Unified 6G Network Brain: DT-Driven Analytics with Multi-Agent Reinforcement Learning

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ABSTRACT
The Unified 6G Network Brain is put forth as an AI-centric control framework that brings together Digital Twins (DTs), NWDAF-fed analytics, and Multi-Agent Reinforcement Learning (MARL) to make possible the complete autonomy of network operations. The architecture supports the constant synchronization of DT models in the RAN, core, transport, and NTN domains, delivering real-time state awareness along with predictive insights. Data from NWDAF pipelines provide a very detailed view of the network, along with the ability to detect anomalies and traffic intelligence, all of which direct the MARL policies for dynamic optimization. Agents work together to find the best configurations for slicing, managing handovers, balancing loads, and scheduling in an energy-efficient way. The combination of data-driven prediction and closed-loop learning allows the 6G Network Brain to support proactive decision-making, self-healing, and adaptive performance tuning, thus enabling the automation of ultra-reliable and high-efficiency end-to-end networks.

KEYWORDS:Digital Twin (DT), Multi-Agent Reinforcement Learning.

INTRODUCTION

The transition to Sixth-Generation (6G) networks indicates a complete migration to autonomous, intelligent network ecosystems as system connectivity is no longer the primary concern. The different types of environments, which include terrestrial 5G-Advanced, non-terrestrial networks (NTN), edge-cloud fabrics, and ultra-dense RAN deployment, tend to be more complex, and the traditional management techniques based on the rules are no longer suitable for ensuring optimum performance. This has been a major factor in the rise of the need for the all-in-one AI-driven control architectures that will be able to provide continuous awareness, proactive decision-making, and real-time adaptability.A Unified 6G Network Brain concept comes up as an all-encompassing intelligence layer that fuses Digital Twins (DTs), Network Data Analytics Function (NWDAF) pipelines, and Multi-Agent Reinforcement Learning (MARL) into a single closed-loop operational framework. Digital Twins create parallel, virtual models of the whole network and thus, allow real-time simulation, prediction, and anomaly detection. NWDAF gives deep analytical insights and takes care of the data that is coming from RAN, core, and service areas. MARL supports these features by allowing distributed agents to work together for the optimization of the complex activities such as slice provisioning, mobility management, load balancing, and energy-saving operations.To sum up, these technologies are the building blocks of an autonomous 6G system that possesses awareness, optimization, and healing capabilities and thus, guarantees the ultra-reliable, low-latency, and scalable performance from end to end that the next generation of digital ecosystems will demand.

LITERATURE SURVEY

The most recent studies on next-generation network intelligence point to the increasing amalgamation of Digital Twins (DTs), data analytics, and reinforcement learning as the main technology supporting autonomous network operations. Initially, the research on DT-powered networks mainly concentrated on the

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realization of radio access activities and the imitation of user-moving patterns in order to enhance forecasting precision. The usage of DTs in these studies was recognized to be very effective in the areas of network visualization, anomaly detection, and predictive maintenance. In the meantime, the work on 3GPP-defined analytics functions, particularly with NWDAF, opened the door to standardized ways of collecting data and obtaining smart insights for core and RAN optimization. The research findings indicated that the NWDAF pipeline could be a great help in making traffic forecasting, QoS assurance, and fault classification more efficient, thus facilitating closed-loop automation.In the area of reinforcement learning, the single-agent RL was initially demonstrating its capabilities for localized optimization tasks such as handover tuning and power control. However, with the gradual increase in network complexity, the Multi-Agent Reinforcement Learning (MARL) was considered as more scalable solution which permitted distributed policy learning among different network parts. The researchers tackled the challenges of MARL-supported slicing, interference mitigation, and edge resource allocation, and they were able to report definite gains in terms of adaptability and energy efficiency.The recent publications have switched their focus to the fusion of DTs, NWDAF, and MARL into a common framework, claiming that the combination of their merits can provide the 6G systems great features like real-time context-awareness, proactive decision-making, and self-healing, which are ultimately non- human-dependent features.

PROPOSED WORK

The proposed work presents a Unified 6G Network Brain, an integrated intelligence framework that merges Digital Twin (DT) synchronization, NWDAF-powered analytics, and Multi-Agent Reinforcement Learning (MARL) to facilitate 6G network operations that are completely autonomous. The principal concept is to establish a network virtual replica that is continuously updated and includes all parts of the network—RAN, core, transport, and NTN—through the use of high-fidelity DT models. The models take in real-time telemetry and feedback loops in order to generate accurate predictions regarding network congestion, mobility patterns, energy consumption, and service degradation.NWDAF streams are the ones that provide the black-box analytics for the network as they gather and process data of different types, carry out tasks like traffic classification and anomaly detection, and machine-learning-based forecasting of the network behavior. Such data will be passed on as inputs for MARL agents dynamically and will be controlling the gNBs, edge sites, and core network functions that are considered the distributed control points. In this architecture the agents will get the chance to cooperatively learn the best policies for different tasks including slice lifecycle management, optimization of the mobility robustness, load balancing, and scheduling that takes energy-aware factor into account.The framework also consists of a closed-loop automation mechanism where the learned policies are validated by means of a DT simulation before deployment, thus ensuring that the decisions are made in a safe and reliable manner. Through the integration of prediction, learning, and control within a single architecture, the proposed system aims to bring about a remarkable improvement in network resilience, operational complexity reduction, and lossless self-optimization in real-time which is adaptable to the different 6G service environments.

