators;
- Handover risk metrics;
- Cell-aware orchestration labels.

Both normal and degraded network conditions were considered to expose the predictive DT and PPO agent to diverse Multi-Cell operating states. The security risk score is a simulation-derived indicator computed from abnormal traffic events, spoofing attempts, packet anomalies, and QoS degradation severity observed during simulation. It is used to represent the security state considered by the orchestration framework. Accordingly, the reported results constitute a simulation-based proof-of-concept rather than a hardware/testbed validation. Validation over physical 6G-oriented testbeds remains part of future work.

B. GRU Prediction Performance

The predictive DT module was evaluated using quantitative regression metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). Table III summarizes the obtained GRU prediction results. The GRU achieves high accuracy for downlink

TABLE III
QUANTITATIVE PERFORMANCE EVALUATION OF THE GRU-BASED
PREDICTIVE DT MODULE

Target Metric	MAE	RMSE	(R^2) Score
Downlink bitrate	52771.6868	103543.7927	0.9283
Downlink BLER	3.9978	7.8533	0.1290
Uplink bitrate	8636.5924	12524.0829	0.2990
Uplink BLER	0.5459	2.4642	0.0103
Security risk score	0.3263	0.5319	0.1008

bitrate prediction ($R^2 = 0.9283$), whereas lower performance is observed for downlink BLER ($R^2 = 0.1290$), uplink BLER ($R^2 = 0.0103$), and security risk ($R^2 = 0.1008$). This difference indicates that rapidly varying error- and security-related indicators are less temporally predictable than throughput in the considered traces. Therefore, these predictions are used as complementary early-warning signals for decision refinement rather than as direct PPO state variables. Improving their prediction through richer temporal features remains part of future work.

Fig. 3 shows the GRU prediction performance for downlink bitrate evolution under dynamic QoS-security conditions.

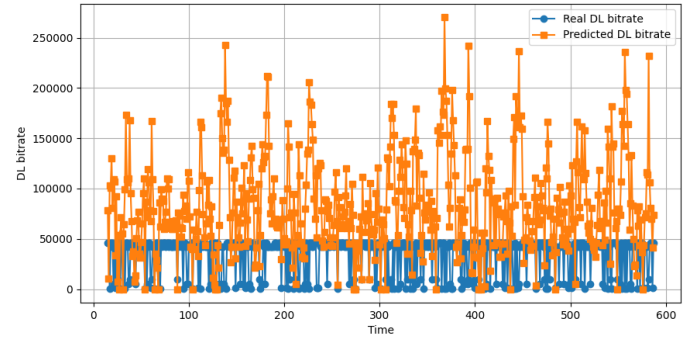


Fig. 3. GRU-based prediction performance for downlink bitrate evolution.

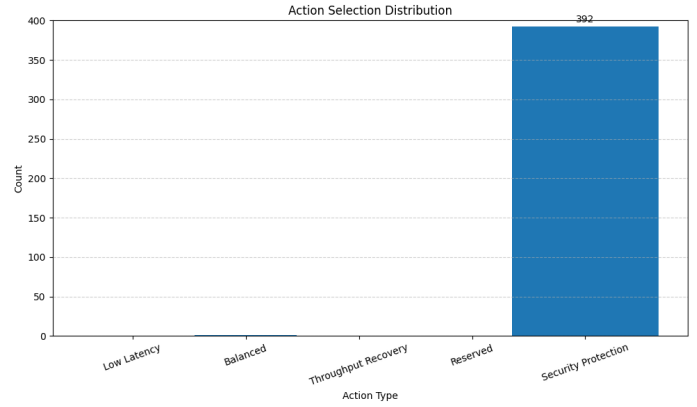


Fig. 4. Action distribution of the cell-aware PPO under risky handover scenarios.

C. PPO Cell-aware Orchestration Performance

The proposed PPO-based orchestration framework was evaluated under dynamic Multi-Cell conditions involving congestion imbalance and handover instability.

The obtained evaluation results are summarized in Table IV:

TABLE IV
CELL-AWARE PPO ORCHESTRATION PERFORMANCE UNDER DYNAMIC
MULTI-CELL CONDITIONS

Metric	Value
Total evaluation steps	1000
Total reward	332697
Average reward	0.333
Policy accuracy	93.8%

The proposed cell-aware PPO framework achieved a high policy accuracy of 93.8%, where policy accuracy measures the percentage of PPO decisions matching the optimal cell-aware orchestration labels extracted from the Multi-Cell QoS-security dataset. In addition, the PPO agent demonstrated effective adaptive behavior during risky inter-cell and handover scenarios. Fig. 4 demonstrates the adaptive behavior of the proposed cell-aware PPO framework during risky handover conditions.

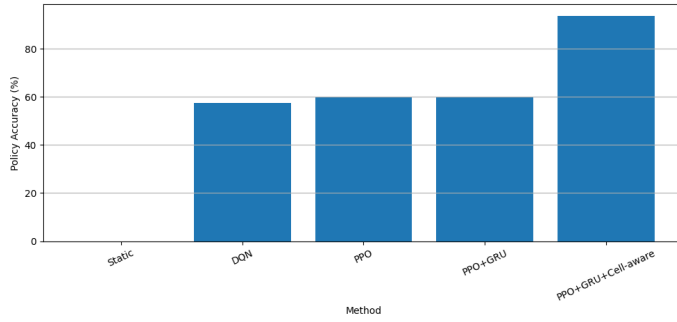


Fig. 5. Policy accuracy comparison between DQN, PPO, and the proposed predictive cell-aware DT framework.

