International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Digital Twin Enabled Human–AI Collaboration Framework for Autonomous Wireless Network Management

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Abstract: The next generation of wireless networks is moving to 5G-Advanced and 6G, which have a high complexity and dynamic operation demands never seen before. Although Artificial Intelligence (AI) provides an avenue to autonomous network management, black-box models pose a significant danger in terms of safety, interpretability, and regulatory compliance. The current article suggests the implementation of a new framework of Digital Twin Enabled Human-AI Collaboration that may close the gap between completely automated systems and human knowledge. The framework allows for checking AI-driven optimization actions against real-world limits by using a detailed digital twin, which serves as a safe simulation space. The architecture incorporates four domain-specific layers: physical telemetry, digital twin simulation, human-AI collaboration, and explainability. The three different types of human-managed oversight that contribute to policy co-evolution. The framework is a guide for creating safe, easy-to-understand, and constantly learning systems that ensure computer efficiency works well with human understanding, improving how resources are used and reducing costs.

Keywords: *6G Network Management, Digital Twin (DT), Human-AI Collaboration, Explainable AI (XAI), Autonomous Wireless Networks*

1. Introduction

The development of wireless communication systems for 5G-Advanced and 6G has brought about unprecedented complexity in managing the network. This development demands the transition to smart automation paradigms that go beyond traditional rule-based self-organizing network (SON) paradigms. It is estimated that the global mobile data traffic will increase at a compound annual growth rate (CAGR) of more than 25 percent until the year 2030, and this increase will put tremendous strain on the network optimization and resource allocation capabilities [1]. To meet such demands, the incorporation of Artificial Intelligence (AI) into Radio Access Network (RAN) management revealed enormous potential to optimize spectral efficiency, latency, and general Quality of Service (QoS) in various dense deployment settings [1].

Digital Twin (DT) technology has now become an enabler of this demanded network intelligence. Using high-fidelity virtual models of physical infrastructure, DTs support sophisticated simulation, trajectory forecasting, and proactive decision validation. The technical analyses of the Internet of Things (IoT) and its telecommunications applications indicate that virtual models can shorten network planning by 30-80 percent [2]. Additionally, they improve accuracy in optimization by allowing detailed "what-if" analyses, which let users explore design models and operational situations in a safe digital environment.

Nevertheless, even with these technical innovations, there is a gap in the core of current autonomous network management systems: there is no systematic introduction of human expertise in the decision-making processes of the AI. Although AI is superior at high-dimensional data processing, human radiofrequency (RF) engineers also have highly valuable tacit knowledge, situational awareness, and field experience that complement computational intelligence.

To address this gap, the given paper proposes a fully developed Digital Twin-Enabled Human-AI Collaboration Framework. The proposed architecture serves as a guide for telecommunications operators, equipment manufacturers, and researchers by creating a reference model that establishes well-organized mechanisms for human supervision, understandable automation, and the co-evolution of policies. The purpose is to deploy a secure, transparent, and adaptable autonomous ecosystem that can meet the

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demands of the next generation of wireless systems that are rigorous.

2. Background and Motivation

The move to autonomous wireless network management is an essential step on the way from reactive optimization to predictive and prescriptive intelligence. Traditionally, Self-Organizing Network (SON) features like coverage and capacity optimization (CCO) and mobility robustness optimization (MRO) have relied on set rules and fixed settings. Even though these automated functions reduced the need for manual setup by about 60 percent, their inability to learn and adapt limited performance gains to small improvements, usually between 8 percent and 12 percent in key performance indicators (KPIs).

DRL and modern neural network structures provide significant improvements to these optimization problems. The studies about the AI-based resource allocation show that DRL agents may gain coverage benefits of 15 to 22 percent of the ones that are achieved by rule-based methods, and, in the meantime, inter-cell interference is minimized by continuous adaptation [3]. Despite these benefits, fully automated AI systems can pose significant challenges in terms of interpretability and accountability within operations. One common theme network operators give is that they are reluctant to deploy "black-box" algorithms because they fear unwanted KPI trade-offs, and they would struggle to justify autonomous decisions to regulatory agencies.

The problems with fully automated methods are most obvious when AI models encounter unusual situations or traffic patterns that they weren't trained on. In these cases, human RF engineers will provide some much-needed contextual intelligence based on field experience and an awareness of site-specific constraints that cannot be easily modeled by data alone. It has been indicated that human-machine teaming within the complex environment can outperform purely automated systems by 18 to 35 percent, especially in situations where the system needs a high level of judgment and exceptions [4].

