



Digital twins in 6G networks

Revolutionizing connectivity and RAN performance

White paper

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This white paper provides a detailed examination of digital twins, specifically geo-spatial and network digital twins, in sixth generation (6G) communication networks, with a focus on their benefits for connectivity and radio access networks (RAN). We outline the existing promising solutions that deploy geo-spatial digital twins to improve RAN performance and lay down the practical considerations for meaningful future research and development on this topic.

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Digital twins in wireless networks

Digital twins are virtual, high-fidelity representations of physical systems, enabling simulation, analysis and optimization. While physical systems are constrained by time and space, digital twins remove these boundaries and augment the systems with history and future predictions. Digital twins remove spatial constraints by enabling remote access and monitoring physical assets from anywhere, allowing stakeholders to interact with and analyze the digital replica without being physically present. Digital twins can be stored over desirable periods of time and can be used to predict the future state of the physical twin, hence removing time boundaries. Digital twins are, however, constrained by digital processing capabilities and communications capacity, which limits them to being an abstraction of the physical system.

These technologies are increasingly relevant due to the complexity of modern wireless networks, driven by 5G and the anticipated evolution to 6G. In wireless communication networks, digital twins are categorized into geo-spatial digital twins, which model the physical environment (e.g., terrain, buildings, user distribution), and radio network digital twins, which mirror the network itself (e.g., base stations and RAN functions).

Geo-spatial digital twins: modeling the physical environment

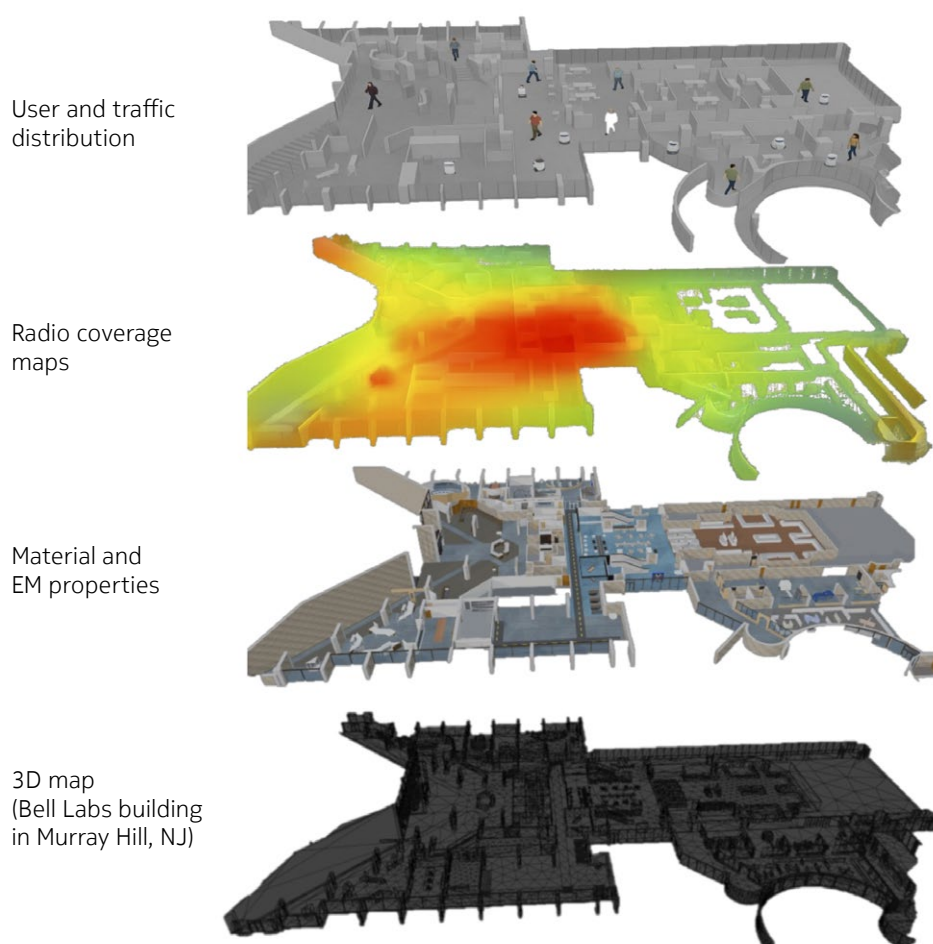
The environment where a network is deployed can significantly impact its performance. In radio propagation, factors such as terrain, structure of objects, their mobility, and the materials present play a key role. In user tracking, localization and positioning, and multi-antenna beamforming, the dynamics of moving objects and mobile users become crucial. In radio resource management and scheduling, user-cell associations and handovers, device-to-device networking, and multi-user beamforming, the relative positioning of network nodes, such as base stations and user devices, are very important.

Geo-spatial digital twins are multi-layered geographical maps and environmental data that contain a 3D map of the environment overlaid with information about the materials and the distribution and locations of objects. Other telemetry data can also be captured that can help anticipate the future dynamics of these objects, such as sensory information and trajectory and activity tracking.

