Integrating Network Digital Twinning into Future AI-based 6G Systems: The 6G-TWIN Vision

Sébastien Faye, Miguel Camelo, Jean-Sébastien Sottet, Christoph Sommer, Mario Franke,
Julien Baudouin, German Castellanos, Régis Decorme, Maria Pia Fanti, Ramin Fuladi, Gunes Kesik,
Beatriz Mendes, Chris Murphy, Stephen Parker, Simon Pryor, Sidi Mohammed Senouci, Ion Turcanu

***Abstract*—As we move closer to the 6G era, the complexity and dynamism of communication networks is set to increase significantly. This requires more sophisticated, automated management solutions, while retaining human oversight. To meet these new challenges, it is essential to build new architectures that provide a secure environment for closed-loop network automation and to enable optimal resource planning, management and control. In this context, this paper presents the vision of the European 6G-TWIN consortium, which focuses on the creation of a cyber-physical continuum that seamlessly merges the physical world with its digital representation, through the concept of Network Digital Twin (NDT) and its integration into an Artificial Intelligence (AI)-based 6G architecture. This initiative aims to bridge the gap between the increasing complexity of networks and their operational performance, potentially improving real-time user experiences across multiple domains. This paper specifically highlights the associated key challenges and the approach taken by 6G-TWIN to address them.**

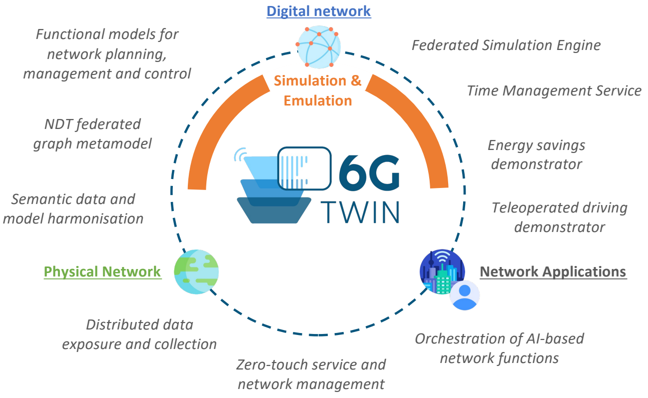

Figure 1. Technology components of 6G-TWIN.

I. INTRODUCTION

The rapid pace of digitization in various sectors, from transportation to manufacturing, is expected to drive the need for high-speed, low-latency communication and computing services in the coming years. To meet this demand, it is essential to develop revolutionary paradigms for the future 6G architecture and provide solutions beyond the current 5G Service-Based Architecture (SBA) capabilities.

One of the primary technical objectives highlighted in most European roadmaps for 6G [1] is to provide Artificial Intelligence (AI)-native management of dense, highly distributed, and potentially cell-free multi-domain networks based on heterogeneous Radio Access Network (RAN) technologies, including classical sub-6 GHz, mmWave, and sub-THz, as well as infrastructures, services, and business cases that prioritize sustainability and energy efficiency. However, fulfilling this vision requires a consistent and reliable unified and open communication and computing architecture (OCCA) that enables zero-touch management and seamless operations across heterogeneous and distributed networks, going beyond conventional approaches. Standardization bodies and key industry stakeholders should also be involved in the process. Additionally, technology must be integrated into the market to ensure a smooth transition from research to commercial deployment.

In this context, the concept of Network Digital Twins (NDTs) appears to be an ideal solution for testing a multitude of scenarios and architectural components before deploying them in the real world. However, to date, very few initiatives have focused on developing a reference architecture for NDTs. Recently, the International Telecommunication Union (ITU) proposed a high-level model [2], and some efforts have been made in the manufacturing sector. However, so far, nothing else has been designed, developed, and tested for more complex applications.

Therefore, there is a need to take a major leap forward and propose new methods, simulation, and modeling tools around the concept of NDT and demonstrate their interest in tangible use cases. An important opening towards open communities is also needed to ensure these solutions' adoption and future exploitation. In this context, the 6G-TWIN project[1] aims to propose and validate a system architecture for future 6G networks using a set of technological components that are illustrated in Figure 1.