By enabling the creation of controlled virtual spaces, Digital Twin technology holds the potential to bridge this gap. These twins allow for the analysis and simulation of optimization actions prior to their execution in real time. A high-fidelity digital twin includes coordinated copies of the network's physical elements, radio propagation models, and traffic demand generators. Tests have shown that these digital twins can match real network performance 92 percent of the time for regular optimization tasks, which helps define the risks of using AI for automation. Digital twins guarantee that efficiency facilitated by AI does not compromise service level agreements (SLAs) due to their comprehensive impact assessment.

This table highlights the performance limitations of traditional systems compared to the proposed collaborative approach. The performance limitations of traditional systems relative to the proposed collaborative approach are summarized in Table 1, which compares operational overhead reduction and KPI improvement gains across three management paradigms.

Table 1: Performance Comparison of Network Management Paradigms [3, 4]

Management Paradigm	Control Mechanism	Operational Overhead Reduction	KPI Improvement Gain
Traditional SON	Threshold-based / Static	~60%	8%–12%
AI-Driven (DRL)	Data-driven / Adaptive	High (Automated)	15%–22%
Human-AI Teaming	Collaborative / Contextual	Optimized Oversight	18%–35%

3. Proposed Framework Architecture

The suggested Digital Twin Enabled Human-AI Collaboration Framework is made up of four connected layers designed to help with complete autonomous optimization while still ensuring strong human control and clear decision-making.

3.1 Physical Network and Digital Twin Layers

The physical network layer includes the operational 5G-Advanced/6G infrastructure, which generates large amounts of telemetry. Large urban deployments generate data volumes exceeding several terabytes daily, necessitating the use of high-efficiency ingestion pipelines [5]. This information serves as the primary input for the Digital Twin Layer, which acts as the computational core. This layer combines three-dimensional terrain and pre-calibrated path loss coefficients to simulate radio propagation with a mean absolute error of approximately 6 to 8 dB of physical drive test results [5]. The progress of the twin projects' key performance indicators, like data transfer rates and successful handovers, in each possible setup was achieved by combining these radio models with tools that create traffic demand.

3.2 Human–AI Collaboration Layer

This layer coordinates the synergy between computational power and human intuition. The AI modules build on different architectures, such as Graph Neural Networks (GNNs) to learn topological dependencies between network cells and Deep Reinforcement Learning (DRL) to learn sequential parameter tuning [6]. To make sure that this autonomy is consistent with the goals of operation, the Human Feedback Interface provides a visual representation of the suggested actions, anticipated results, and the confidence interval. The trust layer enables the engineers to test AI recommendations against the organizational policies and site-specific constraints that are coded into the governance modules [6].

3.3 Explainability and Trust Layer

To reduce the risks of the black-box optimization process, the Explainability and Trust Layer incorporates several interpretability mechanisms. The use of feature attribution is a method used to measure the impact of certain input variables on an AI decision; the engineers can determine which network conditions caused a certain recommendation [6].

Additionally, the counterfactual analysis feature allows the system to show different situations, demonstrating how changes in conditions would have affected the AI's suggested actions. This layer alerts any configuration that is nearing SLA limits by presenting risk and safety impact projections to make sure that autonomous operations are both accountable and adhere to telecommunications regulations. The complete four-layer architecture of the proposed framework, illustrating the interaction between the physical network, digital twin, human–AI collaboration, and explainability layers, is presented in Figure 1.

