This article has been accepted for publication in IEEE Communications Standards Magazine. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/MCOMSTD.2025.3575511

WIND: A Wireless Intelligent Network Digital Twin for Federated Learning and Multi-Layer Optimization

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***Abstract*—The forthcoming wireless network is expected to support a wide range of applications, from supporting autonomous vehicles to massive Internet of Things (IoT) deployments. However, the coexistence of diverse applications under a unified framework presents several challenges, including seamless resource allocation, latency management, and system-wide optimization. Considering these requirements, this paper introduces WIND (Wireless Intelligent Network Digital Twin), a self-adaptive, self-regulating, and self-monitoring framework that integrates Federated Learning (FL) and multi-layer digital twins to optimize wireless networks. Unlike traditional Digital Twin (DT) models, the proposed framework extends beyond network modeling, incorporating both communication infrastructure and application-layer DTs to create a unified, intelligent, and context-aware wireless ecosystem. Besides, WIND utilizes local Machine Learning (ML) models at the edge node to handle low-latency resource allocation. At the same time, a global FL framework ensures long-term network optimization without centralized data collection. This hierarchical approach enables dynamic adaptation to traffic conditions, providing improved efficiency, security, and scalability. Moreover, the proposed framework is validated through a case study on federated reinforcement learning for radio resource management. Furthermore, the paper emphasizes the essential aspects, including the associated challenges, standardization efforts, and future directions opening the research in this domain.**

***Index Terms*—5G, Digital Twin, Artifical Intelligence, Machine Learning, Federated Learning, Radio Resource Management, Multi-Layer Optimization.**

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This work is supported by The Scientific and Technological Research Council of Turkey (TUBITAK) 1515 Frontier R&D Laboratories Support Program for BTS Advanced AI Hub: BTS Autonomous Networks and Data Innovation Lab. Project 5239903.

I. Introduction

The forthcoming wireless network is expected to accommodate a wide range of use cases, each with a different level of Quality of Service (QoS) requirements. Furthermore, the rapid expansion of autonomous systems and the industrial Internet of Things (IoT) demands that modern wireless networks support heterogeneous traffic, ultra-low latency, and stringent reliability constraints. Addressing these challenges requires a fundamentally new approach to network optimization and intelligent decision-making [1]. The notion of the Digital Twin (DT) [2] emerges to be the most preferred and convenient solution among the available options. Specifically, DT creates real-time virtual replicas of wireless networks for dynamic analysis, optimization, and predictive modeling. While traditional DTs in wireless networks exclusively focus on network modeling, the next-generation intelligent wireless ecosystem demands an integrated approach that can simultaneously model the network infrastructure and the applications running on top of it. Accordingly, the dual-layer DT approach ensures a symbiotic relationship between physical entities and their virtual representations, allowing for real-time synchronization and intelligent decision-making.

Considering the increasing complexity of modern wireless networks, we introduce WIND (**W**ireless **I**ntelligent **N**etwork **D**igital Twin), a self-adaptive, self-regulating, and self-monitoring system-of-systems that leverages Federated Learning (FL) and Multi-Layer DTs for real-time optimization and intelligent resource management. Unlike conventional DT implementations, which primarily focus on network modeling, WIND extends beyond traditional approaches by integrating both the communication network and application-layer DTs, enabling a seamless and dynamic interaction between infrastructure and services. The key contributions of this work are as follows: *a)* A novel Multi-Layer DT architecture that integrates both communication and application-layer digital twins, allowing real-time monitoring, optimization, and predictive modeling for next-generation wireless networks. *b)* An adaptive FL-driven resource management framework, where local Machine Learning (ML) models based on Reinforcement Learning (RL) algorithms at the edge enable low-latency decision-making, while Federated Reinforcement Learning (FRL) ensures global optimization across the network without requiring raw data exchange, improving both scalability and privacy preservation. *c)* A traffic-aware scheduling mechanism that dynamically prioritizes different traffic classes based on QoS requirements,