The remainder of this paper successively: presents the main challenges associated with the integration of NDT in AI-based network architectures, such as those targeted by the future 6G

S. Faye*, J.S. Sottet, and I. Turcanu are with the Luxembourg Institute of Science and Technology (LIST), Luxembourg. M. Camelo is with University of Antwerp - imec, Belgium. C. Sommer and M. Franke are with Technische Universität Dresden, Germany. J. Baudouin is with Proximus Luxembourg, Luxembourg. G. Castellanos, S. Parker and S. Pryor are with Acceleran, Belgium. R. Decorme is with Research to Market Solution France, France. M. P. Fanti is with Politecnico di Bari, Italy. R. Fuladi and G. Kesik are with Ericsson Araştırma Geliştirme ve Bilişim Hizmetleri A.Ş., Türkiye. B. Mendes is with Ubiwhere, Portugal. C. Murphy is with VIAVI Solutions, UK. S. M. Senouci is with Université de Bourgogne, France. * Corresponding author: sebastien.faye@list.lu

[1] Project website: https://www.6g-twin.eu/

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(Section II); introduces the approach adopted by the European 6G-TWIN project (Section III); and discusses the potential for new applications (Section IV).

II. CHALLENGES FROM THE LITERATURE

A. *Designing an AI-native 6G architecture*

In recent years, industry and academia have started the early research and development stages to transition from 5G (SBA architecture [3]) to 6G. Innovative technology research has started being conducted globally, e.g., via European Funding programs such as Horizon Europe, and it could be integrated beyond 5G/6G. However, study items for 6G are not anticipated to be seen in the 3rd Generation Partnership Project (3GPP) until after 2023, even if some preliminary work on native integration of AI and Machine Learning (ML) is starting [4], [5]. Moreover, it is possible that the first 6G services may only emerge after 2030 [6]. Of course, these expectations are subject to change, and it is fundamental to consider the impact research could have on standards.

Future 6G networks will be highly complex, requiring longer deployment times, greater expenditure, and increased management efforts. Despite this, network operators seek intelligent, self-organizing, and cost-effective 6G networks to minimize operating costs. The integration of AI, and specifically ML, offers practical solutions to address these challenges [7]. Recent work is beginning to propose new service and network architectures for 6G with native AI support [8]–[11].

This initial work highlights the potential of integrating AI into network systems and reveals the critical challenges ahead. Orchestrating the collection and exposure of data across various network domains for the training and validation of AI-based network models, while preserving security and privacy, is one of the key challenges [4], [8], [11]. In addition, algorithms capable of managing and orchestrating intelligence are needed [4], [8], [11], as well as strategies for incorporating AI-based functionality into management frameworks to achieve Zero-touch Service and network Management (ZSM) successfully [5], [10], [12].

B. *Using digital twin technologies for 6G networking*

The Digital Twin (DT) concept first emerged from the manufacturing industry as a digital replica (i.e., a twin) of a production line or a product [13]. A DT considers three major elements: (i) a physical entity of the real world, (ii) its counterpart in the virtual world (i.e., the twin), and (iii) a bi-directional data exchange connecting these two worlds. In practice, it is hard to achieve this bi-directionality, and most of the advanced works only consider the realization of a digital shadow (i.e., a digital replica with few or even no possible feedback actions). A DT has to deal with comprehensive and very heterogeneous information through models ranging from simple blueprints to complex behavioral and AI frameworks [14]. Therefore, a DT includes a static representation of the twinned physical system and a dynamic representation, usually done via simulation or prospective scenario modeling.

The combination of various applications coming from heterogeneous stakeholders and their respective datasets and models require a holistic governance, which adapts existing approaches such as federated systems or distributed governance. Our approach considers that DTs have to deal with larger scales, which implies an open-world scenario [15]. In this context, many challenges arise, such as the need to support security, harmonize multiple data sources and models, support its evolution, etc.

