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, Machine Learning, Artifical Intelligence**

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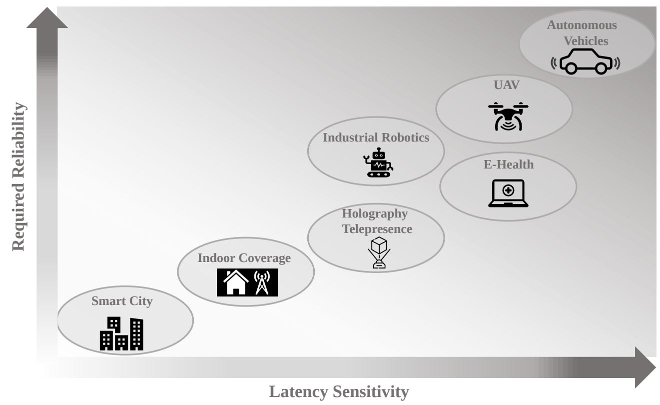

Fig. 1. An illustration of required latency and reliability in 5G/6G use-cases.

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) requirement, as depicted in Fig. 1. 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 emergence of this topic, we introduce WIND (Wireless Intelligent Network Digital 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. Unlike conventional DT implementations, the proposed framework possesses the

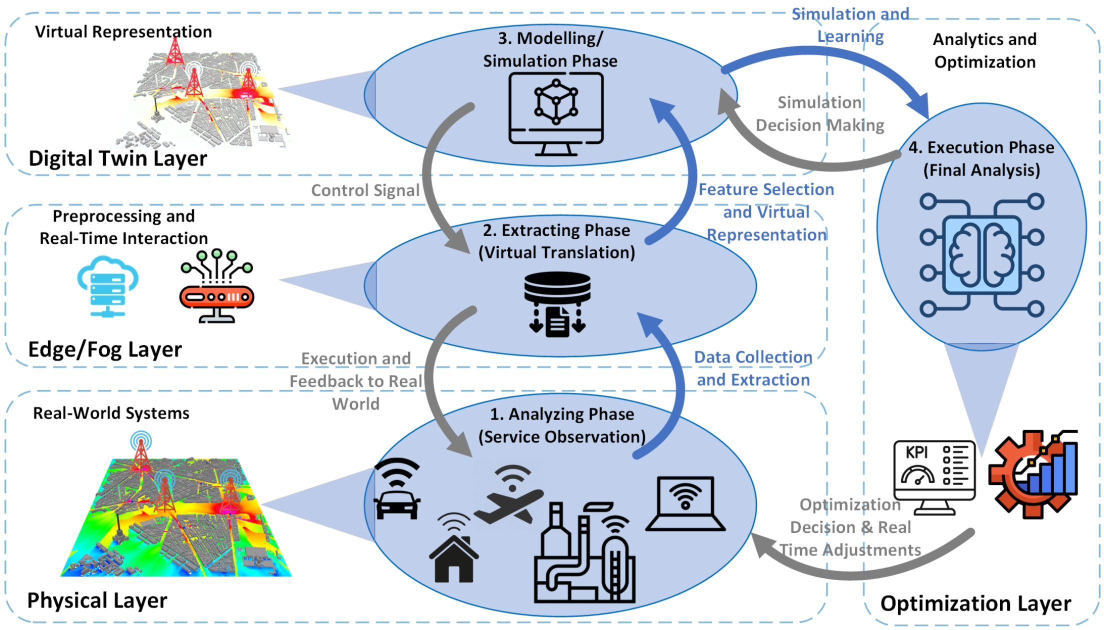

Fig. 2. Digital twin simplified layered architecture.

following novelties: *a)* the proposed model provides both the communication network and application-layer digital twins, ensuring seamless interaction between infrastructure and services, *b)* utilizes edge-based machine learning (ML) for immediate resource allocation, reducing latency and improving responsiveness, and *c)* incorporates FL for global optimization, enabling long-term enhancements in network efficiency and scalability.

By combining localized intelligence at the edge with global learning via federated optimization, WIND transforms traditional network operations into an intelligent, self-optimizing ecosystem. The remainder of this paper outlines the theoretical foundations of WIND, describes its system model, presenting simulation results demonstrating its real-world applicability. Further, the paper emphasizes the essential aspects, including the associated challenges, standardization efforts, and future directions opening the research in this domain.