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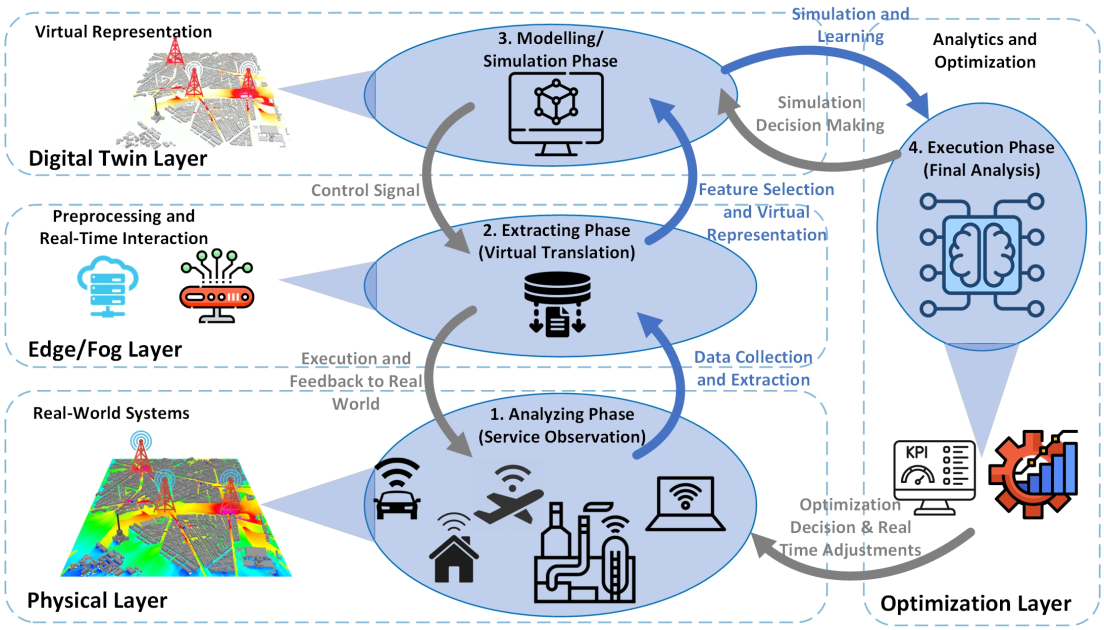

Fig. 1. Multi-Layer Digital Twin (DT) Architecture

ensuring efficient and fair resource allocation across heterogeneous applications. *d)* An FRL-based case study for radio resource management, demonstrating how WIND enhances scheduling efficiency, QoS, and traffic prioritization compared to conventional scheduling policies. *e)* A comprehensive discussion on key challenges, standardization efforts, and future research directions in DT-driven wireless networks, addressing critical aspects such as security, synchronization, and energy efficiency.

II. Multi-Layer DT Architecture: A Wireless Perspective

The DT models aim to create a virtual representation of the physical system, functioning in two distinct modes: real-time monitoring and control alongside the physical system, and pre-deployment simulation for predictive analysis and optimization. This differentiates DTs from traditional simulations such as Sim Scale and AMEsim, which model specific scenarios but lack continuous feedback loops and real-time interaction. In contrast, DT models dynamically synchronize with real-world data, enabling monitoring, analysis, and optimization through evolving learning techniques [3].

Within the wireless communications, simulation environments have been essential for performance evaluation. Meanwhile, AI-driven learning techniques have proven effective in optimizing network operations. DTs bridge these approaches by integrating simulation-based testing with real-time learning and adaptation. Fig. 1 depicts the proposed Multi-Layer DT architecture consisting of four layers, as follows:

i. Physical Layer: The DT process begins with the Analyzing Phase (AP) located at the Physical layer, which involves extensive data gathering and event mapping from real-world systems. For wireless systems, this data may include the number of cellular users, serving stations, vehicle density, and mobile user speed. Data is captured through various means, such as sensors, cameras, and edge computing devices, providing insights into network performance metrics, including cost, reliability, efficiency, and scalability. This phase ensures that the DT has access to comprehensive and up-to-date information.

ii. Edge/Fog Layer: Once the data is analyzed, the Extraction Phase (EP) located at the Edge/Fog layer, focuses on efficiently selecting and processing relevant information. This phase employs ML and Deep Learning (DL) algorithms to extract critical insights, optimize feature selection, and translate real-world data into a digital format. A feedback loop operates between the analyzing and extracting phases, ensuring continuous refinement of extracted data and allowing control signals to regulate data collection processes dynamically. Since the EP is located at the Edge Layer, being closer to the real-world system it also handles real-time adjustments, making short-term, quick changes (e.g., traffic offloading, latency mitigation, adaptive scheduling and dynamic resource allocation).

iii. Digital Twin Layer: The DT layer consists of the Modeling/Simulation Phase that represents the core of the DT system, responsible for representing real-world data in a virtual space. The extracted information is processed using advanced simulation tools and AI-based frameworks. This phase operates in two modes: *(1) Real-time monitoring and control*: The DT functions alongside the real-world system, continuously adjusting parameters through edge computing and AI-driven insights. *(2) Pre-deployment simulation and testing*: Before actual implementation, network changes can be tested in a simulated environment to assess performance and impact, reducing risks in real-world deployment. This is crucial for strategic decisions like network expansions, infrastructure upgrades, and optimization strategies without disrupting real-world operations. This phase includes multiple training and optimization cycles, ensuring that simulations remain aligned with real-world conditions and adapting dynamically to new challenges.