While the concept of DTs is well known in industry, it is quite new to the telecommunications sector [16], [17]. One of the most promising 6G DT use-cases is a DT of the actual 6G network itself, a so-called “6G Network DT”. This can be an offline network DT, used for DevOps staging and zero-touch automation, but it can also evolve towards online real-time DTs, involved in the operation and optimization of the network itself. The basic concept of DTs needs to be refined in the specific context of wireless networks [16], [18].

Implementing an NDT therefore requires dealing with many challenges [19], notably operating with large scenarios, which is already the case for the original DT concept, as well as understanding and modeling the communication flow (and storing relevant information), and finally managing the uncertainty.

C. *Simulating Network Digital Twins (NDTs)*

General-purpose network simulation models in the literature commonly follow a discrete event paradigm and focus on packet-level simulation. This means that, rather than simulating every bit of a packet, the simulator models a packet erasure channel, calculating packet error rates based on bit error probability and packet size. This achieves a good balance between precision and computational complexity but is limited in terms of both granularity and scalability: neither finer details of a single link nor large-scale scenarios can be simulated with such models.

A wide variety of specialized network simulators following this approach also exist, each focusing on dedicated domains such as vehicular networking, air [20] and space [21] networks, as well as cellular networks [22]. Similarly, there are a number of general-purpose network simulators which focus on single links but are limited in terms of scalability as well as those which focus on large-scale scenarios but are limited in terms of granularity. Similar considerations as for network simulation apply to the simulation of road traffic, energy, and network management. Thus, the current state of the art in network simulation is characterized by a large number of specialized simulators, each focusing on a specific domain, and a small number of general-purpose simulators, each focusing on a specific scale.

A promising approach to overcome these limitations while avoiding the need to re-implement, re-validate, and re-verify all individually existing model implementations from various domains is to couple multiple simulators, each focusing on a specific domain or scale, to form a federated simulation engine. This approach has been explored in the literature, and the first