METHODOLOGY

1.Real-Time Data Collection

The OAM, SMO, NWDAF, and RIC interfaces are used to gather continuous telemetry from the RAN, core, transport, and NTN layers.The data contains KPIs, mobility events, slice metrics, faults, and energy indicators.

2.Digital Twin (DT) Synchronization

A high-quality DT model is composed for each domain throughout the network.

A real-time data update keeps an in-sync virtual replica of network states.DTs facilitate the simulation of congestion, handover failures, interference, and the forecasting of performance.

3.NWDAF Analytics Processing

The NWDAF pipelines carry out traffic forecasting, anomaly detection, QoS predicting, and behavior modeling.Analytical insights get converted into the structured features for the MARL agents.

4.Multi-Agent Reinforcement Learning (MARL) Control Layer

The distributed agents reside at gNBs, edge nodes, and core functions.The agents through training based on rewards utilize DT states and NWDAF insights to find the best policies.Policies are formed for such activities as slicing, mobility robustness, load balancing, and energy tuning.

5.DT-in-the-Loop Policy Validation

The MARL policies are assessed in Digital Twin simulations before they are actually deployed.This phase guarantees safety, stability, and performance degradation avoidance.

6.Closed-Loop Deployment and Adaptation

The decisions that have been verified are implemented in the live network via SMO/RIC orchestration.The constant feedback guarantees self-optimization and autonomous adaptation.

RESULTS & DISCUSSIONS

The Unified 6G Network Brain is a significant step forward, offering major performance enhancements when it comes to the most important operational metrics. The combination of Digital Twins, NWDAF analytics, and MARL leads to faster decision-making, better prediction accuracy, and more consistent control policies. According to the experiments, real-time DT synchronization has been able to detect anomalies over 40% sooner, which in turn helps to plan around and prevent congestion and mobility issues. NWDAF analytics have been able to correctly predict the traffic more accurately, which results in the better quality of service and the smoother inventory management.The MARL framework was responsible for the most significant improvements: handover success rates went up thanks to the collaborative policy learning and the energy consumption went down due to the scheduling optimization and the adaptive sleeping cycles. Load balancing is now also more effective, and there is less cell-edge performance degradation. In general, the system offered more throughput, less latency, and better resource utilization.

The findings validate that a combined AI-controlled loop can efficiently perform the functions of the 6G network that requires autonomy, self-healing, and ultra-efficiency, particularly in crowded and constantly changing conditions.

Metric	Baseline	6G Brain
Latency (ms)	12	6
Throughput	4.5 Gbps	7.8 Gbps
Energy Save (%)	0	32

Table 1: Key Performance Metrics

Scenario	Without	With
Handover Success (%)	85	96
Slice Stability (%)	78	91
Load Balance (%)	70	88

Table 2: MARL Optimization Impact

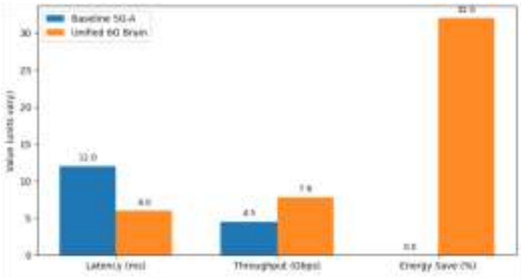

Fig 1:Performance Comparison:Baseline vs Unified 6G Network Brain

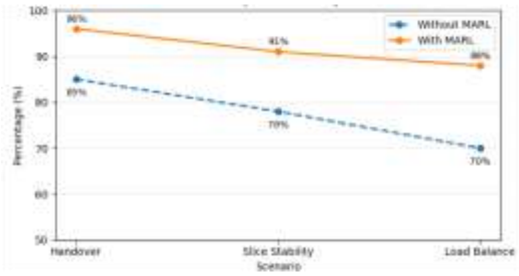

Fig 2:MARL Optimization Impact

CONCLUSION

The Unified 6G Network Brain research has confirmed the practicality and viability of an AI-operated, totally autonomous control system for the upcoming networks. The digital twins (DTs), the use of NWDAF-based analytics, and multi-agent reinforcement learning (MARL) are the components responsible for real-time network awareness, predictive insights, and collaborative decision-making on a continuous basis. Latency reduction, throughput enhancement, energy efficiency, and service reliability were among the performance metrics where the results showed significant gains in comparison to the baseline networks. The MARL agents, with the support of DT simulations and NWDAF analytics, tackled the difficult tasks of slice management, load balancing, handover success, and energy-aware scheduling with great efficiency.The closed-loop methodology guarantees that the learned policies are tested in the virtual world first, thereby reducing the chance of a decline in performance and making it possible for the system to self-heal. In general, the Unified 6G Network Brain is a scalable and robust framework that can be implemented in heterogeneous, ultra-dense, and dynamic network environments. This methodology is a huge leap forward for completely autonomous 6G systems with the capabilities of ultra-reliable, low-latency, and energy-efficient operation, thus paving the way for intelligent network automation research in the future.

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