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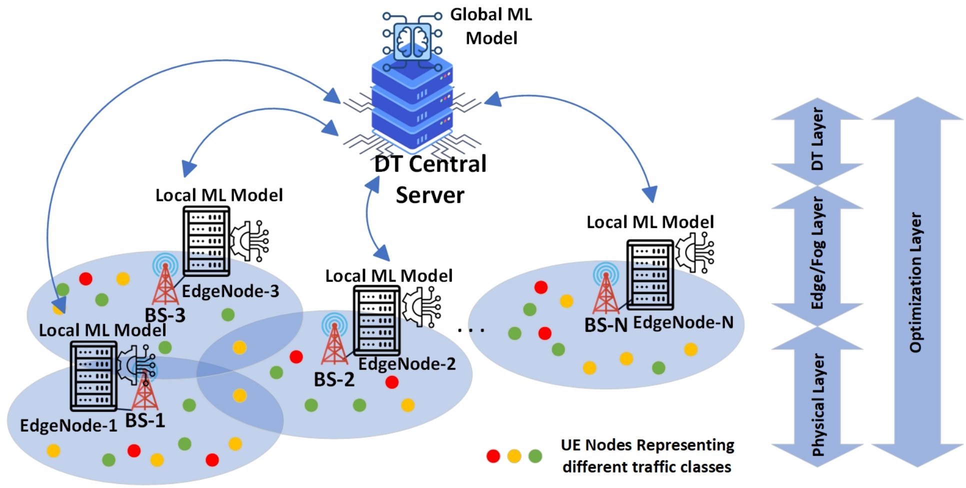

Fig. 2. An illustration of the WIND system model.

iv. Optimization Layer: Located at the Optimization Layer, the execution phase, represents the final stage, where the refined digital model provides actionable insights for both real-time network optimization and strategic deployment decisions. In real-time operations, AI models drive network adjustments and send optimization decisions for immediate actions to the physical layer for long-term improvements. Meanwhile, pre-deployment simulations aid decision-makers in strategic planning and infrastructure expansions by testing and validating network adjustments before real-world implementation. By enabling the information flow from the Optimization Layer back to the DT Layer, we allow for experimentation and simulation before AI/ML recommendations are applied to the real-world system.

Through these structured interactions, the proposed Multi-Layer DT framework ensures a seamless integration between simulation, AI-driven learning, and real-time operational adjustments, maximizing efficiency and adaptability in complex wireless network environments.

III. WIND: Wireless Intelligent Network DT

The rapid expansion of wireless networks is expected to connect billions of users and devices, exhibiting different traffic patterns and resource requirements, which raise the demand for an intelligent and adaptive management approach. Figure 2 introduces the WIND system model, that is mapped to the proposed layered architecture as follows:

- *Edge Layer for Low-Latency Decisions:* Local ML models at edge nodes manage immediate resource allocation, leveraging RL-based algorithms to dynamically prioritize traffic classes and allocate radio resources. This enables efficient real-time decision-making while maximizing QoS revenue.
- *FL for Long-Term Optimization:* The DT central server aggregates local RL model updates, refining a global RL model that enhances network-wide performance continuously, all without requiring centralized data collection.

This integration of hierarchical ML learning with edge-local models managing short-term adaptations and FL optimizing long-term performance creates a self-adaptive, traffic-aware wireless network.