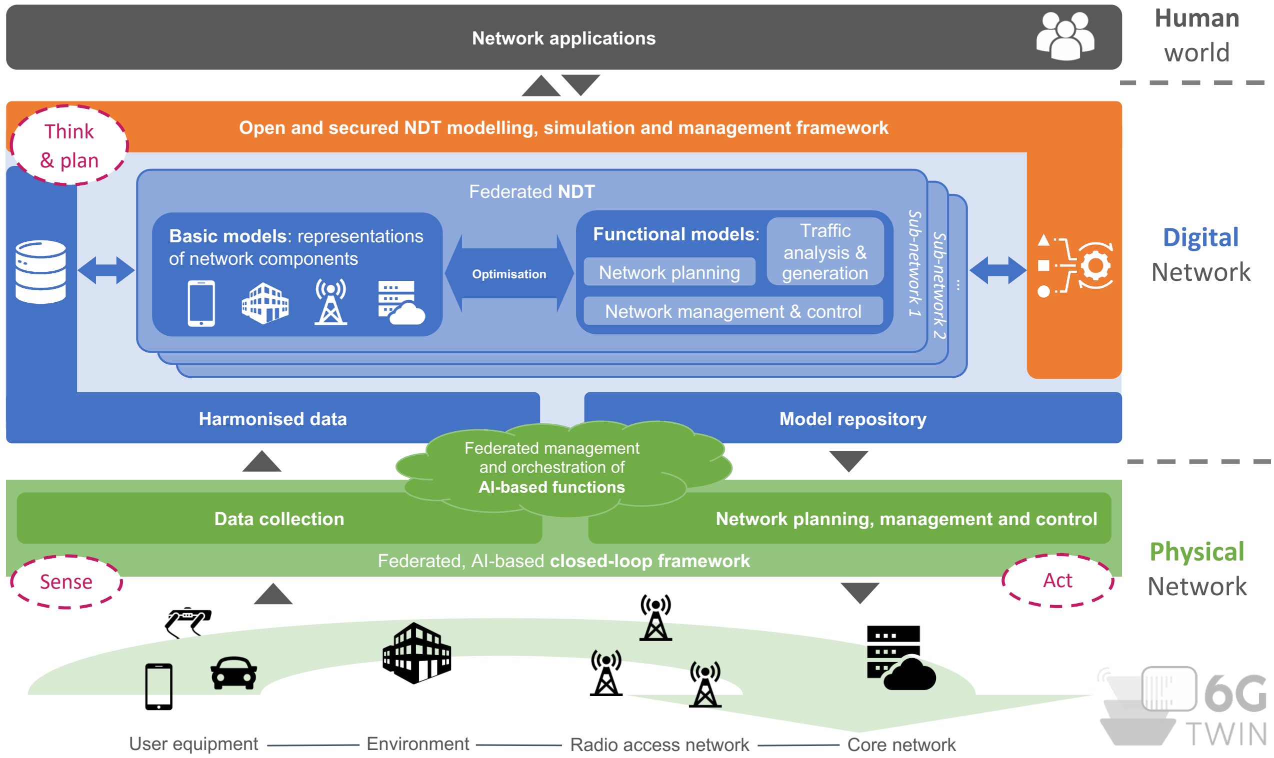

Figure 2. High-level architecture of 6G-TWIN.

simulation engines have been developed, though they, too, are limited in terms of the number and type of simulators they support or are heavily focused on specific domains and scales.

What is needed for building a 6G NDT is a federated simulation engine which is able to couple a wide variety of the many existing simulators, from road traffic to AI-based network management, each focusing on a specific domain or scale, and which is able to simulate large-scale scenarios with heterogeneous granularity.

III. 6G-TWIN Approach & Vision

6G-TWIN proposes a unified AI-native architecture with support for NDT that consists of three distinct layers, as shown in Figure 2 and explained below.

A. Layer 1: Physical Network – AI-based Architecture

The base of Figure 2 (green) represents the physical network and the operations performed on it. This includes User Equipment (UE), the surrounding environment that can influence the propagation patterns, the RAN, and the core network. Each of these components is supported by computing and networking resources deployed at the (far) edge and cloud data centers. Although these domains already exist from previous network generations, the future 6G network architecture is expected to be significantly different from its predecessors in terms of its design principles and operating mechanisms.

The 6G network architecture proposed by 6G-TWIN will be built from the ground up with AI as an integral part of its design and operation. This AI-based network architecture by design, as described in Figure 3, will enable the deployment of AI-based Network Functions (NFs) and Network Services (NSs) to automate various tasks, optimize network performance and enhance the user experience. 6G-TWIN will go beyond state of the art [8] by also integrating an NDT as part of its AI-native architecture, which will provide a safe sandbox to train and validate AI-based NF/NS before they are deployed on the real network, as shown in orange part of Figure 3.

6G-TWIN will also evolve the traditional MANagement and Orchestration (MANO) frameworks for NF/NS towards a framework that not only performs the traditional lifecycle management of NF/NS (onboarding, deployment, scaling, termination) but also includes the mechanisms to perform the orchestration and management of AI-based NF/NS (training, deployment, and monitoring of AI models). This will be achieved by providing a novel MANO framework that supports operations such as the lifecycle management of the AI-based NFs and NSs, orchestrating the composition of advanced AI-based NF/NS and coordinating interactions between their inner models. This is fundamental since the performance of an AI-based NF/NS does not only depend on networking Key Performance Indicators (KPIs) (e.g., Quality of Service (QoS), Quality of Experience (QoE)) but also on learning-related KPIs (e.g., accuracy, loss, accumulative reward).