Radio frequency (RF) digital twins are an important layer of information in this framework. Stochastic models of the channel, model-based approaches that solve Maxwell's partial differential electromagnetic field equations, and trained neural networks (NNs) that learn to imitate RF propagation can all contribute to the creation of the RF coverage maps. Further development of these approaches and combining them into physics-informed data-driven models for accurate RF maps remains an active field of research. The RF raytracing tools in recent years have enjoyed advances in GPU-based acceleration and can now handle complex scenes and high angular resolutions in relatively short time. This provides near-real-time raytracing-based received power estimation that is within 10 dB root mean squared error (RMSE) gap to real measurement. By calibrating the radio environment parameters, such as the material properties, one can further improve on the accuracy of such ray tracing tools at the cost of partial measurement data

Additional layers of information could include weather conditions and forecast, and implications derived from calendar events and daily incidents on user and traffic distribution. By modeling the physical environment and utilizing AI-powered prediction tools, the uncertainty in estimating unknown parameters can be reduced, allowing for added determinism in service availability.

Figure 1. Geo-spatial digital twins as multi-layered geographical maps and environmental data



Radio network digital twins: mirroring network operations

Radio network digital twins (RNDT) represent a significant advance in the management, orchestration and optimization of operational networks. These virtual replicas support network automation by retrieving relevant, accurate, and timely data from the real network, user service requirements, and specific use cases. This integration allows RNDTs to evaluate hypothetical operational scenarios virtually, without disrupting the physical network. By simulating different scenarios, RNDTs can predict outcomes and optimize network performance, ensuring that changes are validated before implementation.

RNDTs can be descriptive, providing performance monitoring for network operators, data analysis, identifying potential issues through appropriate visualization, and behavioral, i.e., simulating network behavior and performing “what-if” analysis. RNDTs typically utilize various database types, with knowledge graphs enhancing the visualization of complex network dependencies.

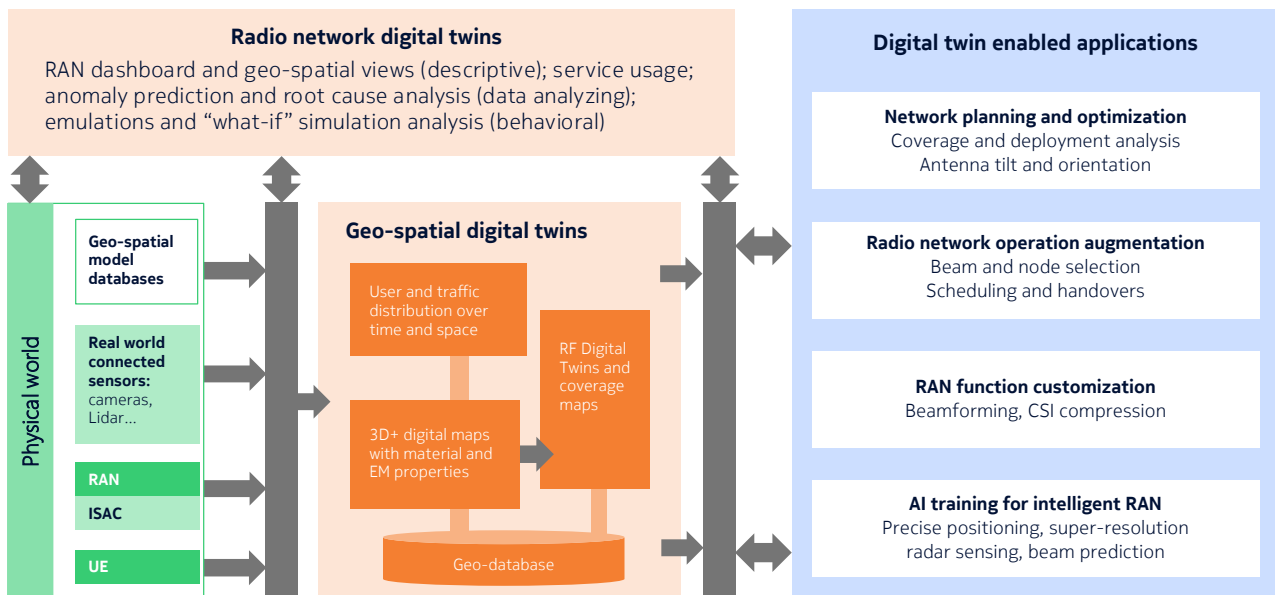
By analyzing data gathered from network operations and accounting for interdependencies and correlations among occurrences, troubleshooting insights are derived through predictive analysis. RNDTs can then examine potential scenarios to identify the most likely root cause and provide operators with meaningful troubleshooting guidelines. Additionally, RNDTs offer a low-cost and safe environment for experimentation and personnel training.

