A Functional Framework for Network Digital Twins

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***Abstract*—This paper proposes a structured framework for Network Digital Twins (NDTs) in 6G, addressing the lack of formal definitions and standardised architectural guidelines in the field. By refining the conceptual foundations of NDTs, it introduces a functional architecture, clarifies key components such as AI-driven workflows, a simulation framework, data management, and orchestration, and provides concrete examples illustrating their role in network automation, optimisation, and predictive analytics. The goal is to offer a cohesive reference model that guides the community in shaping NDTs development, ensuring interoperability, scalability, adaptability, and seamless integration into AI-native 6G networks for improved intelligence and efficiency.**

I. Introduction

The evolution from 5G to 6G is anticipated to bring transformative advancements to communication networks, enabling demanding applications such as Immersive Communications and Hyper-Reliable Low-Latency Communications (HRLLC). Beyond meeting the technical requirements, 6G aims to address broader societal objectives, including energy efficiency, enhanced sustainability, and universal connectivity. Achieving these ambitions requires rethinking traditional network paradigms and moving towards adaptive architectures capable of integrating intelligence at every layer.

One concept gaining prominence in this context is the Network Digital Twin (NDT). NDTs represent a virtual counterpart to the physical network, enabling real-time monitoring, operational analysis, and predictive capabilities. By providing a detailed representation of network behaviour, configuration, and state, NDTs facilitate operational complexity reduction, the optimization of resources, and the enhancement of scalability and reliability required for future networks. Moreover, NDTs are expected to serve as a sandbox for the reliable and safe training/testing of AI-based network functions and services.

While the concept of NDT has been explored in the literature, existing works often fall into two extremes: either they present highly specific implementations that lack generalisability, or they remain too abstract to provide actionable insights. Furthermore, a clear and consistent definition of what constitutes an NDT, its scope, and its functional requirements are often missing. This gap prevents a unified, practical approach to NDTs in next-gen networks.

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This paper addresses this gap by proposing a structured framework and a tangible approach to NDTs. Moreover, it introduces an enhanced functional architecture for NDTs, expanding upon the 6G-TWIN vision established during the project's first year. Building on the framework initially presented in [1], this updated architecture establishes the foundation for integrating digital twins into AI-based 6G systems through a layered approach, combining physical and digital network representations. The proposed architecture is designed to bridge the divide between theoretical conceptualisation and real-world implementation, offering a functional model that is both adaptable and applicable to diverse 6G use cases.

We thus propose a new functional architecture for integrating and using NDTs with AI and simulation components. This includes a comprehensive NDT management entity to oversee lifecycle and interactions between persistent and on-demand layers, ensuring seamless transitions between data-driven and simulation-driven workflows. Integration of AI workflows is also critical, as current architectures lack well-defined mechanisms to train, implement, and validate AI models, which are essential for predictive reliability. In addition, a structured mechanism is needed to enable dynamic transitions between real-world data and simulated environments, allowing simulations to refine the behaviour of the network proactively. Finally, scalability and heterogeneity must be addressed through a modular and extensible design to support the diverse data, technologies, and scenarios inherent in 6G networks.

II. Related Work

One of the main contributions in the NDT architecture definition comes from the International Telecommunication Union - Telecommunication Standardization Sector (ITU-T) [2], which has outlined key guidelines for the core features and functionalities of NDTs. The founding components of the NDT are defined as: data, mapping, modelling, and interfaces.

The **data component** serves as the backbone, ensuring harmonized and integrated information through a unified repository. **Real-time mapping** sets NDTs apart from traditional simulations by enabling continuous data exchange between physical and virtual networks. **Modelling** replicates the essential attributes and functionalities of physical counterparts while also translating application requirements into objective-specific functions. Finally, standardized **interfaces** enhance compatibility and scalability by linking physical networks to virtual ones via southbound interfaces and virtual networks to applications through northbound interfaces.

