Digital Twin as a Service for 6G Radio Access Networks: Functional Model and Key Challenges

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***Abstract*— This paper presents a scalable and flexible functional model for the 6G-Radio Access Network Digital Twin (6G-RANDT), designed through a service-oriented approach to support next-generation radio access network optimization and intelligent management. The proposed model includes an application programming interface for seamless interaction with a 6G-RANDT consumer, 6G-RANDT instances for RAN emulation and simulation, and a 6G-RANDT orchestrator for management and data integration. Several 6G-RANDT typologies and measurement requirements are explored to address diverse use cases. Moreover, key challenges in 6G-RANDT development are discussed. To evaluate the impact of modeling accuracy in 6G-RANDTs, we conducted a cellular capacity modeling experiment in which different 6G-RANDT instances were used to train a reinforcement learning (RL)-based capacity-sharing algorithm. Results show that the impact of capacity modeling strategies on the 6G-RANDT instance accuracy and RL agent performance is highly dependent on the cell environment, emphasizing the need for tailored 6G-RANDT services based on specific RAN environment conditions and applications.**

***Keywords*— 6G, RAN, Digital Twin, functional model, network optimization, capacity modeling.**

I. INTRODUCTION

The sixth generation (6G) of mobile communications networks is expected to become a transformative shift in wireless connectivity driven by the integration of advanced technologies and infrastructure, incorporating non-terrestrial networks (NTN), large scale IoT deployments, quantum and terahertz communications, and reconfigurable intelligent surfaces (RIS) [1]. Alongside IMT-2030 requirements such as immersive communications and ubiquitous connectivity [2], these innovations will transform Radio Access Networks (RANs) into complex and heterogeneous environments, necessitating sophisticated tools to effectively manage such complexity and demands. To address these challenges, Artificial Intelligence (AI)-native management applications are being incorporated into the 6G development roadmap [3], and Digital Twins (DT) are emerging as a pivotal technology to enable the design, analysis, operation, automation, and intelligence of 6G wireless networks [4][5].

In recent years, the concept of DT has emerged as an advanced simulated environment paradigm that leverages real-time data from physical entities to construct detailed virtual representations [6]. A specific application is the Network Digital Twin (NDT), or Digital Twin Network (DTN), which provides a virtual counterpart of real-world networks. NDTs have gained significant attention for their potential to revolutionize network management, optimization, what-if analysis, troubleshooting, and planning [7]. Extensive research has been conducted to shed light on the NDT architecture and use cases, with contributions from academia and standardization/specification bodies. The International Telecommunication Union (ITU) identifies four key dimensions [8]: data, real-time mapping, modeling, and interfaces, with a model comprising physical, digital twin, and network application layers. Building on the ITU framework, the European Telecommunications Standards Institute (ETSI) classifies NDTs by use case, network interaction, and size [9], while the Internet Engineering Task Force (IETF) extends the ITU model with an NDT example for intent-driven network control [10]. In mobile networks, the Third Generation Partnership Project (3GPP) in [11] focuses on NDT applications for network management, policy verification, and machine learning (ML) training. More specifically on RANs, the O-RAN Alliance defines use cases [4] and key enablers [5] for a Radio Access Network Digital Twin (RANDT), including a DT dedicated to RF, RAN functions, and cloud, ensuring O-RAN interface compatibility. Academic contributions include surveys [12][13][14] on NDTs from various research projects and industrial forums. As stated in [15], 6G NDTs require twinning capabilities for the RAN, Core Network (CN) and User Equipment (UE). However, developing a complete 6G NDT covering all aspects and scenarios is impractical, making a use case-driven approach necessary. Among RANDT implementations, Colosseum stands out as an O-RAN DT using RF channel emulation and softwarized protocol stacks [16]. A modular RANDT architecture aligned with standards is proposed in [17], showing management and modeling examples. Unlike DTs in other domains, RANDTs require a sophisticated understanding of radio environments with unique propagation features. In this direction, the authors in [18] explore three DT-based radio testing emulation setups and the challenges introduced by new 6G radio technologies. To the best of the authors' knowledge, none of the previous studies proposed a functional model to provide RANDTs as a service, tailored to specific use cases. Moreover, while the authors in [15] propose a data taxonomy for general 6G NDT, particular challenges and data requirements for RANDT implementation across different RAN typologies remain unexplored.