A. Digital Twin-Driven Federated Learning System Model

In Fig. 2, the User Equipment (UE) nodes represent real-world use cases in a virtualized DT environment. Unlike conventional systems that randomly assign resources, the DT-driven approach categorizes UEs based on traffic classes, allowing ML models to allocate resources dynamically based on priority levels. The WIND system consists of three main components: *(1) UE Nodes*: These include mobile devices, IoT sensors, UAVs, and autonomous vehicles, each classified based on traffic requirements (e.g., latency-sensitive, high-bandwidth, or best-effort traffic). This classification ensures that latency-sensitive applications receive prioritized resource allocation. *(2) Edge Nodes and Base Stations (BSs)*: Each BS is connected to an edge node that hosts a local ML model. These models process real-time traffic data, handling immediate decisions such as load balancing, interference mitigation, and resource scheduling. This edge-based learning ensures ultra-low latency responses without overwhelming the central infrastructure. *(3) DT Central Server*: The central decision-making entity aggregates local ML model updates from different edge nodes, refines a global FL model employing a mixed federated averaging as the aggregation technique based on neural network weights and Temporal Difference (TD) errors, and redistributes optimized parameters to improve network performance over time. This approach eliminates raw data transmission, preserving privacy while continuously improving the accuracy of the model.

B. Adaptive Traffic-Aware Learning Process

WIND follows a structured learning and optimization cycle:

- *Cluster Formation and BS Association*: UE nodes form clusters and associate with the nearest BS, enabling local learning and decision-making. Each BS is linked to an edge node, where ML models process real-time traffic and optimize scheduling and resource allocation.
- *Adaptive Traffic Prioritization and Scheduling*: UE nodes are categorized based on their traffic class and associated QoS requirements (e.g., latency-sensitive VR streaming, high-bandwidth best-effort IoT traffic). Each UE cluster employs locally Continuous Actor-Critic Learning Automata (CACLA)

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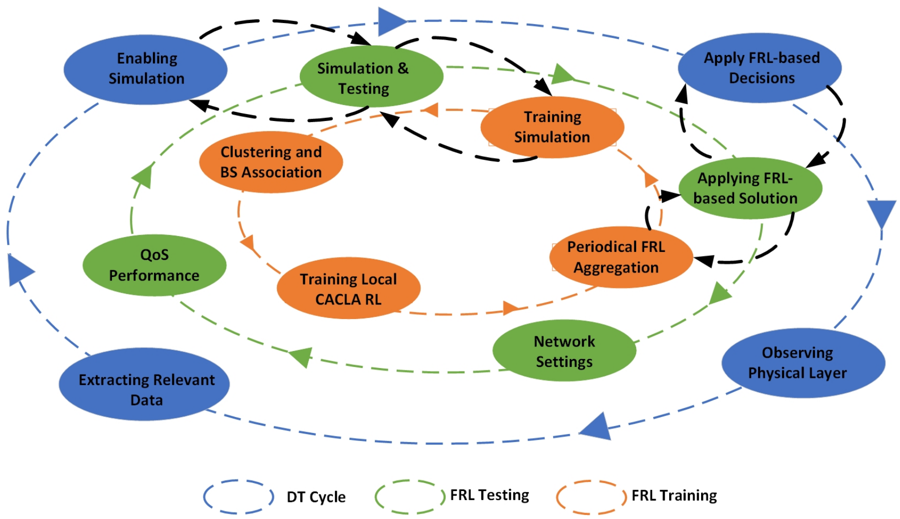

Fig. 3. The Principle of WIND Global Optimization

algorithm to determine the optimal traffic prioritization order and scheduling rule at each Transmission Time Interval (TTI), aiming to maximize QoS revenue for each class [4]. The model updates two Neural Networks (NNs): a critic NN (value function) that estimates the expected return for a given state and an actor NN (policy value) that determines the prioritization order and scheduling rule. The actor network updates only when the critic indicates a positive advantage, ensuring stable learning and efficient resource allocation [5].

- *Federated Learning*: This phase involves the periodic aggregation of model updates from multiple edge nodes to refine a global model. Each edge node trains a local CACLA RL model based on observed traffic patterns and virtual network conditions. During each aggregation cycle, the updated NN information (weights, TD error) for both actor and critic is sent to the DT Central Server, where the FRL-based aggregation is applied: *a)* the federated actor network is updated by averaging the weights of all local actor networks, and *b)* the federated critic network is updated by averaging the TD errors received from the edge nodes. The refined federated actor-critic model is then distributed back to edge nodes, ensuring long-term, network-wide optimization and improving generalization across diverse traffic conditions.
- *Global Optimization*: The process of WIND global optimization follows the model of three nested and interdependent cycles as shown in Fig. 3: DT, FRL Testing, and FRL Training. The DT cycle continuously monitors the physical network, gathers relevant data, and enables a simulation-based environment for modeling. During each cycle, the performance of trained FRL solution is evaluated in the testing phase, measuring QoS revenue optimization across different virtual network conditions. If performance is insufficient, the FRL training cycle is triggered, where local CACLA RL models are trained, and then, federated NNs are periodically updated. Once training is complete, the retrained FRL solution is evaluated through the FRL testing cycle before applying the updated model to the physical network. If QoS performance meets the required thresholds, then the FRL model is deployed at the Edge/Fog layer for real-time scheduling. Otherwise, the training cycle may be extended or request additional data from the DT cycle to improve learning.
- *Continuous Adaptation and Performance Enhancement*: While FL and Global Optimization happen at scheduled intervals, Continuous Adaptation is a real-time, local process at the edge nodes. Each edge node dynamically fine-tunes its ML model parameters based on real-time network conditions, such as sudden traffic surges or varying QoS demands. These local updates allow immediate adaptation to changing conditions without waiting for the next FL aggregation round, ensuring low-latency decision-making for time-sensitive applications.