Other organizations, such as the 3rd Generation Partnership Project (3GPP), are also exploring the role of NDTs in network

Table I
FUNCTIONAL REQUIREMENTS OF THE 6G-TWIN ARCHITECTURE

FR ID: Description
FR.DC.01: The Data Collection Framework ensures the integration of data from various sources and across various domains, extending its capabilities towards the Cloud-to-Far-Edge continuum.
FR.DC.02: The Data Collection Framework provides harmonisation mechanisms for different data formats and standards, ensuring a distributed model for securely sharing and storing data across multiple locations, while also guaranteeing efficiency in data processing, analysis, and scalability.
FR.DC.03: The Data Collection Framework enforces robust access policies that support multiple communication protocols and ensure privacy and security among the connected devices, including current and legacy protocols.
FR.ZSM.01: The ZSM allows a fully automated network management system, discovering and integrating different data points while automatically monitoring the real-time status of the NDT
FR.ZSM.02: The ZSM enables the management and orchestration of network resources, using Al-based NFs/NSs to optimise their allocation, automating CI/CD mechanisms, and supporting programmable interfaces for NDT control.
FR.ZSM.03: The ZSM ensures interoperability between new and existing services, protecting APIs and network resources using necessary Authorisation/Authentication/Accounting (AAA) protocols, allowing for the NDT to have secure and reliable communications.
FR.MANO.01: The F-MANO supports Al-based NFs/NSs to allow for cross-domain and multi-time scale network Lifecycle Management (LCM), managing the deployment and orchestration of workloads.
FR.MANO.02: The F-MANO provides a standardised way to offer MLOps support to the created Al models, handling the relevant CI/CD practices.
FR.MANO.03: The F-MANO exposes a comprehensive and standardised API for secure and reliable communications across the NDT ecosystem, including LCM mechanisms and cross-domain Al-based NFs/NSs.
FR.SIM.01: The Simulation framework employs specifications that describe communication protocols and data structures between itself and the different simulators. Relevant simulation services, such as semantic description of data structures, time management services and exception handling are also handled by the Simulation Framework.
FR.SIM.02: The Simulation Framework integrates the necessary basic and functional models on the simulators as they are available, custom-built according to model parameters.
FR SIM.03: The Simulation Framework tailors the models with machine-readable descriptions of computing, storage, and functionalities requirements, such as model deployment and metric gathering, according to the simulation goals,
FR SIM.04: The Simulation Framework establishes a protocol for the closed-loop framework of the NDT, allowing for the transfer of important simulation information regarding configurations and results.
FR SIM.05: The Simulation Framework produces abstract specifications and configurations for interoperability. It also establishes a synchronisation for time management, event distribution and global state for different working simulators

automation. For instance, 3GPP's technical report TR 28.915 [3], part of Release 19, examines how NDT models can integrate with automation functions and highlights key use cases for NDTs. Similarly, the European Telecommunications Standards Institute (ETSI) [4] and the Internet Engineering Task Force (IETF) [5] offer architectural perspectives on NDTs that align with ITU-T's recommendations.

Different perspectives on NDTs have emerged in the industry. For example, Spirent's white paper [6] defines NDTs as software and hardware emulations of a physical 5G network, enabling iterative prototyping, testing, assurance, and self-optimization. Their architecture modularizes the network, offering flexibility in testing and modelling. Similarly, ZTE's white paper [7] proposes an NDT architecture that incorporates a service layer to organize functions into microservices, enhancing scalability, adaptability, and maintenance.

Research focuses on the application of NDTs within the Radio Access Network (RAN) domain [8], [9], [10], as this represents one of the most intricate and resource-intensive components of 6G infrastructure. In general, we can see that existing works lack a unified, practical framework, often being too abstract or too narrow. Key aspects like Artificial Intelligence (AI) integration, automation, and scalability remain insufficiently addressed, motivating our proposal for a more concrete and adaptable NDT architecture.