In this paper, we propose a functional model of DT for the future 6G RAN, referred to as a 6G-RANDT. The main novelty is that the functional model considers RAN twinning capabilities (e.g. RF, RAN management functions, etc.) as a service to support diverse 6G use cases. Furthermore, we outline three 6G 6G-RANDT typologies to cover different RAN optimization problems and their data requirements. Additionally, we identify key challenges in implementing 6G-RANDTs related to data availability and granularity, 6G-RANDT-assisted ML training, accuracy, complexity, and stakeholders. Finally, we emphasize the relevance of 6G-RANDT modeling by analyzing the quantitative impact of the

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6G-RANDT accuracy in different scenarios when training an RL-based capacity sharing solution.

The rest of the paper is organized as follows: Section II introduces the 6G-RANDT functional model, while Section III outlines the considered 6G-RANDT typologies and their data requirements to address different RAN optimization problems. Section IV explores design considerations and challenges in implementing a 6G-RANDT. Finally, Section V presents a cell capacity modeling example, and Section VI concludes the paper.

II. 6G-RANDT FUNCTIONAL MODEL

There is a broad range of use cases for 6G-RANDT, embracing e.g., planning and dimensioning (e.g., using it to determine the most adequate radio nodes deployment locations and configurations to enhance the coverage and capacity of the network) or network operation/optimization (e.g., for testing algorithmic solutions before they are applied in the real network, allowing adjustment and validation of their parameters). Moreover, in view of wide applicability of ML in RAN management, the 6G-RANDT allows performing the training of e.g., RL solutions.

Different 6G-RANDTs can be designed and implemented to meet the requirements of each specific applicability use case. Thus, the wide range of potential use cases poses the need to flexibly and easily deploy 6G-RANDTs in different parts and functions of the RAN system. In this way, specific 6G-RANDTs can be consumed by network automation functions (e.g. Self-Organizing Network (SON) functions) or by their internal components, as devised in the 3GPP study in [11].

Fig. 1 presents the general functional model of a 6G-RANDT that includes the different functional elements to facilitate an easy and flexible deployment. It is devised to act "as a service", enabling its usage by a 6G-RANDT consumer through a *6G-RANDT Application Programming Interface (API)*. The consumer refers to any entity that uses the 6G-RANDT to test any network element or functionality in a controlled environment without affecting live network operations. These entities include hardware and software vendors (e.g., for developing and testing new or updated solutions), autonomous network applications (e.g., for policy optimization), and MNOs (e.g., for network planning, optimization, and troubleshooting). The proposed 6G-RANDT functional model is designed to handle and generate different *6G-RANDT instances* according to the 6G-RANDT consumer requests. Accordingly, each 6G-RANDT instance twins RAN elements and functionalities based on data gathered from the real 6G RAN and from other data sources. The 6G-RANDT instances and the data acquisition are managed by the *6G-RANDT orchestrator*. In the following, the different building blocks of the 6G-RANDT are described in further detail.

A. 6G-RANDT API

The 6G-RANDT API enables the use of the 6G-RANDT as a service by a 6G-RANDT consumer. Considering the requirements identified in the 3GPP study on the management of NDTs in [11], the 6G-RANDT API supports the following services, which could be extended for specific use cases if required:

- Capabilities exposure: the modeling and configuration capabilities supported by the 6G-RANDT can be provided to a 6G-RANDT consumer under request. These include the possible configurations that can be set to generate a RANDT instance, such as operation modes (e.g., real-time monitoring mode, in which the instance is continuously obtaining data from the real network for anomaly detection and performance analysis; simulation mode, in which RAN scenarios are simulated to test RAN changes; optimization mode, in which the RAN parameters and functionalities are optimized within the instance, etc.), the configuration of model(s) used to simulate/emulate the RAN (e.g. gNB or UE configuration), visualization and reporting options (e.g., type of supported graphs and output data), etc.
- Life-cycle Management (LCM) operations: requests to create, activate, deactivate, configure, re-configure and terminate 6G-RANDT instances.
- Visualization and reporting: enables the visualization and reporting of a 6G-RANDT instance outputs.

