Real-Time Digital Twins: Vision and Research Directions for 6G and Beyond

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The authors presents a vision where real-time digital twins of the physical wireless environments are continuously updated using multi-modal sensing data from the distributed infrastructure and user devices, and are used to make communication and sensing decisions.

Abstract

This article presents a vision where real-time digital twins of the physical wireless environments are continuously updated using multi-modal sensing data from the distributed infrastructure and user devices, and are used to make communication and sensing decisions. This vision is mainly enabled by advances in precise 3D maps, multi-modal sensing, ray-tracing computations, and machine/deep learning. This article details this vision, explains the different approaches for constructing and utilizing these real-time digital twins, discusses the applications and open problems, and presents a research platform that can be used to investigate various digital twin research directions.

Introduction

Heading toward 6G, communication systems are increasingly featuring key trends such as the employment of large numbers of antennas and the use of higher frequency bands [1]. These technology trends bring higher data rates and multiplexing gains to the networks, but also impose critical challenges on the ability of these systems to support highly mobile, energy-constrained, reliable, and low-latency applications. For example, the deployment of large antenna arrays incurs high overhead in channel acquisition and beam sweeping [2]. This makes it difficult for massive MIMO systems to support mobile applications. The use of higher frequency bands at mmWave and sub-THz makes the wireless links very sensitive to line-of-sight (LoS) blockages, which challenges the reliability and latency of the networks [3].

In this article, we present a novel vision in which a *real-time* digital twin is utilized to make operational physical, access, network, and application layer decisions to the real-world communication and sensing systems. The key features of the envisioned digital twin-based wireless systems can be summarized as follows:

- *Enabled by 3D maps and multi-modal sensing:* The envisioned digital twin will leverage precise 3D maps and fuse multi-modal sensory data from distributed devices and infrastructure nodes to construct an accurate real-time digital replica of the physical world.
- *Capable of making real-time decisions:* Leveraging advances in real-time 3D ray-tracing, efficient computing, and machine/deep learning, the envisioned digital twin will be capable of making real-time decisions for wireless communication systems.
- *Continuously refined for better approximation:* We envision the digital twin as a model that will be continuously refined to improve its approximation of the physical world (including the electromagnetic and optical aspects) and to enhance its decision accuracy.
- *A global digital twin shared between devices:* In its ultimate version, we envision this digital twin to be global and shared between devices such that all devices can jointly enhance it and benefit from it using their coordinated sensing and communication decisions.
- *Used for all communication layer decisions:* With the real-time emulation of the physical world, the envisioned digital twin can be utilized to make physical-layer decisions such as channel prediction, as well as access, network, and application layer decisions.

It is important to highlight here that the general concept of digital twins has been studied before in the context of smart manufacturing, intelligent transportation, and healthcare [4]. For wireless communications, prior work has studied network operation topics such as edge computing and service management, in which digital twins simulate the real world at the network level [5]. Prior work has also leveraged digital twins in non-real-time applications such as site engineering [6]. In this article, however, we utilize the digital twin to simulate the real world in *real-time* with a particular emphasis on the physical modeling of the environment and wireless signal propagation. The envisioned real-time digital twin merges 3D maps and real-time sensory data from the physical world to construct a real-time digital replica. By applying real-time ray tracing on the digital replica, the digital twin can produce real-time instantaneous and statistical channel information, which could be leveraged to make decisions for the various layers of the communication systems. In our ultimate vision, the real-time digital twin itself is a machine learning model that keeps learning and evolving. We call this the true digital twin.

This article aims to expose the potential of real-time digital twins for wireless communication and sensing systems in 6G and beyond. In the next sections, we discuss the key enabling technologies, the different approaches for constructing and utilizing these digital twins, and the various applications and future research directions. We also present a research platform that could be used to investigate many interesting digital twin research directions.

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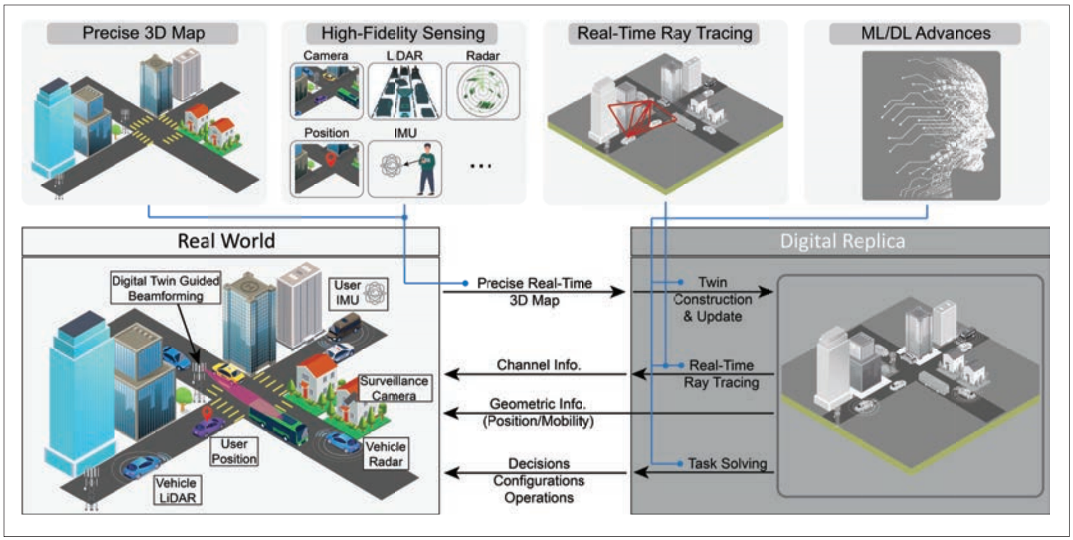