To enable these AI-based NFs/NSs to observe and interact with the network (e.g., controlling it), two main aspects are needed:

1) Novel mechanisms to increase network programmability and support closed-loop management strategies. These will enable AI-based NFs/NSs to learn (e.g., inside a NDT or with continual learning in physical networks) and adapt in real-time in order to automate network provisioning, configuration and optimisation. This is a fundamental step forward that can significantly reduce operational costs, enable rapid network deployment, achieve high scalability, and increase network reliability and availability.
2) Introducing novel mechanisms for efficient data collection and processing pipelines for monitoring information, including handling diverse data formats, protocols, and traffic patterns; cryptographic methods and privileged access management protocols for enhanced security and privacy. These mechanisms harness parallel processing and distributed computing techniques for scalability, accommodating more users, devices, and data streams without sacrificing performance or reliability. Workload distribution across multiple nodes will also be exploited to ensure optimal performance and availability.

6G-TWIN will explore and obtain inspiration from novel concepts on different network segments and investigate and innovate in big data telemetry subsystems and data lake functionalities, such as 3GPP 5G Core (5GC) Network Exposure Function (NEF) and WAIF 6G, 3GPP NetWork Data Analytics Function (NWDAF) and its evolution towards the split Network Management Function (NWMF) / Network Function Automated Framework (NWAF), O-RAN Y1 interface for exposing RAN analytics information to internal and/or external functions and the High Velocity Virtual Event Streaming (HV-VES) collector functionality in the service and network management layer.

B. Layer 2: Digital Network – Data and Models

The middle part of Figure 2 (blue) represents the network DT, which is at the heart of the project, and which has been designed in line with the preliminary work on the topic. In particular, the ITU has provided a first, high-level approach for standardizing a conceptual architecture of an NDT through the recommendation ITU-T y.3090 [2]. ITU specifies two core notions: (i) basic models that consist of the representation of the network topology and elements and (ii) functional models composed of functions related to the behavior of the system. These functions include traffic analysis, network diagnostic, and prognostic, but are described at a high level.

An approach broken down into two areas has been drawn up to consider this architecture: data and models. The data area enables the collection, governance, and harmonization of the data collected. This will ensure a unified, data space-based foundation, regardless of the communication technologies, domains, or network elements involved. The DT model area consists of a set of models to best and dynamically represent the network elements (basic models) and their behavior (estimated and predicted, using AI approaches, i.e., functional models). These models rely on the harmonized data collected and will be developed to optimize network planning, management, and control issues, as well as to provide meaningful KPIs and metrics to operators. These DT models are federated in several layers, allowing complex, interconnected, and dynamic topologies to be imagined depending on the applications to be served.

Our approach to NDT will be based on several technical components aiming to provide a holistic representation of the cyber-physical elements related to the real network. If the concept of NDT is holistic, in practice, it will be distributed among smaller federated NDTs.

a) Basic models: A basic model aims to represent the cyber-physical network system consistently. It should be used to either reflect a current state of the real network or in isolation from reality for simulation, projection scenario, etc. The first phase for building basic models implies establishing a graph structure with multiple interrelated metamodels in a common graph-enabled modelling framework able to support some flexibility and uncertainty. In 6G-TWIN, it will be based on the different references and standards (e.g., ETSI, 3GPP TS 23.501, 5GPPP), ontologies [23] and other metamodels available in the sector (e.g., OASIS TOSCA).

Each metamodel corresponds to a sub-domain community that has already reached consensus and forms a coherent whole. Once this ecosystem of metamodels reaches a stable state, our objective is to propose it for standardisation, e.g., as a smart data model[2] for networks. This will then be our network reference metamodel. In a subsequent phase, we will instantiate this metamodel according to Data provided by the 6G architecture that represents the network at a given state. Basic models typically include, but are not limited to: topology models (i.e., topographic information of a RAN area link to Core elements), computing models (computing resources such as servers and their properties), gNB models and UE models.

b) Functional models: A functional model includes different forms of analytics and AI that handle the basic models. They are drastically different from the basic models as they depict behavior. In 6G-TWIN, we consider three types of functional models:

- **Emulation**: functional models that comprise the operations on the basic model to mimic reality: these are the basic behavioural models. This can include, for instance: propagation models; mobility models; radio and computing performance models, providing KPI measurements in terms of radio (e.g., Bit Error Rate BER), networking (throughput, delay), and computing, etc.
- **Optimisation**: functional models that can improve the system. These can limit themselves to the operations possible on the physical network. Ideally, they provide an output configuration that can be applied by the 6G architecture within the network planning, management, and control components.
- **Anticipation**: functional models that represent diverse kinds of external operations and network configurations