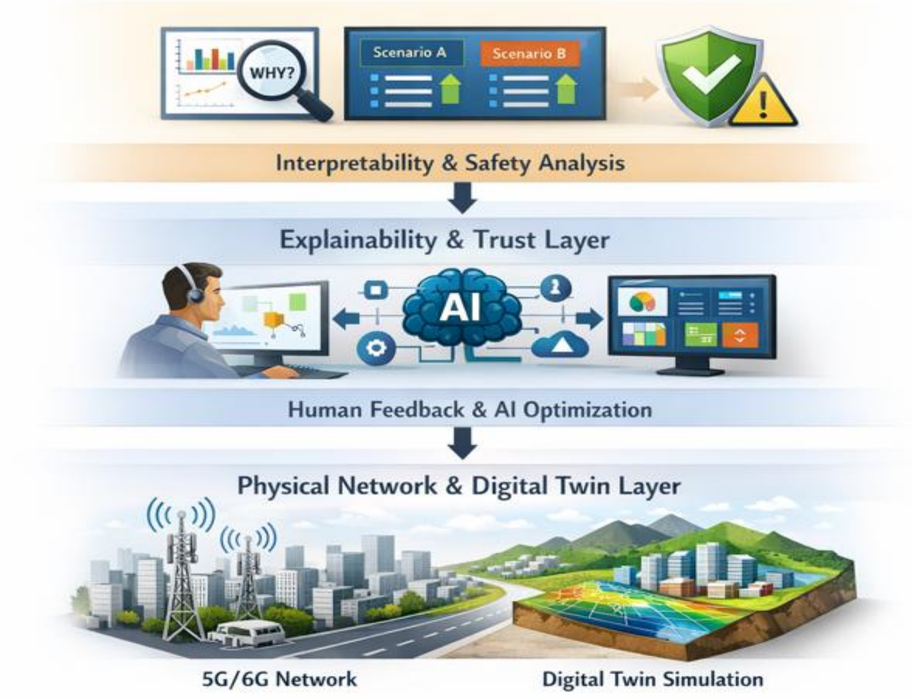

Fig. 1: Digital Twin Enabled Human-AI Collaboration Framework [5, 6]

4. AI Workflow and Human–AI Partnership Modes

The working process of the framework is based on a strict series of actions to be taken to guarantee that the AI-driven actions are carefully screened prior to the live network implementation. First, the AI agent monitors the network condition with the help of the digital twin that ensures real-time matching with the radio settings and environmental conditions. According to this state, the agent will produce a candidate. Optimization actions include adjusting the antenna tilt, transmit power, and handover thresholds across various domains. It has been shown that deep learning agents performing in these high-dimensional spaces can be successful in comparing 50–200 candidate actions per decision epoch to computational tractability [7].

4.1 Simulation and Safety Filtering

The digital twin performs the multi-scenario simulation of every candidate action. This process includes testing how well the system can handle extreme situations, such as sudden increases in demand or equipment failures, which may not be included in past training data. To maintain the stability of the operations, simulation results are compared with the predefined constraint limits by safety filtering modules. Clearly defined safety rules in the learning process can help lower unwanted negative results by 40 to 65 percent compared to optimization without these rules.

4.2 Human–AI Partnership Modes

The framework outlines three levels of collaboration to have varying levels of organizational trust and operational criticality:

- **Human-Supervised Autonomy:** This is one of the conservative ways in which the AI agent creates optimization suggestions, which must be approved by humans prior to implementation. This fits one in, especially in safety-critical sections or high-value enterprise locations [8].
- **Human-Assisted Autonomy:** This system ensures the AI performs approved types of actions independently, but the human engineer oversees the performance. The human gives labels or comments on unexpected outcomes, which act as a form of feedback to correct the future behavior of the AI [8].
- **Human-Guided Policy Evolution:** This approach is the most developed because it systematically changes the AI's reward functions and safety parameters based on the aggregated human responses. This ensures that the operator's strategic organizational goals guide the AI's long-term learning trajectory [7].

The complete AI workflow and the three Human–AI Partnership Modes, from human-supervised autonomy through to human-guided policy evolution, are illustrated in Figure 2.

Fig 2: AI Workflow and Human-AI Partnership Modes [7, 8]

5. Key Advantages and Conceptual Use Cases

The suggested framework is immensely advantageous throughout the lifecycle of autonomous network management, with safety, cost efficiency, and performance stability taking precedence.

5.1 Safety, Explainability, and Operational Efficiency

The first benefit is the achievement of understandable and safe autonomy. With impact assessment through the digital twin, the operators will be able to set the level of validation stringency depending on the sensitivity of the network segment. This progressive level of autonomy can enable the application of AI to high-stakes settings where, hitherto, the use of black-box models was forbidden [9].

Also, the framework greatly minimizes Operational Expenditure (OPEX). Assessments in industry indicate that an all-inclusive digital twin application can cut network optimization costs by a quarter to half [9]. This procedure reduces reliance on physical drive testing and trial-and-error tuning by alternating weeks of field testing with virtual simulations, which take minutes.