Integration of geo-spatial and radio network digital twins: a holistic architecture to site-specific RAN design

Integrating geo-spatial and network digital twins creates a comprehensive model for wireless communication networks. The combined benefits include improved network deployment strategies, better troubleshooting by understanding environmental impacts, and enhanced simulation capabilities for “what-if” analyses [2]. Figure 2 proposes a reference architecture assuring seamless re-use of digital twins by a diverse set of applications or other digital twins. This includes major building blocks identified as:

- The physical world: It encompasses, besides the network functions, also the geo-spatial, enterprise, or industrial environments
- A composable digital twin framework including:
 - The radio network digital twins for network functions
 - The geo-spatial digital twins for the environment, consisting of models and a layered geo-database
- Digital twin-enabled applications.

Figure 2. Integration of geo-spatial digital twins and radio network digital twins



This integration enables a host of applications in network planning, optimization, customization and intelligence. We will explore several of those examples in the following sections. By leveraging the multi-layered geo-spatial digital twin, this architecture provides a comprehensive understanding of site-specific variations in distributions of users and network load over time and space. The radio network functions can be tailored to the specific needs of each site, enhancing the efficiency and performance of the network. Network operators can gather precise channel distribution metrics for each site or even individual segments within a site. Although creating detailed measurement-based knowledge about channel distribution can be costly, digital twins significantly reduce these costs by providing a virtual representation of the site.

Digital twins and AI: mutually beneficial

AI and digital twins, especially geo-spatial digital twins, create a complementary duo. AI can be used for generating, maintaining and interpreting digital twins while, in turn, digital twins can be used to generate synthetic data for training AI, forming a mutually beneficial relationship. AI-driven methodologies enable precise data ingestion during creation, facilitate continuous performance monitoring and recalibration for maintenance, and support high-fidelity rendering. AI has further shown to be instrumental in interfacing among digital twins and in streamlining operations and decision-making processes [3].

Use of synthetic data as a low-cost alternative to real data is widely practiced in designing site-specific RAN. Naturally, this comes with its own benefits and drawbacks. Crucially, the nature of real data is retrospective, thus, it covers a subset of possibilities that have happened and been recorded. In contrast, synthetic data allows for more explorative AI training and creates instances that are prospective with hypothetical and rare samples included in the set.

Table 1. Real vs. synthetic data for training AI

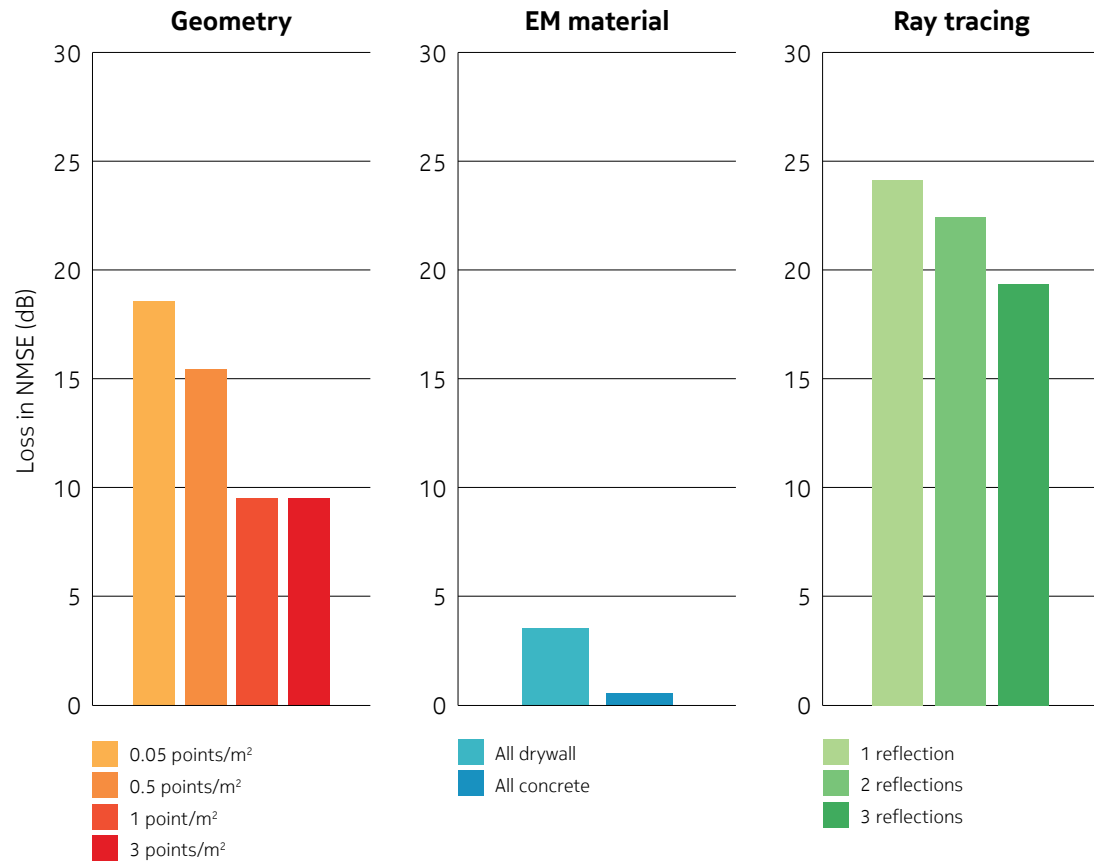
	Real data	Synthetic data (via digital twins)
Temporal nature	Historical / retrospective	Prospective / scenario-based
Coverage	Limited to collected experiences	Can explore rare or hypothetical cases
Bias risk	Real-world biases, under-sampling	Model assumptions, sim-to-real gap
Strength	Grounded in actual physics or behavior	Flexible, controllable, unlimited scale
Weakness	Costly to collect and label	Might not match reality exactly