C. WIND as an Adaptive Learning Framework

By leveraging DT-driven Federated Learning, the proposed WIND framework achieves: (1) *Ultra-low latency communication:* Edge-local RL models handle real-time decisions in the DT cycle, ensuring rapid responses; (2) *Privacy-Preserving AI Optimization:* Federated learning minimizes dependence on centralized data collection by sharing only relevant neural network updates, thereby enhancing security; (3) *Traffic-aware resource management:* The system dynamically prioritizes traffic classes in the short term and selects scheduling strategy per class to prevent overprovisioning, optimizes per-class QoS revenue, and maintains long-term traffic class prioritization.

In addition to improving scheduling efficiency and QoS, WIND is designed to enhance energy efficiency in next-generation wireless networks. Using localized ML models at the Edge/Fog Layer, WIND reduces unnecessary data transmission to central servers, thereby minimizing communication overhead and energy consumption. The FL approach further optimizes energy use by enabling distributed training at edge nodes, eliminating the need for raw data exchanges, which would otherwise consume substantial network resources. Moreover, the traffic-aware scheduling mechanism dynamically allocates network resources based on real-time demand, preventing over-provisioning and reducing power consumption at BSs. Additionally, WIND's multi-layer digital twin architecture can predict traffic variations and proactively adjust network configurations, ensuring that idle BSs enter low-power states when not in use. These combined capabilities

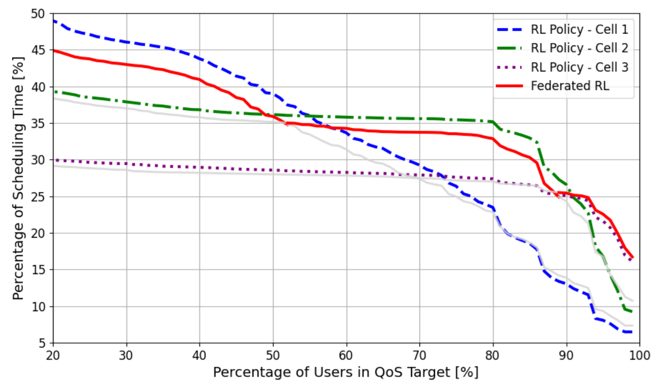

Fig. 4. Federated RL in Scheduling and Radio Resource Allocation.

position WIND as a scalable, energy-efficient solution for future 6G wireless networks, aligning with green networking objectives.

D. WIND: Simulation Results

To evaluate the performance of the proposed WIND architecture, we conducted simulations focusing on FRL-based solution for radio resource management in a wireless network environment. The primary objective is to demonstrate how WIND's hierarchical learning framework, which combines edge-based ML for real-time decisions with FL for long-term network optimization, improves network efficiency, resource allocation, and QoS.

The simulation is conducted using an enhanced LTE-Sim simulator with AI-driven network data processing and algorithms [5]. We consider downlink transmissions with a 100MHz bandwidth across five 20MHz carrier components, each modeled as an urban micro-cell (200m radius, FDD mode). Inter-cell interference is accounted for using a 7-cell cluster model, while Jakes fading models the downlink channels. User mobility follows a random walk model at 3 km/h. The WIND framework operates only on the central cell of each cluster, with surrounding cells generating interference. Additionally, three distinct cells (**cell_1**, **cell_2**, **cell_3**) are simulated with identical structural characteristics but differing user distributions, mobility patterns, service demands, and speeds, ensuring diverse network conditions.