II. The Simplified 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 communication domain, 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. 2 depicts the proposed simplified DT architecture consisting of four layers: Physical Layer, Edge/Fog Layer, DT Layer, and AI/ML Layer. The interaction between the different layers ensures an efficient and dynamic feedback system for continuous improvements that follows four phases, as described below:

i. Analyzing Phase: 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. Extraction Phase: Once the data is analyzed, the extraction Phase (EP) 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, dynamic resource allocation).

iii. Modelling/Simulation Phase: This phase is the core of the DT system, responsible for representing real-world data in a virtual space. The extracted information is processed

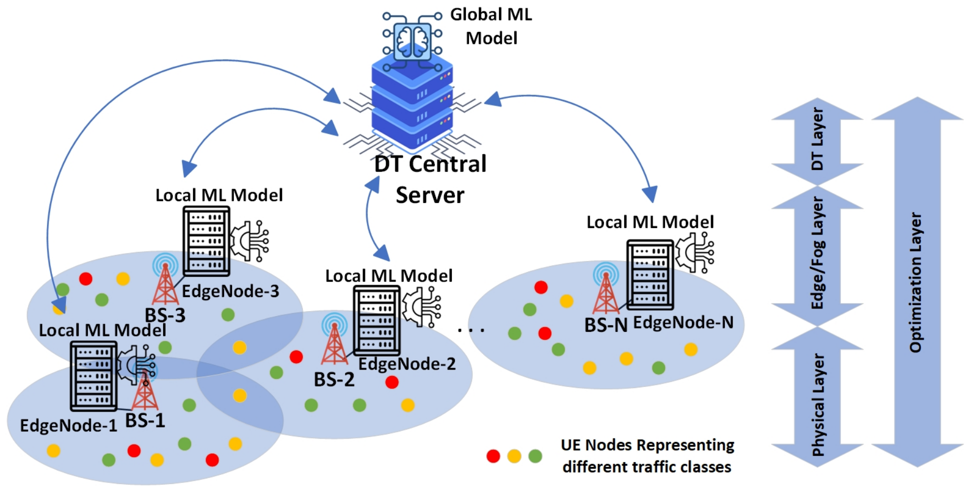

Fig. 3. An illustration of the WIND system model.

using advanced simulation tools like Simulink, Sim Scale, AMEsim, 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.

iv. Execution Phase: Located at the AI/ML Layer 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 AI/ML 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 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. As depicted in Fig. 3, this section presents the proposed architecture WIND, addressing the mentioned challenges by mapping real-world network conditions into a virtual environment for continuous monitoring, prediction, and optimization. Fig. 3 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 handle immediate resource allocation, prioritizing traffic classes dynamically to ensure efficient real-time decision-making.
- *FL for Long-Term Optimization:* The DT central server aggregates local model updates, refining a global ML model that continuously improves network-wide performance without 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. 3, 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:

- *User Equipment Nodes*: These include mobile devices, IoT sensors, UAVs, and autonomous vehicles, each categorized 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.
- *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.

- *DT Central Server*: The central decision-making entity aggregates local ML model updates from different edge nodes, refines a global FL model, and redistributes the optimized parameters to improve network performance over time. This approach eliminates raw data transmission, preserving privacy while continuously enhancing model accuracy.

B. Adaptive Traffic-Aware Learning Process

The Wireless DT system follows a structured learning and optimization cycle:

- *Traffic-Based Prioritization*: UE nodes are categorized based on their traffic class (e.g., latency-sensitive applications such as VR streaming or autonomous vehicles receive higher priority over best-effort IoT traffic). The ML model dynamically adjusts priorities to ensure optimal Quality of Service (QoS).
- *Cluster Formation and BS Association*: Prioritized UE nodes form clusters and associate with the nearest BS, enabling localized learning and decision-making. Each BS is linked to an edge node, where ML models process real-time traffic and optimize short-term resource allocation.
- *FL and Global Optimization*: Instead of transmitting raw data, local ML models at edge nodes train on traffic-specific data and send only model updates to the DT Central Server. The FL process at the DT Central Server aggregates these updates, computes the optimal global parameter, and distributes the refined model back to edge nodes.
- *Continuous Adaptation and Performance Enhancement*: This iterative process enables adaptive learning, ensuring the system continuously improves by integrating real-world traffic dynamics into the global ML model. As a result, the network remains optimized both for immediate needs (low-latency applications) and long-term performance (efficient network-wide management).

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 ML models handle real-time decisions, ensuring rapid responses; (2) *Privacy-Preserving AI Optimization:* Federated learning reduces reliance on centralized data collection, enhancing security; (3) *Traffic-aware resource management:* The system dynamically adjusts allocations based on UE traffic classes, ensuring high-priority traffic receives optimal performance.

This adaptive WIND architecture, integrating local edge intelligence with federated global learning, creates a scalable, self-optimizing wireless network designed to meet the demands of next-generation applications.