FIGURE 1. General idea of the digital twin with the four key enablers: precise 3D map, high-fidelity sensing, real-time ray tracing, and ML/DL. The digital twin can simulate wireless propagation and infer channel information.

Today's Technology Advances Lead to Real-Time Digital Twins

The vision of building real-time digital twins is motivated by the recent advances in 3D maps, multi-modal sensing, ray tracing, and machine/deep learning (ML/DL). Next, we briefly discuss these four key enablers for real-time digital twins (Fig. 1).

Precise 3D Maps

3D maps contain information about the positions, shapes, orientations, and materials of the communication devices and other objects in the environment. The current application trends of AR/XR, autonomous driving, and metaverse technologies created an increasing demand for precise 3D map data. In response to that, the 3D map data collection, processing, and management capabilities have been significantly advanced. Vehicle, airborne, and satellite 3D imaginary sensors are now used to collect and build very accurate 3D maps. Further, the growing computational and database resources are making it possible to process and manage large-scale 3D maps, even at the scale of the full world like Nvidia OmniVerse [7]. Thanks to all these developments, precise 3D maps are becoming more affordable and accessible.

High-Fidelity Sensing

Recent trends in sensing-aided communication, integrated sensing and communication, and internet-of-things (IoT) tend to deploy multi-modal sensors, such as cameras, radars, LiDARs, positioning, at the infrastructure, user equipment, and IoT devices. These distributed sensors can complement each other since they have different observing angles and different types of information, such as position, shape, and mobility measures about stationary and moving objects. This sensing capability can be further enhanced by leveraging the recent advances in multi-modal data fusion [8]. As a result, it is becoming more feasible to acquire high-fidelity sensing information about the surrounding environment in nearly real-time, which is a key enabler for the envisioned digital twin.

Real-Time Ray Tracing

Ray tracing simulators attempt to trace the wireless signal propagation and generate parameters of the propagation paths, such as the angles of arrival/departure and complex path gains. A main limitation of ray tracing simulators is that they typically require considerable computational overhead, and hence, incur high latency. The recent advances in parallel computing hardware and ray-tracing computational approaches, however, are enabling real-time ray-tracing for both wireless and optical signals [9]. This means that, given precise real-time 3D maps, the wireless channels between the (possibly mobile) transmitters and receiver can potentially soon be computed in the digital twins in real-time.

Advances in Machine/Deep Learning

ML/DL have demonstrated powerful capabilities in extracting features, approximating complex functions, and solving optimization problems in wireless communication and sensing/perception. In digital twins, these advances in ML/DL can be utilized to:

- Enhance the quality and reduce the cost of building precise 3D maps
- Improve the efficiency of the multi-modal sensing in terms of sensory data processing, transferring, sharing, and fusion [10]
- Advance the ray tracing accuracy and reduce its latency and computational complexity
- Solve communication and sensing tasks.

All these advances in the enablers are making it more feasible to realize real-time digital twins. In particular, the precise 3D map and high-fidelity sensing complement each other; while the 3D maps mainly contain information about static objects, the high-fidelity sensing can augment these maps with information about dynamic objects in real-time. Applying real-time ray tracing on these real-time 3D maps leads to real-time wireless digital twins. Further, the ML/DL advances can enhance various aspects of these digital twins. The real-time digital twins open opportunities for novel capabilities and applications in wireless communication and sensing systems. These digital twins can, for example, be leveraged to compute channel or channel covariance