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[2] https://smartdatamodels.org/

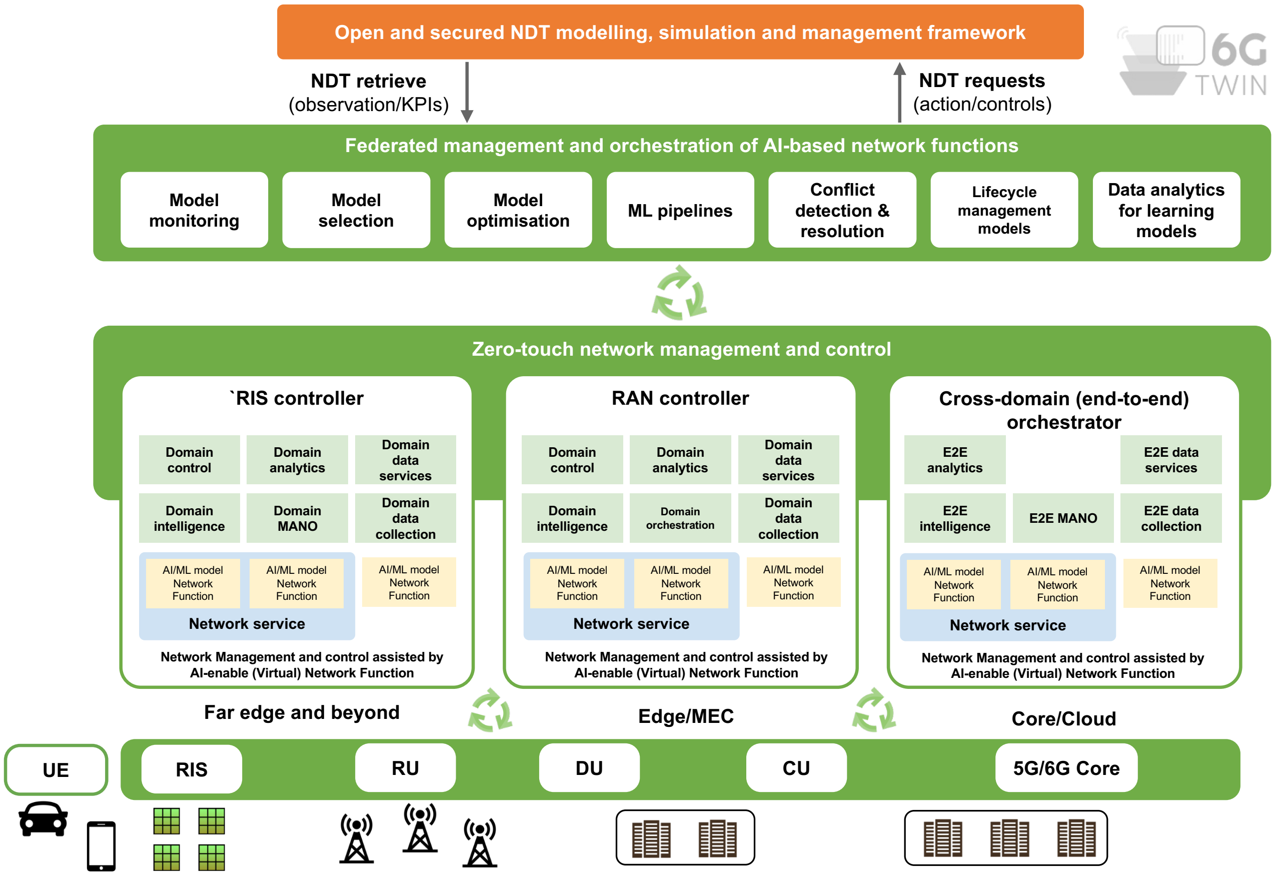

Figure 3. High-level architecture of 6G-TWIN, with a focus on the AI-native components

that can go beyond the current capability or limits of the physical network.