D. WIND: Simulation Results

To evaluate the performance of the proposed WIND architecture, we conducted simulations focusing on federated

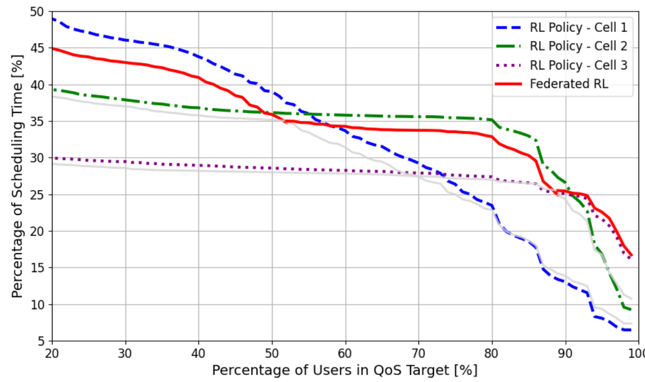

Fig. 4. Federated Reinforcement Learning in Scheduling and Resource Allocation.

reinforcement learning 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 setup modeled a multi-cell wireless network consisting of three macro cells, each with heterogeneous traffic demands. The traffic mix included four distinct application types: 360° video (*20* Mbps), live video streaming (*1* Mbps), VoIP (*32* kbps), and FTP (*256* kbps), representing diverse latency and bandwidth requirements [4]. To ensure a realistic assessment, user mobility patterns varied across cells, influencing channel conditions and service distribution dynamics.

The evaluation process follow the WIND-enabled learning cycle. In the *Analyzing and Extraction Phases*, digital footprints are generated by capturing key parameters such as channel quality indicators (CQI), instantaneous throughput, delay, packet loss, and traffic arrival rates. This information is used to train local ML models at edge nodes, which dynamically adjust scheduling policies to prioritize latency-sensitive traffic while balancing network load. *The modeling and simulation phase* involve training reinforcement learning (RL) models on historical traffic data to identify optimal scheduling strategies [5]. These RL models are then federated across multiple edge nodes, with the DT Central Server aggregating model updates to create a globally optimized scheduling policy.

Performance comparisons between traditional scheduling methods and WIND-enabled federated reinforcement learning reveal significant improvements. Conventional scheduling approaches, such as proportional fair (PF), struggled to balance latency-sensitive services with overall network efficiency, often leading to degraded QoS for critical applications. Fig. 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 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 RL policy maintains a more stable representation,

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 problem under small coherence time window, DTs can be used as predictive models.
6G	The AI/ML's involvement in network management under 6G context may challenge ensuring the network is reliable	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.

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 federated learning 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. 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 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, CHALLENGES AND FUTURE DIRECTION

Section II reviewed a twin network that was extended to the innovative WIND architecture in Section III. Further, this section specifically focuses on the main challenges, standardization efforts, and future research directions that come with the evolution of DT in wireless communication.

A. Use Cases and Standardization

DTs hold the potential to revolutionize various sectors, including industrial IoT, healthcare, and manufacturing. Recognizing their potential, standardization bodies are actively working on DT frameworks. Some of the key sectors are summarized as [2];

Industrial IoT & Healthcare: DTs facilitate autonomous monitoring, tracking, and control of industrial systems. In addition to operational data, DTs can capture environmental data such as location, configuration, financial models, etc., which is particularly helpful in various industrial activities, e.g., predicting future operations and anomalies. Similar to the twin of the wireless system discussed in Section II, DTs can clone a healthcare framework, which may help with cost reduction, patient monitoring, and personalized healthcare.

Automation & Manufacturing: DTs can be used in the automotive sector, e.g., to create the virtual model of connected vehicles. The model referred to in Fig. 2 can be reconfigured to capture vehicles' behavioral and operational data and can help analyze vehicle performance. Besides, twinning can have a significant impact on the way products are designed, manufactured, and maintained, making manufacturing more efficient and optimized while reducing throughput times.

Standardization Efforts: There is a growing interest in DTs, with several standardization efforts underway to establish guidelines. These standardization activities are crucial for ensuring interoperability, security, and efficiency in deploying digital twins within wireless communication networks, thereby facilitating their integration into future wireless systems including; *a) International telecommunication union (UTU):* The ITU telecommunication standardization sector (ITU-T) has been actively developing standards for digital twin networks. Notably, recommendation ITU-T Y.3090 outlines the framework for network 2030 services, *b) IEEE:* besides, the IEEE standards association has initiated efforts, e.g., IEEE P2806 to standardize digital twin technologies across various sectors, including wireless communications, *c) 3rd generation partnership project (3GPP):* within the scope of 5G and evolving 6G technologies, 3GPP has been exploring the incorporation of digital twin concepts to enhance network management and orchestration. These efforts aim to create virtual representations of network elements to improve monitoring, optimization, and predictive maintenance.