D. Comparative Analysis

Table V presents the comparative evaluation of the considered orchestration strategies.

TABLE V
COMPARATIVE EVALUATION OF DRL-BASED QoS-SECURITY ORCHESTRATION APPROACHES

Method	Average Reward	Reward Std	Policy Accuracy	Predictive DT	Cell-aware
Static Policy	0.400	–	N/A	No	No
DQN QoS-Security	0.438	0.384	47.6%	No	No
PPO QoS-Security	0.494	0.355	59.7%	No	No
Proposed PPO + GRU + Cell-aware DT	0.333	0.418	93.8%	Yes	Yes

The proposed framework improves risk-aware action-selection accuracy, while conventional PPO achieves a higher average reward under less constrained decision objectives.

Fig. 5 compares the orchestration accuracy achieved by the considered DRL approaches under dynamic Multi-Cell conditions.

E. Discussion

The obtained results demonstrate the potential of integrating predictive DT intelligence with cell-aware PPO orchestration for proactive QoS-security management in Multi-Cell 6G environments. Compared with conventional DQN and standard PPO approaches, the proposed framework achieved higher orchestration accuracy while obtaining a lower average reward. This lower reward is mainly attributed to the additional cell-aware and handover-risk penalties included in the reward function, as the proposed framework prioritizes risk-aware action selection under dynamic Multi-Cell conditions. Although the GRU achieved high predictive accuracy for downlink bitrate estimation, lower prediction performance was observed for BLER and security-related indicators, highlighting opportunities for further model refinement and feature engineering.

A complete component-wise ablation study was not conducted in the current evaluation. Consequently, the individual

contributions of the GRU prediction and cell-aware mechanisms cannot be fully quantified. A systematic ablation analysis isolating these components is therefore left for future work.

VI. CONCLUSION

This paper presented a predictive AI-native Digital Twin framework for proactive QoS-security orchestration in Multi-Cell 6G environments. The proposed approach combines GRU-based temporal prediction with cell-aware PPO orchestration in order to dynamically adapt network behavior under congestion imbalance, mobility events, and handover-related risks. The simulation results demonstrated that the proposed framework successfully captures important temporal QoS-security trends, particularly for downlink bitrate prediction, while providing accurate cell-aware orchestration under realistic Multi-Cell conditions. In particular, the integration of predictive intelligence and cell-aware DRL significantly improved orchestration accuracy compared with conventional DQN and standard PPO approaches. Overall, the obtained results confirm the potential of combining predictive DT intelligence with DRL-based orchestration for future AI-native 6G systems. An additional direction for future work consists in conducting ablation studies to separately quantify the contribution of predictive GRU intelligence and cell-aware PPO orchestration. Future work will focus on extending the framework toward larger-scale multi-cell environments with higher mobility conditions, heterogeneous traffic profiles, and distributed federated DT orchestration, as well as conducting multi-seed statistical validation and scalability analysis.

REFERENCES

- [1] WU, Wen, HUANG, Xinyu, QIN, Meng, et al. Ai-native network digital twin for intelligent network management in 6g. *IEEE Network*, 2025.
- [2] WANG, Xiaoyun, LU, Lu, LI, Qin, et al. A Task-Driven Design Approach for 6G AI-Native Architecture. *Engineering*, 2025.
- [3] HUANG, Yuhong, KANG, Mancong, ZHU, Yanhong, et al. Digital twin network-based 6G self-evolution. *Sensors*, 2025, vol. 25, no 11, p. 3543.
- [4] ALI, Afan et ARSLAN, Hüseyin. Ai-driven digital twins: Optimizing 5g/6g network slicing with ntns. *IEEE Wireless Communications Letters*, 2025.
- [5] SENGENDO, John et GRANELLI, Fabrizio. AI-Enabled Digital Twins for Next-Generation Networks: Forecasting Traffic and Resource Management in 5G/6G. *arXiv preprint arXiv:2510.20796*, 2025.
- [6] LI, Lanlan. Research on digital twin technology for future 6G. *Intelligent and Converged Networks*, 2025, vol. 6, no 1, p. 20-40.
- [7] ERTURK, Mehmet Ali, DURAN, Kubra, AL-DUBAI, Ahmed, et al. A Digital Twin Platform for QoS Optimization Under DoS Attacks for Next Generation Radio Networks. *arXiv preprint arXiv:2511.18577*, 2025.
- [8] OMHANI, Nouri, KOUBA, Hend, et ZARAI, Faouzi. Artificial intelligence for 5G and 6G networks: A taxonomy-based survey of applications, trends, and challenges. *Technologies*, 2025, vol. 13, no 12, p. 559.
- [9] OGENYI, Fabian Chukwudi, UGWU, Chinyere Nneoma, et UGWU, Okechukwu Paul-Chima. A comprehensive review of AI-native 6G: integrating semantic communications, reconfigurable intelligent surfaces, and edge intelligence for next-generation connectivity. *Frontiers in Communications and Networks*, 2025, vol. 6, p. 1655410.
- [10] GUO, Shuaishuai, ZHONG, Yutong, FENG, Zhenyu, et al. Towards Transparent 6G AI-RAN: A Survey on Explainable Deep Reinforcement Learning for Intelligent Network Slicing. *Journal of Information and Intelligence*, 2025.