Table II
NON-FUNCTIONAL REQUIREMENTS OF THE 6G-TWIN ARCHITECTURE

NFR ID: Description
NFR DC.01: The Data Collection Framework should optimise system resource usage in order to ensure optimal performance of network operations, real-time data analysis, while ensuring minimal delay.
NFR DC.02: The Data Collection Framework should be compatible with all devices and technologies, ensuring interoperability and seamless connectivity, improving the efficiency and flexibility of data collection.
NFR DC.03: The Data Collection Framework should guarantee strong security and privacy measures to protect data from unauthorized access.
NFR.ZSM.01: The ZSM can integrate multiple NDTs for real-time data analytics and automated decision-making across multiple domains and time scales, guaranteeing standardised APIs and interfaces for interoperability between devices and domains, as well as the ability to handle failures.
NFR.ZSM.02: The ZSM will integrate Network analysis, planning, management, and control operations, by using Al-based functions and DevOps principles on running workloads, minimizing latency and optimising energy efficiency.
NFR.ZSM.03: The ZSM shall comply with NDT requirements regarding a secure and private environment across domains.
NFR.MANO.01: The F-MANO can integrate multiple NDTs for real-time data analytics and decision-making across multiple domains, seamlessly integrating various network elements, resorting to relevant industry standards and regulations.
NFR.MANO.02: The F-MANO will use Al-based NFs/NSs for data analytics and decision-making purposes, maintaining network operations by adhering to GitOps, DevOps, and MLOps principles to ensure efficient management and orchestration support to the NDT.
NFR.MANO.03: The F-MANO will support multiple NDT instances and network elements across multiple network domains, efficiently scaling Al model training according to demand and following a cloud-native approach to manage workload LCM.
NFR.SIM.01: The Simulator Framework establishes a platform-independent solution through multiple programming languages, using Open-Source software interfaces
NFR.SIM.02: The Simulation Framework federation overhead allows for secure communication between components and flexible simulations.
NFR.SIM.03: The Simulation Framework will parameterise simulations, to guarantee an efficient verification and validation process, as well as an efficient output of metrics and results.

III. 6G-TWIN'S FUNCTIONAL ARCHITECTURE

An NDT architecture must integrate intelligent mechanisms for seamless orchestration, enabling real-time simulation, analysis, and optimization of network operations. Our proposal includes four key pillars: (i) a data collection framework for dynamic data acquisition, (ii) Zero-touch Service and network Management (ZSM) for AI-driven automation, (iii) Federated MANO (F-MANO) for decentralized network control, and (iv) the Simulation Framework for predictive modeling. To ensure effective implementation, we propose both functional requirements (as outlined in Table I) and non-functional requirements (as detailed in Table II) for a NDT architecture.

More precisely, on the NDT architecture's functional requirements the data collection framework shall enable seamless data integration, access policies, and scalable processing. The ZSM framework shall support AI-driven automation, real-time monitoring, and resource optimization. F-MANO shall ensure AI-based lifecycle management, standardized APIs, and MLOps support. Finally, the Simulation Framework shall enable tailored simulations and platform interoperability. Non-functional requirements emphasize performance and scalability, ensuring optimized resource usage, minimized latency, and platform-independent operation, while maintaining privacy and compliance across all components.