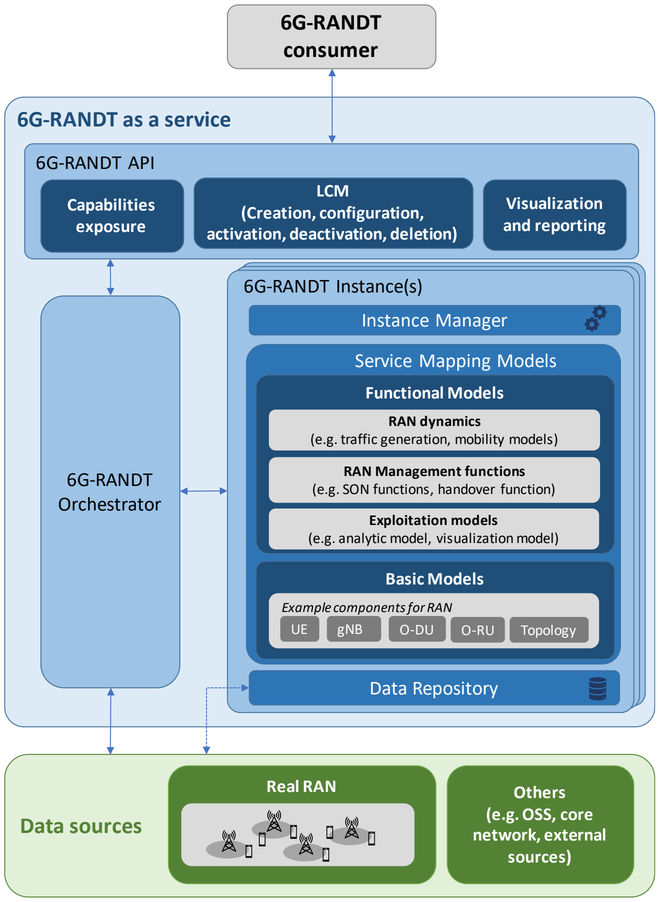

Fig. 1. Functional model of the 6G-RANDT as a service

B. 6G-RANDT Orchestrator

The 6G-RANDT orchestrator serves as the central management entity responsible for handling requests received via the 6G-RANDT API and for the LCM of 6G-RANDT instances. This includes the creation, update and termination of instances as well as its storage management, version control and deployment of internal models. Additionally, the 6G-RANDT orchestrator handles data acquisition for the 6G-RANDT instances, setting up the required interfaces and associated services depending on the data source, e.g. acting as service consumer of performance assurance services over HTTP/TLS and SFTP protocols. The main data source will usually be the real RAN, from which different performance measurements (PMs), measurement reports and configurations can be extracted. Examples of required data for different 6G-RANDTs instances are discussed in Section III. Data can also be obtained from other systems, such as the service profile from the Operation Support System (OSS), the analytical information in core network functionalities (e.g. Network Data Analytics Function (NWDAF) of the 5G system) or existing offline datasets of interest. To ensure a smooth operation when multiple applications interact with a given 6G-RANDT instance, the orchestrator must handle conflicts, including request errors from 6G-RANDT consumers and access control policies.

C. RANDT Instance

A 6G-RANDT instance includes the functionalities required to emulate or simulate the RAN behavior according to the configuration specified by the 6G-RANDT consumer. Taking as a reference the IETF architecture of an NDT in [10], the functionalities in a 6G-RANDT instance are the *data repository*, the *service mapping models* and the *instance manager*. The data repository stores different types of data collected from different sources, which are exploited by the service mapping models to represent the RAN elements and functionalities. Depending on the use case, the specific models implemented in a 6G-RANDT instance can be different. While some implementations may rely on a single model, a modular design is generally preferred due to the complexity of the RAN environment. Two different types of service mapping models are distinguished:

- Basic models: these represent RAN network elements and entities, capturing configuration and environmental details. Examples include scenario topology, gNBs (e.g. gNB-CU, gNB-DU), UE, channel, network slices, etc. Each basic model specifies its configuration and relationships with other elements.
- Functional models: these generate information to support network analysis, twinning, diagnosis, prediction and assurance. Three types are considered: (i) RAN dynamics models, which replicate RAN dynamics like traffic, UE mobility, and channel propagation; (ii) RAN management and optimization models, which drive basic models via RRM policies (e.g., admission control, packet scheduling, handover, etc.), and network optimization functions (e.g., SON functions); and (iii) Exploitation models, which use outputs from other models for monitoring, Key Performance Indicator (KPI) reporting, analysis, and visualization (e.g., KPIs graphs, coverage maps, etc.).

Different modeling approaches can be used for the service mapping models. One possibility is to emulate the exact behavior of network functions, as in [16], where the different O-RAN functions are emulated within the RANDT. Alternatively, simulation-based service mapping models use mathematical or statistical models to mimic the behavior of a given function, as considered in [17]. ML algorithms, including generative models that have recently gained significant potential, can also be used to simulate elements and functionalities. The choice between these approaches depends on different aspects such as data availability, the complexity of the selected approach, and the expected 6G-RANDT instance accuracy. The trade-offs in modeling the different elements are further discussed in Section IV.A.

Finally, the 6G-RANDT instance includes an instance manager, which manages the lifecycle of the internal instance operation and serves applications that require and make use of the information generated. These include interactions between the subcomponents, data feed of the service mapping models, and performance, security, and configuration management based on the changes required by the 6G-RANDT orchestrator.