The packet scheduler works per carrier component, with a maximum of five retransmissions per packet before declaring loss. The traffic mix includes 360° video (20 Mbps), live video streaming (1 Mbps), VoIP (32 kbps), and FTP (256 kbps), distributed as 20%, 60%, 15%, and 5%, respectively, claiming diverse QoS requirements [5]. Each cell is managed by an edge server, where a local CACLA-RL algorithm trains actor-critic NNs to determine the optimal traffic prioritization order and apply an adaptive scheduling rule in the frequency domain at each TTI. Neural network configurations were evaluated in the FRL testing cycle, with the optimal structure consisting of three hidden layers with 150 nodes each, applied to both local and federated actor-critic networks.

The evaluation process follows the WIND global optimization principles as depicted in Fig. 3. In the DT cycle, the *Analyzing and Extraction Phases* generate digital footprints of the physical layer, capturing various observations and measurements such as channel quality indicators, instantaneous throughput, delay, packet loss, and traffic arrival rates. These digital footprints then facilitate the simulation environment through the *The modeling and simulation phase*, enabling the training and testing of FRL-based solutions. Since no FRL solution is initially available, the framework begins with the FRL training cycle, where local actor-critic NNs are trained for 1000s, followed by the application of aggregation methods. The local and federated actor NNs are then compared and evaluated in the FRL testing phase over 500s to assess their QoS provisioning performance. Given that all actor NNs share the same configuration, the computational complexity of executing these solutions in parallel remains nearly identical. Finally, the federated actor NN is integrated into the DT cycle, optimizing latency-sensitive traffic prioritization while balancing network load. Future work will analyze computational complexity in FRL training and testing cycles, the overhead of sharing actor-critic NN updates, and the response time of FL-driven scheduling decisions in the physical layer.

Performance comparisons between local trained RL policies and WIND-enabled federated reinforcement learning reveal significant improvements. Figure 4 illustrates the performance of the trained RL policies for each cell, showing the percentage of users meeting all QoS requirements across different traffic classes, with the amount of time when these QoS objectives are met. The local RL policy for **cell_1** exhibits a sharper decline, as 360° video users are prioritized due to their better channel conditions, while other traffic classes experience lower QoS satisfaction because of varying speeds and less favorable channel conditions. In **cell_2**, the local RL policy maintains a more stable representation, as the algorithm optimizes service distribution, ensuring 360° video users receive their requested QoS, albeit at the expense of other traffic classes, which experience a reduced amount of time for QoS satisfaction. In **cell_3**, the curve is even flatter, reflecting the wider spatial distribution of 360° video users, which influences the overall scheduling dynamics. In contrast, WIND's FL approach dynamically adjust scheduling rules based on real-time traffic conditions and global learning insights, resulting in a more balanced allocation of resources across all traffic classes.

Simulation results demonstrated that WIND improves QoS satisfaction across multiple performance metrics. The percentage of users meeting their QoS requirements (latency, throughput, packet loss) is consistently higher under WIND-enabled scheduling than standalone RL models being used in different network settings. Additionally, the federated RL model exhibits better generalization across cells, ensuring stable performance even in varying network conditions. Unlike single-cell RL training, which optimizes policies for localized conditions but struggle with adaptability, WIND's federated approach leverage knowledge from multiple cells, enabling it to respond effectively to dynamic traffic fluctuations.

Further analysis highlight WIND's impact on network efficiency. By offloading real-time scheduling decisions to edge-based ML models, the framework significantly reduce the computational overhead on central servers while maintaining low-latency responses for time-sensitive applications. This adaptive learning cycle, where short-term adjustments at the edge inform long-term federated optimizations, prove to be

TABLE I
MAJOR CHALLENGES OF WIRELESS COMMUNICATION

Major Areas	Challenges	Remark	Opportunities with DTs
Artificial Intelligence / Machine Learning	The data required to train the models is scarcely available	Enables hi-tech robots, machines and promotes automation	The real-time data integration of DTs and the DT-generated data can be used to train models and test models [6].
Back-Scattering	The backscattering communication utilizes the backscattered signals, which require effective precoders.	It supports the back reflection to save the energy level.	Different precoder designs can be tested using the DTs [7].
Big Data	Processing and storing issues in big data	It is proposed to handle large sizes of data in an efficient manner	DTs use a streamlined data processing and manage the flows intelligently instead of collecting raw data continuously [6].
Internet of Things	Sensing and connectivity issues	Supports of millions of new devices i.e., IoT Industries	DTs can be used to develop and deploy proactive management methods to efficiently manage the IoT devices [8] .
Edge Computing	Reliable and robust system required for implementation	To reduce the latency and improve the edge computing	The task offloading decisions can be made by DTs in real-time while considering the computation resources, energy consumption and other related parameters [9].
Terahertz Communication	Small coherence window and Localization issues	Open new possibilities for high speed devices through broad spectrum	To solve the localization problems under small coherence time window, DTs can be used as predictive models.
6G	The AI/ML's involvement in network management within 6G may pose challenges in ensuring network reliability	There is a major motive to support the diverse applications that have the unique quality of service requirements	The DTs can be used to model the network and predict the outcomes in real-time of one control action before applying to the physical network [10]. This means that the reliability of the network can be increased.