Fidelity of digital twins and impact on benefits

From the perspective of applications that rely on digital twins, rendering fidelity can have widely diverse impacts. Fidelity is mainly determined by the resolution of the 3D map and ray tracing, material properties, and hardware/software modeling for the network functions. As the fidelity of a geo-spatial digital twin increases, the cost of creating and maintaining it increases. As a result, the net benefit diminishes with extreme high fidelity. This emphasizes the need for investigating the impact of digital twin fidelity on downstream applications.

As an example, leveraging a digital twin of the cell site to train a deep learning model for the compression of downlink channel state information (CSI) can substantially reduce the need for expensive real-world channel measurements. For such an end-goal, geometric fidelity, object material properties, and electromagnetic ray-tracing fidelity (quantified by the number of reflections) demonstrate stark difference on the accuracy of channel predictions. This is illustrated in figure 3, showing the sensitivity of the CSI compression/prediction model performance to the fidelity of the various digital twin elements. Notably, knowledge of the material EM properties provides marginal impact compared to ray tracing fidelity and the 3D-geometrical resolution of the scene [4].

Figure 3. Impact of digital twin fidelity on CSI compression. The bars reflect the loss against physical world model as the digital twin fidelity changes, and is measured in normalized mean squared error (NMSE)



Opportunities in radio networks

The convergence of GSDTs and RNDTs opens new dimensions in the planning, optimization, and autonomous operation of next-generation wireless systems. In this section, we explore the planning and operational opportunities brought to radio networks, thanks to such integration.

Network planning and optimization

Radio networks are generally dimensioned statically based on the “worst case” scenario so that the required network and user key performance indicators (KPI) are satisfied even during busy hours. Instead, RNDT can model dynamic network behavior and simulate various what-if scenarios in case of some spatial or temporal hotspot in the network. This can be for example, 10x more users in a certain area during a sports event. The event can be modeled and simulated virtually in an RNDT simulator, which can predict outcomes with different radio resource management strategies. These can be, for example, allocating more frequencies, preemptively moving users to different frequency bands, changes in scheduler configurations, changes in beamforming and MIMO configurations, etc. The most suitable outcome can then be selected, and the cells can even be prepared in advance. The AI frameworks are trained to identify similar events in similar conditions, which can reduce reaction time in the future.

This all means that with the help of RNDT, the network can originally be planned much better to match with the actual needs and avoid over-dimensioning, minimizing operational costs by avoiding unnecessary adjustments post-deployment [5]. Furthermore, during operation the network parameters can be optimized continuously to maximize performance at each time and for each network area. The time scale for prediction-based optimization depends on the capabilities of RNDT. In some limited use cases with small areas (for example, one room in a factory), the optimization can happen in a very short time scale (seconds), while in more typical settings, the time scale could be hours or days, allowing the RNDT simulator to prepare an updated network configuration.

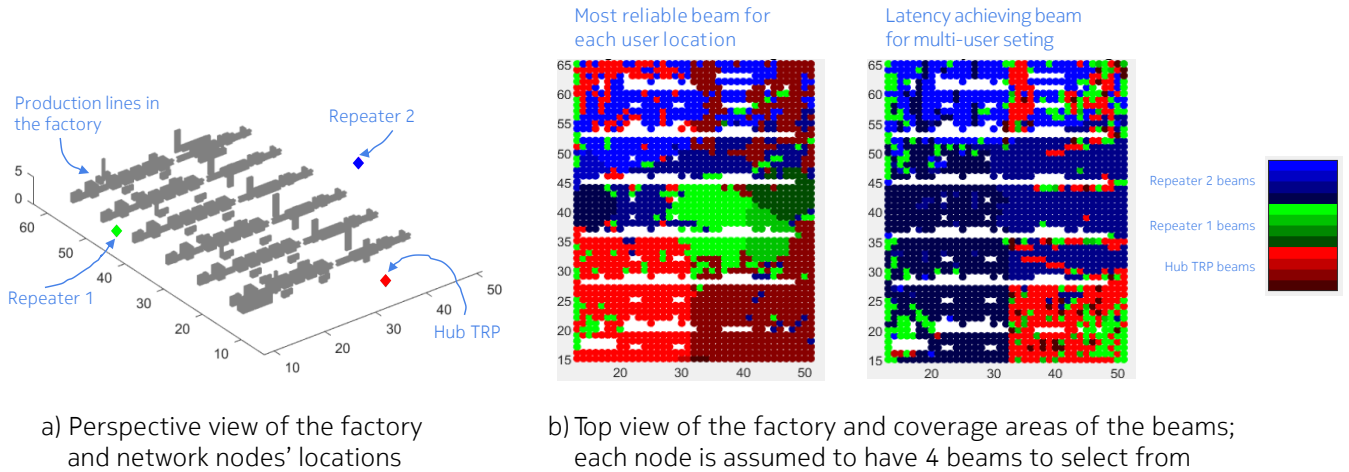
Augmenting dynamic radio network operations

Dynamic operation of RAN functions can similarly benefit from knowledge of the site. This requires a closer to real-time geo-spatial digital twin, which monitors the movements and alterations in the 3D space. RAN functions, particularly with user location information, can leverage such near-real-time geo-spatial digital twins for site- and time-specific operation. In the following, we discuss a few examples of such operation augmentation for RAN.