III. Use case-driven 6G-RANDT typologies and associated measurements

The scope of a 6G-RANDT can broadly vary depending on the problem context and requirements. For example, to deal with low-layer optimization problems such as channel estimation or channel coding, a 6G-RANDT with just a single UE and a single cell driven by PHY and MAC measurement to characterize the channel behavior can be enough. Conversely, upper-layer optimization problems, including resource allocation, packet scheduling, or power control, may require a more complex system models involving multiple UEs or cells using data to characterize e.g. radio resources, sessions, etc. This section identifies three 6G-RANDT typologies, each one referring to a different access scenario (i.e., single-UE/single-cell, multiple-UE/single-cell, and multiple-UE/multiple-cell), and links them to relevant use cases involving RAN functionalities and optimization problems.

Table I presents some examples of key measurement types and use cases that can be addressed with a 6G-RANDT that models a single UE connected to a single cell, such as channel coding/decoding and Single-User Multiple Input Multiple Output (MIMO) techniques. Relevant measurements for these use cases include standardized Layer 1 (L1) and Channel State Information (CSI) reports, as specified in [19]. CSI reports include measurements such as Reference Signal Received Power (RSRP), Signal-to-Interference and Noise Ratio (SINR), Channel Quality Indicator (CQI), Rank Indicator (RI), and Precoder Matrix Indicator (PMI). Additionally, non-standardized internal measurements performed by the gNB and UE, such as channel coefficients and in-phase/quadrature (I/Q) samples, may be used and combined with standardized measurements.

Table II outlines examples of use cases and related measurements addressed by a 6G-RANDT with multiple UEs connected to a single cell, such as Packet Scheduling (PS) and Multi-User MIMO. For example, they can use standardized data such as Performance Measurements (PMs) from [20], instantaneous CSI and L1 reports, and averaged measurements of RSRP, Reference Signal Received Quality (RSRQ) or SINR included in Radio Resource Control (RRC) reports (see 3GPP TS 38.331). Non-standardized data, such as Downlink (DL) buffer status, may further support PS.

The use cases included for multiple UEs and a single cell scenario can also be addressed using a 6G-RANDT with multiple cells. Table III highlights specific use case problems addressed by a 6G-RANDT with multiple users and multiple cells, such as Mobility Robustness Optimization (MRO), Mobility Load Balancing (MLB), handover (HO), Capacity and Coverage Optimization (CCO), network planning, and Inter-Cell Interference Coordination (ICIC). Relevant measurements include mobility management metrics (e.g., inter-gNB/intra-gNB HO requests, successes, and failures) and QoS flow statistics (e.g., number of QoS flows set up or released).

TABLE I. EXAMPLE USE CASES AND ASSOCIATED MEASUREMENTS FOR A SINGLE-UE, SINGLE-CELL 6G-RANDT.

Use cases	Measurements
Channel coding/ decoding, modulation/ demodulation, Single User MIMO	L1 reports, CSI reports, internal non-standardized measurements of gNB/UE.
Channel estimation	Internal non-standardized measurements of gNB/UE.

TABLE II. EXAMPLE USE CASES AND ASSOCIATED MEASUREMENTS FOR MULTIPLE-UE, SINGLE-CELL 6G-RANDT

Use cases	Measurements
PS	CSI reports, Uplink (UL) buffer status reports (see 3GPP TS 38.321), and internal measurements (non-standardized) done by gNB and UE.
Multi User MIMO	L1/CSI reports and internal measurements (non-standardized) done by gNB and UE.
Power control	RRC measurement reports.
Beam management	RRC measurement reports and PMs (beam-related measurements).
Single cell RAN slicing	RRC measurement reports and PMs (CQI and MCS distributions, radio resource utilization, PDU Session/QoS flow/DRB measurements, PDCP data volume, number of active UEs). Same measurements used by PS.
Admission control	PMs (PDU Session/QoS flow/DRB/RRC connection measurements, radio resource utilization, number of active UEs, CQI and MCS distributions).

TABLE III. EXAMPLE USE CASES AND ASSOCIATED MEASUREMENTS FOR MULTIPLE-UE, MULTIPLE-CELL 6G-RANDT

Use cases	Measurements
MRO (HO, user association) and MLB	RRC measurement reports, PMs (HO measurements, radio resource utilization, PDU Session/QoS flow/DRB measurements, CQI and MCS distributions)
CCO, network planning, and network energy saving	RRC measurement reports, PMs (radio resource utilization, beam measurements, PDU Session QoS flow/DRB measurements, PDCP data volume, RSRP, RSRQ, SINR, timing advance, power headroom, CQI and MCS distributions).
ICIC (includes coordinated scheduling)	CSI reports, UL buffer status reports (see 3GPP TS 38.321), and internal measurements (non-standardized) done by gNB and UE (e.g. DL buffers, DL transmit power, etc.).