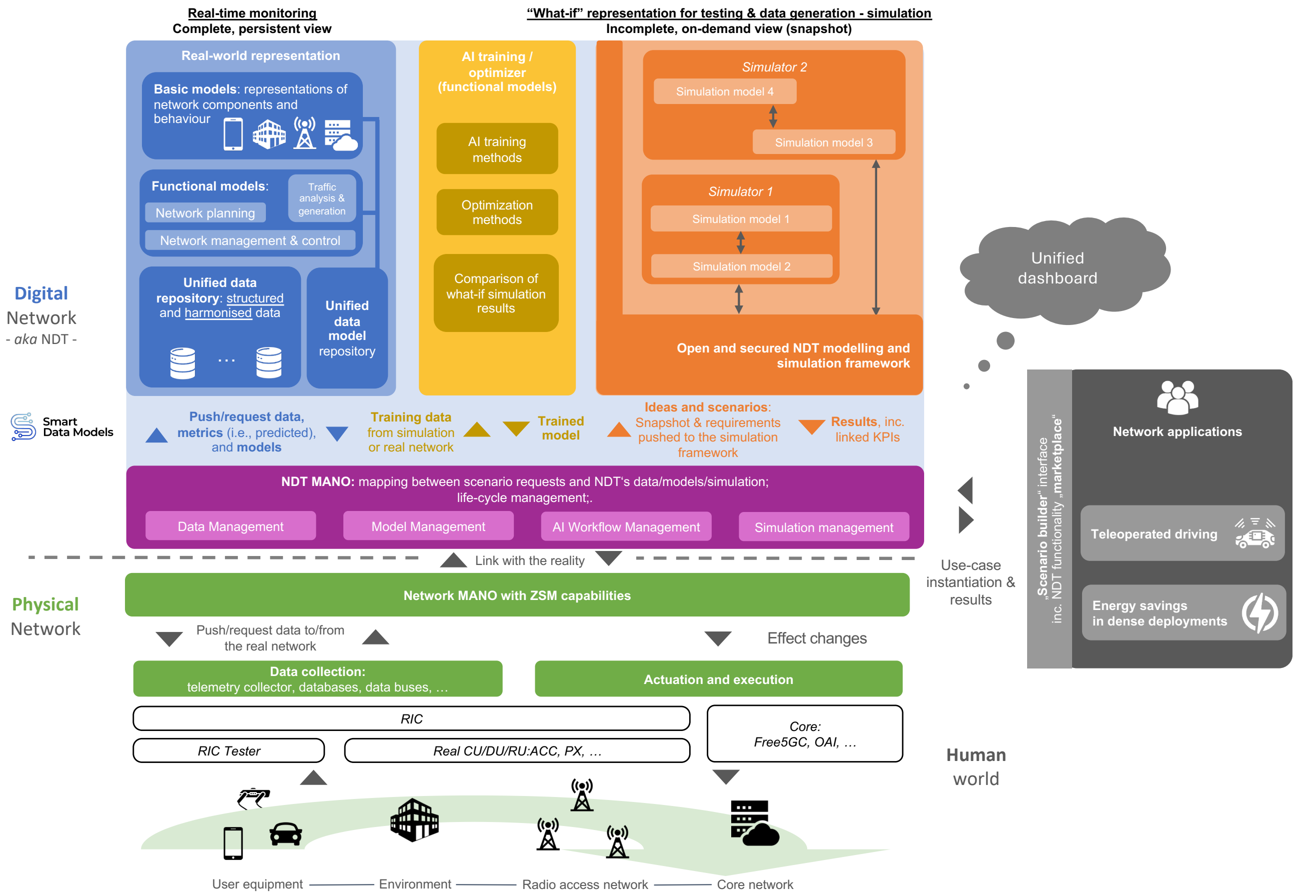

Figure 1. 6G-TWIN's functional architecture

Based on these requirements, Figure 1 represents a functional architecture that has been built as a comprehensive framework for integrating NDT with AI-driven functionalities and simulation components, while providing a comprehensive management layer. It is structured around several interconnected components, each with a distinct role to play in ensuring efficient, scalable, and adaptive operations. They broadly fall into two domains.

The **physical network** (bottom part of the figure) serves a dual purpose through its interconnected components. First, it supplies real-world data to the NDT, facilitating the creation of more accurate models. Second, it receives decisions, recommendations, and trained models for deployment, establishing a continuous closed-loop system that enables automation, predictive modelling, and enhanced performance.

The **digital network** (top part of the figure) consists of multiple components designed to create and maintain a real-time representation of the physical network. It facilitates the structured storage, processing, and utilization of data, ensuring accurate and up-to-date state of NDT modelling [11]. The remainder of the section details the architecture's building blocks with concrete definitions for each layer.

A. Physical Network

The **physical network**, in green colour in the figure, serves as the infrastructure backbone, encompassing the RAN, Core Network (CN), Transport Network (TN), and edge and cloud computing resources. Guided by **network programmability** [12] and **Zero-touch Service and network Management (ZSM)** [13], it enables AI-driven automation and dynamic optimization. This layer includes the data collection framework, management and orchestration layer, and mechanisms to implement optimization outcomes. In this context, NDTs work as analytical services, supporting data-driven decision-making. They enable safe training and testing of algorithms or directly generate decisions for controllers and orchestrators to apply to the physical network. This enables efficient cross-domain coordination with continuous feedback loops for self-optimization and adaptive management.

To create a digital replica of the physical network, the **data collection framework** integrates real-time network data into the NDT framework. It efficiently ingests, harmonizes, and processes telemetry data in compliance with industry standards. Supporting diverse data formats, traffic patterns, and security protocols, it leverages parallel processing and distributed computing for scalability. The framework consists of two sublayers: the **telemetry data layer**, positioned in the physical domain, captures and processes real-time raw network telemetry data from various interfaces, and the **harmonization data layer**, located in the digital domain, aggregates, formats, and delivers this standardizes information into **smart data models**[1] for simulation and decision-making. Pre-processing ensures alignment with standard-defined data structures, such as 3GPP TS 28.552 [14] and 3GPP TS 38.314 [15]. These layers are interconnected through data communication buses, ensuring seamless data flow between the physical and digital domains, while dynamic routing, prioritization, and error checking improve responsiveness and reliability.