Node and beam selection for users

Beam management involves aligning beams during initial access and tracking them as users move. Naïve strategies, like exhaustive beam searches, create significant overhead and become inefficient as array sizes and beam space grow. This has driven the adoption of supervised learning techniques to propose beams or estimate mmWave channels more efficiently.

Figure 4. Digital 3D map of a factory is used to evaluate node and beam selection strategies for connected users



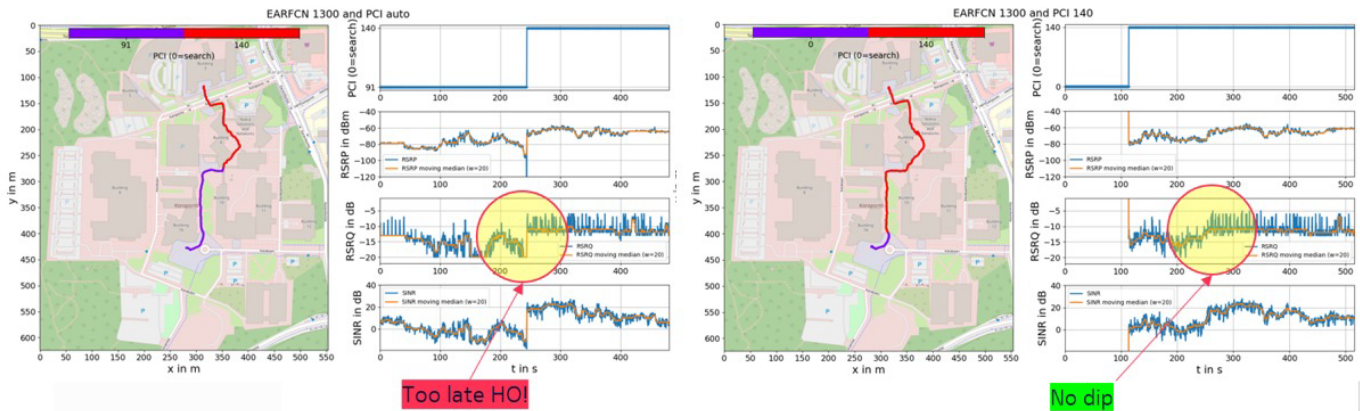
Geo-spatial digital twins, augmented with user location data, can generate training data and manage beamforming with reduced overhead. Figure 4 illustrates how a 3D map of a factory, combined with network node and user location knowledge, enables RF digital twins to optimize beam selection. In this example, a transmission-reception point (TRP) and two beamforming repeaters provide enhanced coverage. Beam selection strategies vary based on objectives, such as single-user link reliability versus multi-user latency constraints. As factory layouts and user locations evolve, the digital twin updates to reevaluate strategies, reducing operation latency by up to 50% for reliable, low-latency communication [6].

Without user location information, the RAN can predict the next best serving beam and proactively switch beams without waiting for measurement reports. User trajectories, shaped by roads, walkways, traffic laws, and social customs, can be mirrored in a geo-spatial digital twin. Supervised neural networks then learn patterns in users' beam index sequences. The learned trajectories enable proactive beam switching by the RAN [7].

Smooth inter-cell handover

Figure 5 illustrates how RNDT improves inter-cell handover by leveraging geo-spatial digital twin data. The figure shows a pedestrian user's trajectory, with path color indicating the connected cell, based on real measurements from a live network. Without RNDT (left), a late handover request causes signal strength to drop sharply for several seconds. With RNDT (right), additional information—such as building layouts, obstacles, line-of-sight, user waypoints, and pre-calculated signal quality estimates—enables earlier handover triggering, maintaining strong signal quality throughout the route.

Figure 5. Example of how RNDT can be used to improve base station handover performance



Site-specific understanding of channel state

A critical challenge in cellular systems is proper estimation and exchange of channel state information (CSI). The existing compression and decompression techniques can be categorized in three approaches.

1. Standardized model-based encoder and decoder

Traditionally, CSI estimation and reporting in networks like LTE and 5G rely on standardized encoder and decoder pairs. These systems use generic channel models, where the gNodeB transmits CSI reference signals (CSI-RS), and the user equipment estimates and compresses the channel state using standardized codecs. The compressed CSI is then reported back to the gNB for decompression. While effective, these methods are not site-specific, limiting performance in unique environments.