IV. 6G-RANDT: DESIGN CONSIDERATIONS AND CHALLENGES

Designing a 6G-RANDT involves key challenges, including the availability and quality of real network data, the trade-off between modeling accuracy and computational complexity, and the choice between online and offline operation. Additionally, a 6G-RANDT plays a critical role in ML training, where it must provide a representative and adaptable environment to ensure model accuracy and generalization. These aspects are elaborated in this section, including also a discussion on the involved stakeholders.

A. Availability, quantity and quality of real network data

A key distinguishing factor of a 6G-RANDT compared to traditional link- or system-level simulators is its ability to incorporate real network measurements. In this respect, the MNO is cornerstone in providing access to network data and developing an ecosystem around 6G-RANDTs. The effectiveness of 6G-RANDTs depends on both data quality and sample density. While data from production networks is highly valuable, its availability and diversity are often limited, especially for different network configurations [21]. Currently, the picture from the actual status of the RAN that one can get is based on a broad range of counters, as listed in Section III. However, two main drawbacks are identified. On the one hand, network data is often reported in long averaging windows (e.g. 15 minutes) providing only a coarse view of system behavior. With 6G-RAN embracing advanced features like MU-MIMO and sub-ms packet scheduling, more granular data and a broader set of counters are needed to accurately capture real-time network dynamics. On the other hand, addressing these new use cases like MU-MIMO require expanding the set of counters, including e.g., channel estimation measurements. Generative AI (GAI) algorithms can help to overcome these challenges, e.g. by synthesizing high-resolution data when network data is scarce or inaccessible, enhancing the digital representation of the network.

B. 6G-RANDT complexity

Modeling a 6G-RANDT presents significant challenges due to intrinsic RAN characteristics, such as non-homogeneous spatial and temporal user distributions, time-varying and user-specific propagation conditions, very diverse traffic and mobility patterns, and advanced baseband signal processing technologies such as MU-MIMO and beamforming. Moreover, factors like radio resource utilization, intercell interference, and the influence of RAN control functions (e.g., handover, packet scheduling) further complicate accurate radio scenario characterization. Additionally, advanced technologies such as RIS, THz bands, and massive antenna arrays demand computationally intensive modeling (e.g. ray tracing) and rapid processing of large volumes of data.

To faithfully replicate physical network features at all scales (i.e. from a specific network site to a massive, city-scale) in the virtual domain, advanced computing capabilities (e.g. hardware accelerators, parallel computing, specialized hardware accelerators, multi-GPU scaling, etc.) are required. Thus, the overall 6G-RANDT (and cost) can be a barrier to its actual use at production level, and even prohibitive for certain actors in the research community and small and medium-size companies. In this perspective, the different 6G-RANDT typologies outlined in Section III enable simpler realizations with features tuned to the needs of the use case at hand.

C. Accurate modeling versus complexity trade-off

The complexity of the 6G-RANDT can be expected to be a recurrent concern, underscoring the need for a well-balanced modeling approach that accounts for the accuracy versus complexity trade-off. That is, a simple model will typically have low computational cost at the expense of a less accurate characterization of the reality. However, the level of accuracy in the modeling needs to be balanced to the considered use case and the target objectives. That is, certain aspects of the reality may not need to be modelled in detail if they do not have strong influence on the problem under study. Therefore, the design of a 6G-RANDT needs to tailor the level of detail and models to the problem at hand to avoid excessive framework complexity while addressing the diverse and dynamic nature of next-generation RANs.

D. On-line / off-line operation

By on-line operation we refer to the case that the 6G-RANDT gathers live data from the real network, performs any kind of estimation/prediction which results in an action that is applied in the real network nearly in real time. This would be associated to the ideal vision of fully automated network management. Obviously, on-line operation poses stringent requirements that deserve the accurate modeling versus complexity trade-off discussed above to be carefully resolved. Besides, embedding a 6G-RANDT able to operate on-line in the MNO's ecosystem embraces uncountable practical hurdles when considering the reality of day-to-day operations, variety of tools in place, internal organizational issues, etc. Therefore, on-line operation is envisaged only in the long-term horizon.

In the above perspective, the advent of 6G-RANDT in practice can be seen progressively, taking advantage of the fact that many appealing use cases can be exploited off-line. For example, a 6G-RANDT can be used for testing and tuning the parameters of a scheduling algorithm, which can be later on deployed in the real network.