5.2 Continuous Learning and Adaptation

The framework solves the problem of "distributional shift" when the performance of AI deteriorates with the change in the real-world environments. The AI agents are long-term reliable in the dynamic 6G environments through a multi-source learning methodology that applies real-world KPI measurements, digitally twinned synthetic rare events, and human-centered expertise feedback [10].

5.3 Conceptual Use Cases

Some of the most important things that the framework can be used to do are:

- **Automated Coverage & Capacity Optimization (CCO):** AI agents search antenna tilting and power mixes in the digital twin. Human engineers review these recommendations for clusters of important infrastructure to implement zero-risk distribution [10].
- **The twin coordinates interference with safety checks by anticipating Physical Cell Identity (PCI) conflicts and beam interference patterns.** Safety modules automatically block any configuration that could potentially lead to a catastrophic enhancement of inter-cell interference.
- **The AI employs cell sleep mode to reduce power consumption during periods of low traffic.** A human-controlled policy will guarantee that certain areas of coverage for specific VIP services or emergency services will be covered even where the AI does not achieve its energy-saving objectives [9].

Table 2 summarises the quantified economic and operational benefits of implementing the proposed framework across four benefit categories, together with their associated strategic use cases.

Table 2: Quantified Advantages and Strategic Use Cases [2, 8, 9, 10]

Benefit Category	Impact Metric	Primary Use Case
Operational Cost	25%–40% OPEX Reduction	Remote Optimization
Planning Speed	30%–40% Cycle Reduction	6G Site Deployment
Decision Safety	40%–65% Failure Reduction	Safety-Constrained Tilt
Energy Efficiency	Adaptive Sleep Modes	Energy Saving/VIP Override

Table 2: Quantified Advantages and Strategic Use Cases [2, 8, 9, 10]

6. Challenges and Future Research Directions

Although the given framework has some conceptual strengths, a number of technical and organizational issues have to be addressed before such a widespread implementation in 6G ecosystems will be possible.

6.1 Scalability and Fidelity

The computation of digital twin fidelity in high - dimensional networks represents a technical limit. The 5G-Advanced and future 6G deployments can contain thousands of cells in a single metropolitan region, and the propagation modeling and behavioral simulation will have to be highly accurate. To maintain a prediction accuracy level of 92% correlation [4] and to effectively scale to such a large size, substantial improvements in distributed simulation architectures and computational performance are necessary [9].

6.2 Synchronization and Latency

Time-sensitive optimization depends on real-time synchronization of physical and virtual network images. Nowadays, the latencies of synchronization can reach several minutes or even hours [10]. This latency is inadequate in situations where a quick response is needed, like interference suppression during a surge of traffic, an emergency, or an unexpected equipment breakdown. Future research should focus on low-latency data pipelines to ensure timely digital twin updates in real-time.

6.3 Human-AI Calibration and Bias

There is a necessity to balance the cost of human involvement and the benefit of the operation. Over supervision can cancel the efficiency gain of automation, whereas a lack of supervision would result in an exposure to risks [8]. Also, there is a big risk of spreading bias, and AI agents might unknowingly keep using outdated methods or make unfair choices in resource distribution unless there are safe and clear controls in place.

6.4. Standardization and Regulation

Multi-vendor interoperability needs to be standardized in model exchange formats and digital twin interfaces. Although similar organizations such as 3GPP and the O-RAN Alliance have started related Detailed specifications for work items are still being developed [5]. Finally, rules and guidelines need to change to ensure responsibility and safety in AI-driven networks, allowing for improvements that benefit the public while keeping the network secure.

7. Conclusion

This article has outlined a design for a framework that allows humans and AI to work together using digital twins, focusing on ensuring safety and transparency in the next generation of wireless networks. The ability of digital twins to predict outcomes, AI's skill in learning and adapting, and human engineers' understanding of context together help overcome the limits of traditional network management that

This analysis shows that using a multi-layered approach, supported by partnership structures and explainability tools, leads to a strong connection (92%), a shorter network planning time (30-40% less), and lower operational costs (25-40% less). Although there are technical issues to tackle, like timing delays and the need for detailed digital twins, the proposed framework provides a solid and flexible foundation for self-managing 6G systems. Finally, the digital twin validation enables the human intuition and machine intelligences to work in harmony, which will unlock the full power of the intelligent wireless infrastructure in the future.

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