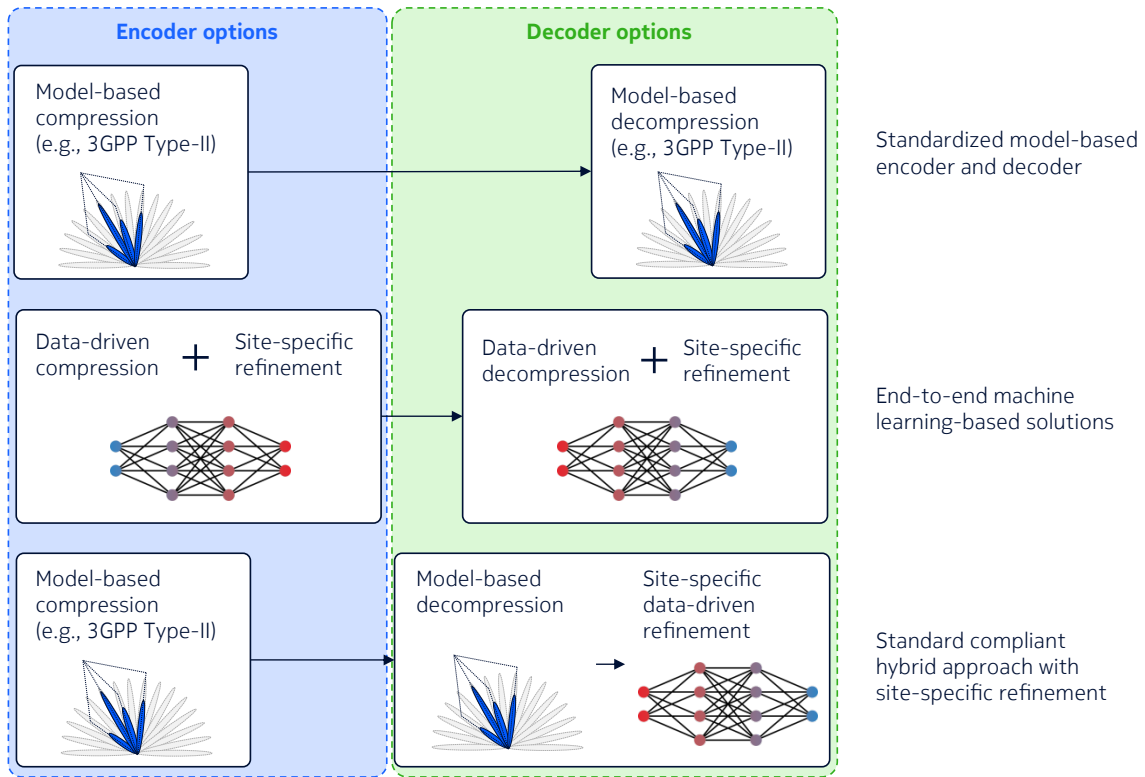
2. End-to-end machine learning-based solutions

Data-driven, end-to-end machine learning solutions for CSI compression and decompression, promise adaptability to site-specific conditions. Standardizing such solutions poses challenges, particularly in ensuring interoperability across diverse user and network vendor systems [8].

3. Standard-compliant hybrid approach with site-specific refinement

The third approach introduces a novel, hybrid solution that combines the robustness of standardized methods with the adaptability of machine learning. This method employs standard encoder and decoder pairs for initial CSI compression and decompression, ensuring compliance with existing network standards. Subsequently, a machine learning-based refinement module enhances the decompressed CSI using site-specific channel state knowledge [9].