E. 6G-RANDT for ML training

RANDTs can be used to train and evaluate ML algorithms, as envisaged in [4]. Specifically, RL algorithms which learn by trial and error, can use a 6G-RANDT instance as a sandbox without disrupting the normal network behavior. The training stage of a general ML algorithm involves feeding data into a model, adjusting its parameters through optimization (e.g., gradient descent), and minimizing the output's error using a loss function. Consequently, the quality of training data significantly impacts the algorithm's learning process and final performance on unseen data. Therefore, several challenges arise in designing a 6G-RANDT for ML training to ensure model accuracy when deployed in a real network.

On the one hand, RAN environments are dynamic and diverse, with conditions varying across cells and over time. For example, fluctuations in user distribution patterns, different cell configurations (e.g., transmit power, resource block configuration, frequency bands), radio propagation effects, interference from neighboring cells, and changes in the network topology create a wide and diverse range of plausible scenarios that the ML algorithm can face. On the other hand, since a 6G-RANDT is inherently data-driven, it may predominantly capture common situations, potentially limiting the ML model's ability to generalize to rare or unexpected conditions. Therefore, a 6G-RANDT used for training must not only replicate similar network conditions but also diverse and rare scenarios that may arise in the real RAN. In this direction, data augmentation can be leveraged to enhance the diversity of the training set, improving model generalization. However, expanding training scenarios to include rare and diverse conditions may require extremely large datasets, long training times and, in general, larger models (e.g., more layers in a deep neural network) to learn the patterns in the data.

F. 6G-RANDT stakeholders

While the use of 6G-RANDTs in 6G has gained a lot of attention recently, not much discussion is available in the open literature regarding the underlying stakeholders and business models that can stimulate the creation of a market around it. Given the complexity of designing and deploying a 6G-RANDT, questions about who is going to develop these platforms and who is going to exploit them arise.

Specialized companies already offering radio network planning and optimization software platforms are natural actors to develop 6G-RANDTs, likely addressing use cases requiring a multi-cell multi-user perspective (see Section III for a discussion on possible typologies). Nevertheless, the wide range of potential applications opens the door to more specialized, use-case oriented platforms addressing e.g., radio propagation using ray tracing [22]. In this respect, 6G radio equipment vendors, which already offer all kind of solutions for the network management and operation, are likely to develop their own 6G-RANDT (or a number of 6G-RANDTs more loosely or tightly coupled among them) for its own purpose (i.e., for research and development purposes) and/or for licensing to customers (e.g., MNOs).

The emergence of a disaggregated and open 6G-RAN expands the market by enabling third-party players (e.g., rApps and xApps developers in O-RAN terminology) to enter the ecosystem. These developers can become 6G-RANDT consumers, using the platform to test and validate solutions as well as train ML models.

MNOs are expected to play a pivotal role in making 6G-RANDT a reality, as these platforms rely on real-world network measurements. Therefore, the MNO may have a more active role and not be limited to buy and implement management solutions developed by others. Meanwhile, cloud and computing providers are key enablers of the 6G-RANDT by offering scalable compute and storage resources, as well as acceleration hardware such as GPUs and TPUs. Together with edge computing capabilities, these providers enable the low-latency and real-time processing of the 6G-RANDT execution closer to real-world network conditions.

V. Example: Modeling Cell Capacity

This section emphasizes the relevance of modeling in 6G-RANDT design. As discussed in Section IV.B, when attempting to characterize any aspect of a 6G-RANDT one needs to determine the proper level of detail according to the problem at hand. In general, greater detail involves greater complexity. To resolve this trade-off, the impact of a more or less accurate modeling on the performance metrics of interest needs to be considered.

To illustrate these aspects, this section presents as an example the case of cell capacity modeling. This problem appears in many use cases (e.g. cell planning, resource allocation, traffic offloading, SON, etc.). Besides that, contractual Service Level Agreements (SLAs) often include performance commitments and/or guaranteed bit rates that rely on prior knowledge of the system capacity to offer new services and demonstrate the SLA fulfilment. Specifically, Section V.A below describes how cell capacity can be modelled based on measurements. Then, Section V.B illustrates how cell capacity varies in practice by showing two illustrative cells taken from a real 5G network deployment. Finally, given that different modeling approaches would result in different 6G-RANDT instances, Section V.C considers the use case of RL training and assesses how two different ways of modeling cell capacity affect the effectiveness of the trained model. All results were obtained using a Python environment.