The **network MANagement and Orchestration (MANO)** automates network operations, overseeing interactions between the physical network, NDT, and simulation components. It manages the lifecycle of network functions, orchestrates AI-based decision-making, and automates deployments. The MANO framework incorporates domain analytics powered by Zero-touch Service and network Management (ZSM) closed loops, enabling intelligent decision-making through an NDT-driven control mechanism. Finally, the **actuation and execution** interfaces apply optimization decisions to the network.

B. NDT MANagement and Orchestration (MANO)

In purple, the **NDT MANO** layer governs the integration and operation of all components within the NDT architecture, ensuring synchronized interactions between the physical network and the NDT elements, composed of data, models, a simulation framework, and AI training mechanisms. It enables dynamic adaptation to evolving network requirements while maintaining system efficiency.

At its core, this layer ensures the lifecycle management of the NDT instances. This includes the NDT instance decomposition into basic and functional models, the creation, deployment, and continuous refinement of such models, and potentially coordinating the interaction among NDT instances. This layer orchestrates the generation of NDT instances through the different management blocks. The **model management** obtains the appropriate NDT models from the model repository. In contrast, the **data management** ensures the real-time network data feeds such models, enabling a continuous refinement of models, simulations, and AI-driven functionalities.

Through the **AI workflow management** and the **simulation management**, this layer allows the NDT instances to be used with a dual purpose: a) to serve as a sandbox where AI algorithms can be trained and validated before deployment in the physical network and b) to generate hypothetical ("what-if") scenarios to try setups and evaluate how the physical network would respond to those setups. Thus, this layer enables seamless transitions between real-time network data and simulation-based testing, ensuring that simulation results are validated and reintegrated into the operational network. This feedback loop is essential for adaptive decision-making and network optimization. Moreover, a unified deployment interface streamlines the configuration, monitoring, and execution of advanced network scenarios, facilitating efficient model orchestration and real-time performance tracking across diverse applications.

[1]https://smartdatamodels.org/

C. Real-world representation

In blue, this layer allows the creation of the necessary models to represent the physical network accurately. At its core, the **unified data repository (UDR)** is a centralized storage system aggregating historical and real-time data from network infrastructure, sensors, and external contextual sources. It enables efficient data harmonization and retrieval to support decision-making within the NDT framework.

The **unified data model (UDM)** defines the structure of network representations, consisting of basic and functional models. **Basic models** capture the real-time state of physical and virtual network elements, including configurations, topology, and environmental conditions, ensuring an accurate emulation of network dynamics. They serve as a foundation for validation and control mechanisms. In contrast, **functional models** build upon these insights to optimize network operations, predict behaviour, and improve decision-making, often incorporating AI-driven techniques. The interaction between the model and data management components ensures the lifecycle management of NDT instances, aligning them with application-layer needs. This layer enables a continuously evolving and self-adaptive NDT environment by facilitating seamless integration between data and model repositories, and simulation models.

D. NDT modelling and simulation framework

In orange, the **digital twin simulation framework** enables decision-making by coupling simulation models and simulators within the NDT architecture. **Simulators** such as OMNeT++, ns-3, VIAVI TeraVM RAN Scenario Generator (RSG), and MATLAB are software tools capable of running various simulation models. **Simulation models** abstract key network elements, including User Equipments (UEs), gNodeBs (gNBs), and core networks (that is, *models* in the traditional sense), as well as parameters like trajectories, transmission power, and protocols – all forming a complete *scenario* to be simulated. Simulation models are typically implemented through configuration files specific to each simulator.

To ensure flexibility, the **simulation framework** allows the integration of multiple simulators rather than restricting decision-making to a single tool. It enables the interoperability of simulation models across different platforms by facilitating real-time data exchange between simulators, similar to Functional Mock-up Interface (FMI) [16] and the High Level Architecture (HLA) [17]. This openness is reinforced by an open-source implementation, allowing developers to adapt the framework as needed.