Figure 6. Evolution and potential of CSI compression solutions

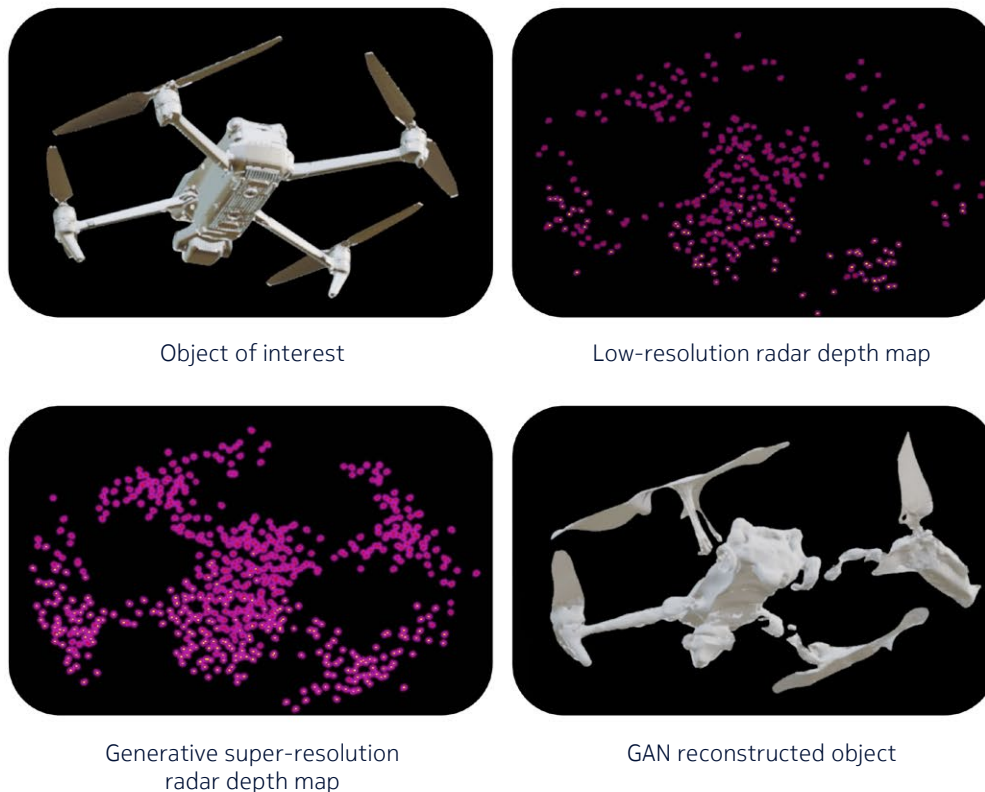


The hybrid method offers a compelling pathway to harness site-specific information effectively while maintaining interoperability and nearly matching the performance of the end-to-end ML-based solution. This balance is crucial for realizing the full potential of site-specific channel state knowledge in both existing and future cellular networks.

Enhancing localization and sensing services

Integrated sensing and communication (ISAC) systems are foundational to 6G networks but face challenges in radar sensing, including reduced spatial/temporal resolution, wide beam patterns, and sparse sampling. Traditional image processing struggles with degraded radar images, especially in urban environments where static scenes and clutter dominate. However, the regularity of urban environments offers an opportunity to leverage prior knowledge of typical objects and scene geometry. Generative AI models, such as generative adversarial networks (GANs), can learn these priors to enhance low-resolution radar depth maps into high-resolution 3D reconstructions. This generative enhancement improves object detection and semantic scene understanding, enabling scalable, near-real-time applications like digital twin creation and maintenance.

Figure 7. Radar sensing, especially in the context of ISAC, provides a low-resolution view of the world, and geo-spatial digital twins can help with capturing the appropriate priors, which enables generative super-resolution techniques to improve fidelity of the depth map



Cellular localization often relies on fingerprinting, a technique that creates a database by mapping channel characteristics to specific locations, but this process demands significant human effort. Geo-spatial and raytracing-based RF digital twins can generate synthetic positioning data to complement or reduce the need for extensive real-world measurements. This can be seen as an additional layer to the multi-layered GSDT model of Figure 1. This synthetic data can also enhance AI/ML model training through transfer learning. While environmental factors (e.g., moving objects, weather, structural shifts) and hardware/radio variations can impact accuracy, maintaining near-real-time digital twins for fingerprinting databases may be computationally complex. Nevertheless, digital twins have demonstrated promising results, achieving sub-meter localization errors in non-line-of-sight (NLoS) locations 95% of the time [10].

Envisioning a practical way forward

Levels of knowledge, complexity and performance benefits

With geo-spatial digital twins for wireless network design and optimization, we categorize prior knowledge into a hierarchy. These GSDTs integrate layers of static and dynamic information, as illustrated in figure 1. Higher knowledge levels enable superior performance (e.g., throughput, coverage, latency), but complexity—and thus costs—escalates nonlinearly.

Our framework includes five practical levels (0–4), advancing in specificity, temporality, and autonomy, plus a theoretical upper bound:

Level 0: no prior knowledge—relies on real-time measurements or heuristics, without DTs (e.g., channel estimation pilots). Minimal complexity, but inefficient under variability.

Level 1: generic static knowledge—uses site-agnostic models (e.g., Rayleigh fading, uniform distributions), together with the real-time measurements of Level 0. Low-cost foundational gains, like basic coverage and capacity planning.

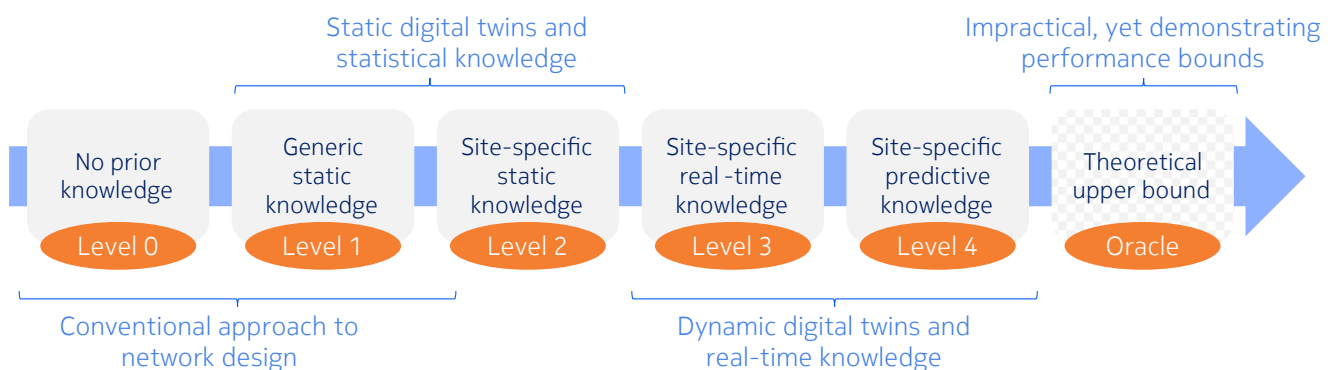
Level 2: site-specific static knowledge—incorporates static geo-spatial data (e.g., 3D maps, user heatmaps). Enables offline simulations (e.g., ray-tracing), boosting interference mitigation at moderate complexity.