These functional models can be implemented as three different classes of models: (i) Analytical models, which are models produced from human knowledge and expertise. (iii) Traditional AI models, which are based on logic, inference, probabilistic or search approaches. They are "white or grey" box models, which means that they can be more easily explained. (iii) Machine-learning models, notably deep-learning models, which are the modern approach of ML. They will have to rely on massive data collection to be accurate and to have a good functional coverage. They will first inevitably rely on the proper structuration of collected data.

c) Harmonised data and model repository: A harmonised data and model repository will serve as the core source of information to populate basic models and will be used as the training set for functional models. In addition, the harmonised repository should be properly governed, such as a digital space, including data privacy and sovereignty.

Providing a unified metamodel, as described in basic models, will not be sufficient. In addition, using data-fusion algorithms and entity resolution will help reduce the dimensions of the data and models to be harmonised. A semantic model associated with a pragmatic representation (i.e., the rationale and the context of the data and models) is also necessary to preserve the meaning behind each piece of collected data. The harmonisation will have to consider semantic (pragmatic and conceptual) drifts and mismatches. It will define a concrete process, based on graphs and logic to identify the drifts and propose solutions to overcome its impact on data and models.

C. *Digital network: federated simulation framework*

The top part of Figure 2 (orange) represents the simulation framework, which manages the lifecycle of the DT, in order for it to allow what-if analyses, interacting with reality (Figure 2, gray) and instantiating DTs on the fly. Such an open-source, secured, and federated simulation framework will also be developed to provide the scientific community with a tangible tool to test their own approaches.

Following the observations made in Section II-C, our approach to a simulation framework will be based on the following principles: Instead of re-implementing existing models from a large number of specialized domains, we will explore a federated simulation engine concept following an agent-based approach and coupling existing simulators. By necessity, this simulation engine will allow both homogeneous (same simulator, different agent) and heterogeneous (same agent, different simulator) simulation and the inclusion of closedsource simulators across different languages and execution platforms while ensuring privacy and security.

This also requires a generic configuration language that maps real-world entities to simulation entities and, then, to simulator-specific models, as well as a standardized interface/API for setup and execution, as well as result retrieval. We will also investigate the potential of novel time synchronization strategies and heuristics that will dynamically adapt to the simulation requirements and the available compute resources, as well as the precision and correctness of the results.

IV. CONCLUSION

The initial exploration towards 6G has been driven by the exponential growth of data-driven applications and the emergence of new use-cases, as highlighted by recent European initiatives like Hexa-X – demonstrating the need for a more advanced and efficient communication infrastructure in more complex and heterogeneous network domains. In the context of 6G-TWIN, our aim is to tackle use-cases that were either overlooked or inadequately addressed in the initial phase of Smart Networks and Services Joint Undertaking (SNS JU) projects, particularly within its *Stream B*, which primarily emphasized deterministic network components and applications in industrial VR/XR. This endeavor serves two key purposes: (i) to test the resilience of our Network Digital Twin (NDT)-based architecture against unexplored constraints, and (ii) to synchronize our objectives with the themes pursued in its *Streams C* and *D* project proposals.

With this perspective in mind, it seems relevant to focus on two critical constraints: on the one hand, the mobility constraints that nodes may experience, which aligns well with a predictive NDT approach; and on the other hand, the energy constraints, which are well suited to a reactive NDT approach to adjust the network elements in real-time and optimize their energy efficiency from end to end. 6G-TWIN will therefore focus on two complementary use-cases, both resulting in demonstrators that will aim to test and validate in labs the solutions developed in the project. These Technology Readiness Level (TRL) 4 laboratory demonstrators will rely as much as possible on open components, such as those provided through the O-RAN initiative, and will integrate relevant existing resources from the community and emerging EU research infrastructures when appropriate, so as not to reinvent the wheel and to minimize development work. The project's results will be released throughout its lifecycle, using the vision presented in this paper as a baseline.

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