Rather than supporting real-time simulation, which is often infeasible due to computational constraints, the framework focuses on scenario reproduction and what-if analysis, particularly for AI training. Since AI models require extensive datasets that are often unavailable in real networks, synthetic data must be generated through simulation.

The simulation framework interaction is managed by the NDT management layer (cf. Section III-B), which retrieves necessary models, configurations, and parameters from the model repository and AI training module. It then instantiates the simulators, manages their execution, collects results, and feeds them back into AI training and model optimization via the NDT management layer. The extracted insights are then leveraged by the NDT management layer to adjust real network parameters, ensuring continuous system improvement.

E. AI training

In yellow, the **AI training** in the NDT framework involves developing functional models using supervised Deep Learning (DL) and Reinforcement Learning (RL).

Supervised deep learning relies on structured datasets generated either by the physical network or by the simulation framework. Preprocessing steps, such as data cleaning, feature selection, and dimensionality reduction, ensure model robustness [18]. The training involves mapping inputs to outputs using a predefined neural network structure, optimizing a loss function, and iteratively refining model parameters [19].

Once required, the data management block in the NDT MANO layer captures the required dataset, which is then processed by the preprocessing module before entering the training stage. This preprocessing step enhances convergence speed and accuracy while mitigating deviations and overfitting. Once trained, the model is returned to the NDT MANO layer, where it is stored as a functional model in the model repository and made available for deployment at runtime.

Reinforcement learning follows an **exploration–exploitation paradigm** where an agent interacts with an environment modelled as a Markov Decision Process. The Simulation Framework provides this environment. Learning involves observing states, selecting actions, receiving rewards, and progressively refining a decision policy. The trained policy and its metadata are stored in the model repository for real-time decision-making within the NDT framework.

F. Unified dashboard

The architecture features a **unified dashboard** (grey) as an interactive interface for stakeholders to configure models, access functionalities, and monitor NDT operations in real-time. This centralized tool enhances network visualization and optimization. Additionally, it supports diverse use-case scenarios, demonstrating adaptability across applications. In our case, two key use cases illustrate its potential: *a)* teleoperated driving, which leverages real-time simulation and predictive analysis for low-latency, reliable remote vehicle operation, and *b)* energy savings in dense deployments, where the NDT optimizes resource management to reduce energy consumption.

In summary, this architecture seamlessly integrates real-time monitoring, predictive modelling, and simulation, providing a scalable and efficient solution for next-generation 6G networks.

IV. Use-cases, evaluation, and examples

The proposed architecture is designed to be flexible, modular, and scalable, accommodating diverse use cases with heterogeneous data sources, technologies, and operational scenarios. To validate its adaptability, two use cases have been considered:

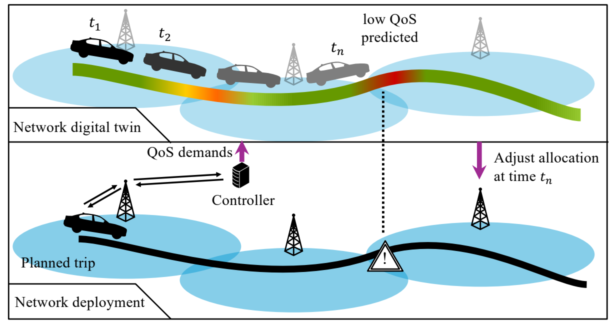

Figure 2. An illustrative example of the teleoperated driving use case.

teleoperated driving and energy efficiency, each addressing distinct societal challenges and performance objectives.

Teleoperated driving focuses on enhancing mobility accessibility, improving road safety and traffic efficiency, reducing urban congestion and pollution, and supporting emergency response operations. Meanwhile, the energy efficiency use case aims to minimise network energy consumption, reduce carbon footprint, and promote energy-aware telecommunications, ensuring sustainable and optimised network operations.