Level 3: site-specific real-time knowledge—fuses live data with trends (e.g., sensor-fed user locations). Supports dynamic adjustments (e.g., 5G beam steering), increasing autonomy and demands.

Level 4: site-specific predictive knowledge—AI/ML predicts evolutions (e.g., mobility forecasts), with self-learning loops for proactive optimization (e.g., 6G resource allocation). High complexity from compute-intensive models.

Theoretical upper bound: oracle knowledge—assumes perfect future-state foresight (e.g., exact trajectories), benchmarking maximum performance like Shannon limits, despite inherent uncertainties.

Figure 8. Levels of prior knowledge in the landscape of wireless network design and operation



Advancing levels yields potential benefits, e.g., in the form of beamforming gain from Level 1 to 3 via enhanced modeling. However, complexity grows faster to maintain real-time monitoring (Level 3), improve fidelity, maintain predictive knowledge (Level 4) and to engage AI.

Conventional networks are designed and optimized at Levels 0–1, using overprovisioning or reactive fixes, leading to inefficiencies. Research often targets Level 4 or oracle ideals for autonomous 6G, but under-explore deltas from Level 3 to 4 and toward the oracle highlight a critical need: quantifying marginal

benefits (e.g., reliability boosts) against surged costs. Intermediate levels (2–3) likely offer better cost-benefit tradeoffs, delivering efficiency with feasible investments in sensors and analytics. The oracle level is essential, revealing improvement headroom. By benchmarking against it, future effort in research and development can be more intelligently invested. Future studies should empirically assess levels, integrating economic models for pragmatic digital twin adoption in evolving wireless ecosystems.

Challenges and open research problems

In the integration of geo-spatial digital twins with radio network digital twins, there remains important hurdles. Key challenges include data accuracy, computational demands, security/privacy risks, and implementation costs. Addressing these is crucial for practical deployment, particularly in dynamic wireless environments where geo-spatial fidelity directly impacts network performance metrics like latency and coverage.

Data accuracy and reliability

Ensuring DTs mirror real-world conditions remains a core issue. Discrepancies arise from sensor noise, incomplete data, or synchronization lags between physical and virtual models [11].

Computational requirements

As discussed earlier, real-time digital twins demand immense resources. Complex modeling, such as ray-tracing in 3D environments or AI-driven predictions, strains edge computing and requires 6G-level bandwidth for data fusion [11].

Cost and implementation

High upfront costs for sensors, software and infrastructure, plus ongoing maintenance may hinder adoption. Deployment complexity involves interoperability standards for geo-network integration, often lacking in heterogeneous systems [12]. More studies must weigh benefits against these expenses.

Takeaway and summary

Radio network digital twins (RNDTs) are a transformative innovation for optimizing radio access networks, combining geo-spatial digital twins with AI-driven insights to enable tailored, site-specific network design and operation. Key takeaways include:

1. AI-driven, site-specific optimization with RNDTs

RNDTs leverage AI to create data-driven models for optimizing network performance, management, orchestration and energy efficiency. By utilizing site-specific data, they enable tailored radio network design and operation.

2. Potential and challenges of geo-spatial digital twins

Geo-spatial digital twins enhance RAN performance, reduce AI training costs and energy consumption, and minimize decision-making overhead and latency. However, further research is needed to address discrepancies between digital twins and their physical counterparts.

3. Modular and reusable architecture

RNDTs should be modular and reusable, with functionality exposed via APIs to support flexibility, interoperability and efficient resource utilization.

4. Cost-performance tradeoffs in RNDT implementation

Advancing RNDTs requires evaluating the cost and complexity of operating networks at different levels of the 5-level model presented in this paper. Understanding these tradeoffs is key to scalable implementation.

RNDTs have the potential to revolutionize RAN design, operation and management. By addressing digital-physical discrepancies and balancing cost-performance tradeoffs, the industry can unlock their full promise. As research progresses, RNDTs are set to play a pivotal role in shaping intelligent, efficient and adaptive radio networks.

Abbreviations

6G	Sixth generation (3GPP)
CSI	Channel state information
CSI-RS	CSI reference signals
GAN	Generative adversarial network
gNB	Next-generation node B (5G new radio base station)
ISAC	Integrated sensing and communication
KPI	Key performance indicator
NMSE	Normalized mean squared error
NN	Neural network
RAN	Radio access network
RF	Radio frequency
RMSE	Root mean squared error
RNDT	Radio network digital twins
TRP	Transmission-reception point

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