B. Challenges and Future Directions

In Table I, we summarize the major domains in the modern wireless communication systems, covering various challenges and opportunities that come with DTs [11].

i. Associated Challenges: The associated challenges are summarized as;

- *DT migration:* DTs are being designed based on the specific characteristics of one environment, which brings migration challenges. Reuse without redesign or redevelopment poses challenges in terms of accuracy and effectiveness.In wireless communication, each user has a unique use case that requires different hardware circuitry and simulation scenarios, leading to compatibility issues in the DT network. Furthermore, wireless topologies frequently change, increasing the likelihood of data corruption during DT migration. In addition, factors such as noise, interference, and bandwidth can affect the position of twin migrations. To address these challenges, it is crucial to carefully assess the available wireless communication options in the new environment and ensure compatibility with the DT system [12].
- *Data management and storage:* In wireless communication, signals are subject to fluctuations, and base stations transmit them to users based on these variations. DT must constantly monitor these changes, resulting in large amounts of data. Additionally, data transmission delays can cause issues with latency and reliability, necessitating scalable storage solutions for DT. To summarize, DT requires effective solutions to address these challenges [13].
- *Safety, security and privacy:* To ensure efficient deployment of DT technology, we must address the issues of safety, security, and privacy in wireless communication. The integration of DT increases the threat landscape as the data and control flows of DTs are vulnerable to interception. This is an important issue due to the open-air operation in wireless communications. Moreover, using and storing the data collected regarding user traffic creates challenges to privacy. To ensure safety, it is necessary to maintain a backup of the wireless network and put efficient security measures [14].
- *Synchronization*: DTs require compatible systems that efficiently convert real-time operations into a physical entity. However, short fluctuations in real-time operations, such as signal quality, can directly degrade system performance. Here, synchronization is crucial for the effective modelling of real-time projects in virtual physical systems. To achieve optimal synchronization, delays must be avoided, and precise conversion techniques are required for DT applications. However, wireless communication faces significant interference and attenuation, leading to reduced signal quality and reliability. Overcoming these challenges requires advanced hardware and agile software capable of transferring data to the physical system in a reliable manner. By carefully planning and implementing suitable technology solutions, it is possible to minimize synchronization issues and achieve accurate and timely synchronization [14], [15].

ii. Future Directions: We mentioned the advantages of DT. It opens a lot of possibilities for the future. A few of them are mentioned below.

- *New Era of Modern Technologies:* To improve performance of wireless communication systems , various technologies (i.e., AI, ML, DL, blockchain, cloud computing, multi-access edge computing, IoT, etc.) are available as was highlighted in Table I. To implement them on the ground level, various modifications are required at the architecture level (i.e., antenna, radio unit, remote radio head, etc.). DT integrated system can help to modernize the cellular system. This will make the system more flexible and efficient in terms of power and spectrum utilization.
- *Different types of QoS Requirement:* Nowadays, cellular communication has created a lot of new applications in the market. Similarly, various non-cellular devices (i.e., LORA, Bluetooth, sigfox, ethernet, wi-fi) are also available in the market. All such devices are wirelessly connected to each other. These all have varied requirements in terms of data rate, range, latency, and reliability. So, to fulfil the QoS requirement of the users from the existing infrastructure is quite tough. In the future, this is expected to become more diverse. Integration of DT can modernize the existing infrastructure and it will make the architecture more capable for the future.
- *Features of Self-Automation System:* After observing the infrastructure of previous generations (i.e.,2G, 3G, 4G), we conclude that at the start of every generation, vendors have to modify the overall setup, including the user equipment. Due to this, a vendor needs to invest a huge amount of capital at the time of set-up installation. To reduce this amount, vendors prefer to add automation in every sub-part of the cellular system. It will reduce hardware dependency and make the system more flexible and

software-oriented. In addition, it will be easy to upgrade the architecture for the next generation (i.e., Beyond 5G). Moreover, this will also reduce the deployment cost for the next generation. DT has the potential to adapt to these changes and make the system self-automatic.

- *Emergence of decoupling and virtualization at the software end:* 5G/6G use cases have a high level of diversity. Due to this, existing infrastructure faces various issues at the time of beam-forming, user coordination, resource allocation, baseband processing, etc. To improve this, some vendors started a decoupling and virtualization on the Radio Access Network (RAN) side. DT can make the virtualization and decoupling of every sub-system in an efficient way.
- Towards localization and sensing type applications: 5G is making cellular technologies more advanced, and upcoming generations (i.e., Beyond-5G, 6G) put a target to make it more prominent. It targets future possibilities, i.e., UAVs, drone swarms, autonomous vehicles, industrial robots, underwater communication, etc. These applications are very sensitive and need a high level of reliability. We need modern localization, sensing, and control schemes to improve their performance. Integration of DT in cellular infrastructure makes these features more efficient.

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.

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