A. Cell capacity modeling

Considering a 5G NR cell with W Physical Resource Blocks (PRBs) and PRB bandwidth B, the downlink cell capacity C (bits/s) is defined as the amount of data that can be transmitted per unit of time across all served UEs. A UE's average spectral efficiency S (bits/s/Hz) across the cell bandwidth depends on the wideband CQI associated with a modulation order and code rate, and number of MIMO layers used to transmit the signal. Then, the data per unit of time that can be transmitted to the UE in one PRB is $B{\cdot}S$. As UEs move around the cell, their spectral efficiencies change, causing cell capacity to vary over time. Furthermore, since the spatio-temporal distribution of UEs varies from one cell to another, as well as the features of the surrounding area of the cell (i.e. buildings, parks, hills, etc.), cell capacity is cell-specific (i.e., different cells may have different capacities even if they have the same bandwidth).

Based on the above, the modeling of cell capacity can be based on measurements, expecting higher accuracy than using e.g., theoretical approaches [23][24]. In particular, among the possible PMs defined in [20], the approach in this paper uses the set of counters *CARR.WBCQIDist.BinX.BinY.BinZ* that collect the distribution of the wideband CQI values reported by the UEs of the cell. Here, X represents the CQI index (0 to 15), Y represents the number of MIMO layers, and Z represents the index of the table in [19] that provides the mapping between the CQI value X and the modulation order and code rate. Our available dataset considers the CQI index from Table 5.2.2.1-3 of [19], supporting a maximum modulation of 256QAM, with a maximum of 4 layers, and counters reported every hour.

Let $b(X,Y,t)$ denote the value of the counter *CARR.WBCQIDist.BinX.BinY.BinZ* at measurement period t. It corresponds to the number of samples collected from UEs in a cell corresponding to CQI=X, with modulation order $m(X)$, code rate $c(X)$, and number of layers Y. Then, we define $S(X,Y) = \varepsilon{\cdot}m(X){\cdot}c(X){\cdot}Y$ as the spectral efficiency value associated with $b(X,Y,t)$. The parameter ε is a factor that accounts for the cyclic prefix, the overhead associated to control channels and reference signals based on [25], and the fraction of time devoted to DL in case of using Time Division Duplex (TDD). As a result, the DL cell capacity $C(t)$ at time period t is estimated as:

TABLE IV. CELL CONFIGURATION PARAMETERS AND PMS CHARACTERISTICS

Parameter	Value
Cell configuration	
PRB Bandwidth (*B*)	360 kHz
Available PRBs per cell (*W*)	273 PRBs
Operating Band	n78 (3.3-3.8 GHz)
Duplexing scheme	TDD with 74% of DL symbols
Overhead parameter (ε)	0.59
PMs dataset characteristics	
Total number of counters	60 (X∈[0, 15] x Y∈ [1, 4])
Measurements reporting periodicity	1h
Total measurements periods	24 (1 day)

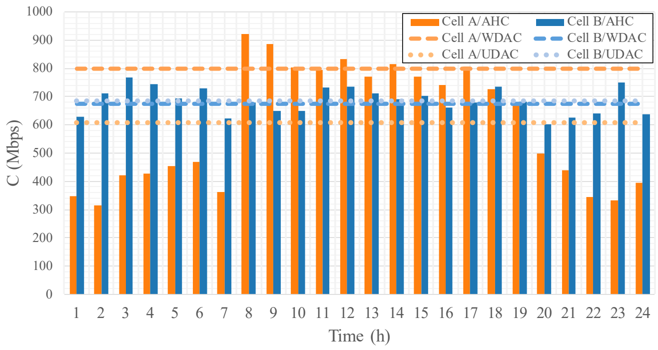

Fig. 2. Capacity evolution for cell A (orange) and cell B (blue).

$$C(t) = W{\cdot}B{\cdot}S(t) = W{\cdot}B{\cdot}\frac{1}{N(t)}\sum_{X=0}^{15}\sum_{Y=1}^{4} b(X,Y,t)\cdot S(X,Y) \quad (1)$$

where $S(t)$ is the average spectral efficiency in the cell at time period t and $N(t)$ is the total number of samples for all the counters at measurement period t (i.e., the aggregate of all the $b(X,Y,t)$ values).

B. Cell capacity assessment

We consider two cells, named cell A and cell B, whose configuration parameters and dataset characteristics, including PMs, are listed in Table IV. These cells were selected for their different environmental features. Cell A is located in a suburban office environment while cell B in an urban residential environment.

Fig. 2 illustrates the capacity evolution for each cell, represented by the average hourly capacity (AHC), derived from processing PMs using (1). The figure also includes two daily averages: the weighted daily average capacity (WDAC), which assigns greater influence to hours with more samples (i.e., higher $N(t)$), and the unweighted daily average capacity (UDAC), which is computed as the mean of the 24 hourly values, treating all hours equally regardless of the number of samples recorded.