A. Teleoperated Driving

Teleoperated or remote driving refers to the concept where a vehicle is controlled or driven remotely by either a human operator or a cloud-based automated operator. This innovative approach bridges the gap between autonomous driving and manual driving, leveraging advanced network and communication technologies [20]. However, the performance and safety of teleoperated driving are highly dependent on network conditions [21]. Factors such as latency, end-to-end available bandwidth, packet loss, network availability, and reliability play a critical role. These conditions can vary significantly depending on the location, physical environment, and network load, impacting the overall efficacy of teleoperation.

These requirements underline the critical role of robust network performance in enabling safe and effective teleoperated driving, leading to its integration into future mobility solutions.

Example: Figure 2 depicts a vehicle being remotely operated via a 6G network that relies extensively on Virtual Network Functions (VNFs). In this configuration, teleoperation requires data fusion and pre-processing on edge servers to mitigate the vehicles' limited computational power while minimizing the transmitted data volume, thereby reducing network congestion. Additionally, edge servers can be deactivated during periods of inactivity.

Before the journey commences, the **NDT MANO** instructs the **simulation framework** – based on system and scenario configurations from the **unified dashboard** and relying on **basic and functional models** that replicate the physical world – to operate the vehicle in a fully simulated environment accurately representing real-world conditions. The simulation results are then reported to the NDT MANO, which evaluates whether the network can provide sufficient edge computing resources along the planned route. If deficiencies are identified, additional resources (e.g., edge computing capacity or VNFs) are allocated within the simulation until the virtual journey completes successfully. The resulting optimized configuration parameters are subsequently transmitted to the relevant **controllers** via the **network MANO**, which interfaces with real-world **actuators**.

B. Energy Efficiency

The deployment of cellular networks becomes denser and denser in order to satisfy growing demands in ubiquitous Enhanced Mobile Broadband (eMBB) communication. One of the main 6G challenges is the control of energy consumption and energy saving. Recent studies [22] have shown that the telecommunication sector contributes approximately 51% of carbon emissions with information and communication technology. The objective of energy saving is twofold. First, it is a strong business driver as it will reduce the operating expenses (OPEX) for mobile operators. Second, it will contribute to the sustainability of the networks, as both RAN and Core will become greener due to a reduction in power consumption.

From a technological point of view, 6G networks require dynamic configuration based on the load, channel conditions, and end-user quality of service requirements. For example, over-provisioning of resources when the load is low leads to ineffective energy consumption. To solve this problem, the activity of underutilized gNBs can be reduced, or they can be even switched off. Similarly, smart algorithms for dynamic power allocation, physical layer operations (such as beamforming), radio, and computing resource management are needed. Standardization entities, such as ETSI and O-RAN, see energy saving as one of the promising use cases for NDTs, as they create a detailed digital replica of a complex cellular network and provide a powerful way for verification of energy-saving actions [4], [23].

Example: In 6G-TWIN, we consider a multi-RAT heterogeneous network operating at two frequency bands, high-frequency (mmWave or sub-THz) and regular 5G (e.g., C-band). Higher frequencies offer significantly higher bandwidth at an expense of worse propagation properties due to vulnerability to blockages, higher path loss, and oxygen absorption. However, due to lower wavelength, the size of the antenna becomes smaller, which allows building antenna arrays consisting of a large number of closely-spaced antenna elements. Such antenna arrays are perfectly suitable for beamforming of the signal towards the direction of the receiver. Besides, Reconfigurable Intelligent Surfaces (RISs) can be used to overcome loss of Line of Sight (LoS) due to blockages. In this scenario, high-frequency gNBs take the role of micro base stations that serve users in the localized areas when high bandwidth is needed, e.g., when heavy load applications such as XR are used. On the other hand, C-band gNBs perform as macro base stations providing coverage for all users in the cell.

We will leverage NDT to perform the network management in the following domains: (1) data generation for training of AI-based beam prediction algorithms; (2) digital playground for decision-making agents in RAN and Core.

V. Conclusion and Future Work

This paper proposed an NDT framework integrating AI, simulation, and adaptive management targeting future 6G systems. The proposed architecture enables seamless data-driven and simulation-driven transitions while ensuring scalability. Future work includes proposing and validating basic and functional models for concrete applications, along with early implementation to assess performance and feasibility.

Acknowledgment

The 6G-TWIN project has received funding from the Smart Networks and Services Joint Undertaking (SNS JU) under the European Union's Horizon Europe research and innovation program under Grant Agreement No 101136314.

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