highly effective in balancing network resource utilization, improving service reliability, and reducing congestion.

Overall, the simulation results validate WIND's capability to optimize next-generation wireless networks by bridging real-time edge intelligence with federated global learning. The framework's ability to continuously refine scheduling policies based on evolving network conditions makes it a scalable, self-adaptive solution for future wireless ecosystems, particularly in 6G and beyond networks.

IV. USE CASES, STANDARDIZATION, CHALLENGES AND FUTURE DIRECTION

This section focuses on the main challenges, standardization efforts, and future research directions related to the evolution of DT in wireless communication.

A. Use Cases

DTs have the potential to revolutionize various sectors, including industrial IoT, healthcare, and manufacturing. Recognizing their impact, standardization bodies are actively working to develop frameworks for DT integration. Key sectors where DTs hold great potential [2]:

- *Industrial IoT & Healthcare:* DTs enable autonomous monitoring, tracking, and control of industrial systems. Beyond operational data, they can capture environmental data such as location, configuration, and financial models, which are crucial for activities such as anomaly detection and future operations prediction. Similarly, DTs can be used to create virtual models of healthcare systems, which may help reduce costs, improve patient monitoring, and enable personalized healthcare delivery.
- *Automation & Manufacturing:* DTs have a wide range of applications in the automotive sector, such as creating virtual models of connected vehicles. The model depicted in Fig. 1 can be adapted to capture the behavioral and operational data of intelligent transportation systems, helping to analyze the performance of connected vehicles. Additionally, DTs can transform the design, manufacturing, and maintenance of products, leading to more efficient processes, optimized operations, and reduced throughput times.

B. Standardization Efforts

There is growing interest in DTs, and several standardization initiatives are underway to establish guidelines for their effective deployment. These efforts are essential to ensuring interoperability, security, and efficiency in the integration of DTs into wireless communication networks. Key standardization bodies include: *a) International Telecommunication Union (ITU):* The ITU Telecommunication Standardization Sector (ITU-T) is actively developing standards for DT networks. Notably, Recommendation ITU-T Y.3090 outlines the framework for 2030 network services, *b) IEEE:* The IEEE Standards Association has initiated efforts, such as IEEE P2806, to standardize DT technologies across various sectors, including wireless communications. *c) 3rd Generation Partnership Project (3GPP):* Within the context of 5G and evolving 6G technologies, 3GPP has been exploring the incorporation of DT concepts to enhance network management and orchestration. These initiatives aim to create virtual representations of network elements to improve monitoring, optimization, and predictive maintenance.

C. Challenges

Table I summarizes the key challenges and opportunities associated with DTs in modern wireless communication systems [11]. These challenges include:

- *DT migration:* DTs are often designed for specific environments, leading to challenges when migrating them to new contexts. Reusing a DT model without redesigning or redeveloping it can result in reduced accuracy and effectiveness. In wireless communications, each user may have unique requirements, leading to compatibility issues when migrating the DT across different networks. Additionally, constantly changing wireless topologies increase the risk of data corruption during

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migration. Factors such as noise, interference, and bandwidth limitations can further affect the DT's accuracy. To mitigate these challenges, it is important to evaluate the available options in the new wireless communication environment and ensure compatibility with the existing DT model [12].