The three capacity indicators differ significantly for cell A due to the specific user distribution pattern in this environment. Since the office area is located near the cell site, users experience good propagation conditions, which is translated in a high spectral efficiency and high capacity during office hours. Outside this period, the premises are closed, and traffic is more evenly distributed over the service area, where some areas exhibit worse propagation conditions that degrade the spectral efficiency. On the other hand, the higher user concentration between 8h and 19h leads to a larger number of collected samples, which makes WDAC closely following AHC during this period, and deviating significantly from UDAC.

In contrast, cell B exhibits more stable user distribution during the day and, as a result, AHC reflects a more stable capacity throughout the day. This characteristic, along with a uniform hourly distribution of samples, causes the daily averages to closely resemble AHC, and WDAC and UDAC to be almost indistinguishable.

C. Impact of cell capacity modeling on RL training

When training RL algorithms with 6G-RANDTs, modeling accuracy plays a critical role, as it determines how the RL agent perceives the environment. During training, the agent learns a policy that maps states to actions based on the environment dynamics. If the training environment deviates from the real-world conditions, the learned policy may become suboptimal, leading to actions that degrade network performance during inference. In this context, this section analyzes the impact of 6G-RANDT modeling accuracy on RL performance considering a Deep Q-Network multi-agent RL algorithm for capacity sharing in RAN slicing [26]. The algorithm allocates capacity to slices based on the available capacity and the slices' offered load. Further details on algorithm configuration and hyperparameters can be found in [26]. The RL algorithm, as a 6G-RANDT consumer, requests a 6G-RANDT instance to simulate the real environment and exchanges the state and action signals via the 6G-RANDT API. Two cell capacity modelings are considered in the 6G-RANDT: AHC (illustrating a more detailed approach) and

WDAC (illustrating a simpler approach). To evaluate the performance of the trained RL agent, we introduce the Optimality Ratio (OR) metric, defined as the ratio between the average accumulated reward in evaluation and the reward obtained through an exhaustive search approach that represents an ideal capacity sharing system.

Results shown in Table V indicate that WDAC-based training offers very good OR for cell B (> 90%) but quite poor OR for cell A (< 80%). This is because the simpler cell capacity modeling associated to WDAC may be enough to capture the cell capacity dynamics in cell B where traffic is quite evenly distributed in time and space, but is not able to capture the complexities of cell A, where traffic exhibits spatial concentrations during some periods of the day. In turn, AHC-based training results in high OR for both cells, above 90%, because the modeling considered during training represents the real conditions in a more accurate way.

These results highlight that, depending on the target environment, the 6G-RANDT instance accuracy plays a critical role to keep realistic training conditions. While this discussion has focused on a specific RL algorithm, similar problems and conclusions may apply to network functions requiring cell capacity metrics, such as non-ML-based network optimization methods, cell planning, and SON functions. On this basis, if the MNO intends to deploy an RL algorithm across a large RAN and the complexity of the 6G-RANDT becomes an issue for the use case at hand (e.g., because of computational complexity and real time operation constraints), a simpler 6G-RANDT could work for cells exhibiting a low-variance capacity behavior. Instead, for cells exhibiting larger capacity variations related to the operational environment, a detailed 6G-RANDT and specific training would be required. To this end, the identification of cell typologies with the aid of classifiers [27] would be of much help.

TABLE V. OR COMPARISON FOR THE FOUR 6G-RANDT INSTANCE CONFIGURATIONS

	Cell A	Cell B
AHC	91.06%	93.03%
WDAC	78.17%	92.69%

VI. CONCLUSIONS

This paper has presented a functional model for 6G Radio Access Network Digital Twins (6G-RANDTs), aligning with the vision of the 6G ecosystem. The proposed functional model follows a service-oriented approach, providing a flexible and scalable framework that includes an API for seamless interaction, 6G-RANDT instance(s) for RAN emulation and simulation, and a 6G-RANDT orchestrator for management and data integration. Several 6G-RANDT typologies and measurements were discussed to address different use cases, along with key challenges in next-generation 6G-RANDT development.

To assess the impact of modeling accuracy on 6G-RANDT, a practical example of cellular capacity modeling was presented. Three approaches for processing real-world measurements were applied and compared across two different cell environments, highlighting how environmental characteristics influence their differences. Then, an RL-based capacity sharing algorithm was trained on 6G-RANDT instances that modeled the capacity using different approaches. The results reflected the critical role of selecting an appropriate level of detail when modeling cell capacity in 6G-RANDT, as it can significantly affect algorithm performance depending on the target environment.

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