- *Data management and storage:* Wireless communication signals are subject to fluctuations, which are captured by BSs and transmitted to users. As DTs continuously monitor these variations, they generate large data volumes leading to latency and reliability issues. Effective data management and scalable storage solutions are necessary to address these challenges and ensure the smooth operation of DT systems [13].
- *Safety, security and privacy:* Ensuring the secure deployment of DT technology requires addressing key safety, security, and privacy challenges in wireless communication. The integration of DTs expands the threat landscape, as the data and control flows between physical and virtual entities are vulnerable to interception and cyberattacks, particularly in open-air wireless environments. Furthermore, storing and processing real-time user traffic data raises concerns about unauthorized access and privacy breaches. Furthermore, while FL improves privacy by keeping raw data at the edge devices, it introduces new security risks, including model poisoning attacks, inference attacks, and communication interception. These vulnerabilities necessitate robust security measures, such as secure encryption protocols, anomaly detection mechanisms, Byzantine-resilient aggregation, and privacy-preserving techniques, to ensure the integrity, confidentiality, and resilience of DT and FL-driven wireless networks. Implementing backup systems and intrusion detection mechanisms further enhances network reliability against potential threats [14].
- *Synchronization*: DTs depend on synchronized systems that convert real-time operations into virtual models. Fluctuations in real-time operations, like signal quality degradation, can adversely affect system performance. Synchronization is critical for effectively modeling real-time projects in virtual systems. To achieve optimal synchronization, delays must be minimized, and accurate conversion techniques must be employed. Wireless communication systems often face interference and attenuation, which can degrade signal quality and reliability. Overcoming these challenges requires advanced hardware and agile software that can reliably transfer data to the physical system. Proper technology implementation minimizes synchronization issues, ensuring accuracy and timeliness [14], [15].

D. Future Research Directions:

As discussed, DTs offer numerous advantages, opening up exciting possibilities for the future. Some key future research directions include:

- *New Era of Modern Technologies:* To enhance the performance of wireless communication systems, various advanced technologies (e.g., AI, ML, DL, Blockchain, Cloud Computing, Multi-Access Edge Computing, IoT, etc.) can be integrated, as shown in Table I. Implementing these technologies at the ground level requires modifications to architecture components such as antennas, radio units, and remote radio heads. A DT-integrated system can help modernize cellular systems, making them more flexible and efficient in terms of power and spectrum utilization.
- *Different types of QoS Requirements:* Modern cellular communication has enabled a wide range of applications, while various non-cellular devices (e.g., LORA, Bluetooth, Sigfox, Ethernet, Wi-Fi) are also wirelessly interconnected. These devices have differing requirements in terms of data rate, range, latency, and reliability. Meeting these QoS requirements using existing infrastructure is challenging, and as these needs diversify in the future, DT integration can help modernize and enhance infrastructure to meet these demands.
- *Features of Self-Automation Systems:* A review of previous cellular generations (i.e., 3G, 4G) reveals that significant capital investment is required to modify infrastructure during each generation's rollout. To reduce costs, vendors are moving towards automation of cellular system components. This will reduce hardware dependence, making the system more flexible and software-oriented, and ease the transition to future generations (e.g., Beyond 5G). DTs can support self-automation by enabling system adaptation and reducing deployment costs.
- *Emergence of decoupling and virtualization at the software end:* 5G/6G use cases involve diverse requirements that place stress on existing infrastructure in areas such as beamforming, user coordination, resource allocation, and baseband processing. Some vendors are addressing these challenges through decoupling and virtualization of the radio access networks. DTs can streamline the virtualization and decoupling of subsystems, improving efficiency and scalability.
- Towards localization and sensing type applications: 5G is advancing cellular technologies, with Beyond-5G and 6G targeting even more complex applications, including UAVs, drone swarms, autonomous vehicles, industrial robots, and underwater communications. These applications require high reliability and robust localization, sensing, and control systems. Integrating DTs into cellular infrastructure will enhance these capabilities, making such applications more efficient and reliable.

V. Conclusions

This paper introduced WIND (Wireless Intelligent Network Digital Twin), a novel framework that extends beyond traditional digital twins for wireless networks by incorporating both network-layer and application-layer intelligence. By integrating hierarchical ML models, where edge-based models handle real-time, low-latency resource allocation and FL optimizes long-term network performance, WIND enables a self-adaptive, self-regulating, and self-monitoring wireless ecosystem. The proposed WIND framework establishes a multi-layer DT that models both the underlying communication network and the applications running on top of it, ensuring seamless interaction between infrastructure and services. Through this dual-layer approach, WIND enhances context-aware network adaptation, allowing for more efficient and intelligent decision-making. The combination of localized ML models at the edge and FL at the global level ensures that short-term optimizations do not compromise long-term network efficiency, making the system robust and scalable. Future work will explore more comprehensive performance evaluation results and comparative analysis with other state-of-the-art solutions.

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