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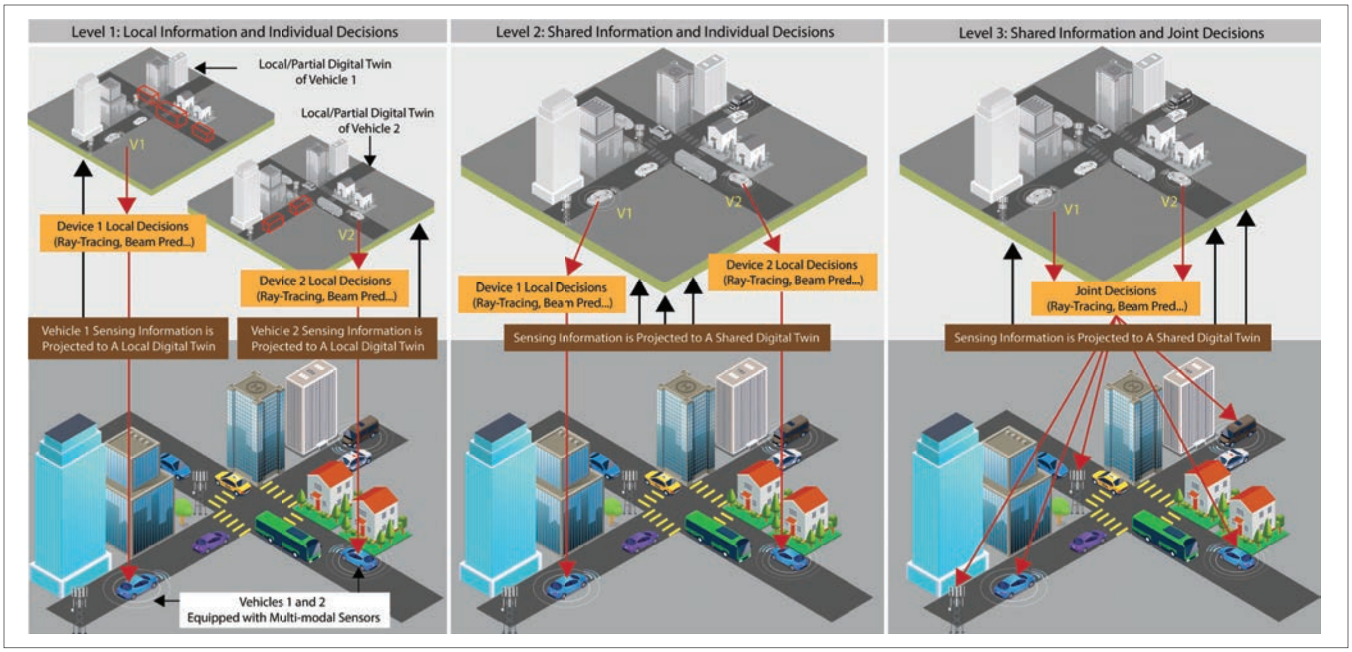

FIGURE 2. Three operating modes of the digital twin system: a) Local information and individual decision; b) Shared information and individual decision; c) Shared information and joint/cooperative decision.

information, predict LoS link blockages, proactively predict handover, and even predict application-specific caching requirements.

True Digital Twins That Keep Learning

There are different approaches of how such a real-time digital twin could be leveraged. In this section, we first discuss two main approaches where digital twins are used for training ML models or making real-time decisions. Then, we present our vision for true digital twins that keep learning and improving over time.

Digital Twins for Training ML Models

With precise 3D maps and accurate ray-tracing simulators, we can build high-fidelity and site-specific synthetic datasets. These datasets could be utilized to train ML models for various wireless communication and sensing tasks. In particular, these synthetic datasets could be generated on a large scale and with high variance, which is hard and expensive to collect in the real world. The ML models that are trained on these site-specific synthetic datasets could then be deployed to make inferences/decisions for the physical world. Further, these models could be refined using limited real-world datasets for better and more robust performance. This approach relaxes the latency requirements as the digital twins are not used for real-time decisions. The drawback, however, is that these ML models are not benefiting from the global real-time sensing and awareness that the real-time digital twins have, which may limit their performance.

Digital Twins for Real-Time Decisions

Another approach is to use these real-time digital twins to make real-time or near real-time decisions for the physical-world communication and sensing systems. For example, an FDD massive MIMO base station (BS) can use the real-time digital twin to predict the downlink channel or, at least, the dominant subspace of this channel, which saves large channel training and feedback overhead. Mobile users may also use this digital twin, for example, to predict if their LoS links are going to be blocked by a moving scatterer or whether they need to switch to other beams. This approach can, therefore, benefit from the real-time nature of the digital twin and the richer awareness about the surrounding environment in making real-time decisions. The drawback, however, is that the decisions that are solely made based on the digital twin will be very sensitive to the modeling accuracy, which challenges the robustness of these decisions.

True Digital Twins

The previous two approaches have a clear trade-off between the ability to benefit from the real-time awareness of the digital twins to make efficient decisions (e.g., in terms of wireless resources and mobility support) and the ability to ensure the robustness of these decisions. This motivates what we call *true digital twins*. The true digital twins can be thought of as ML models themselves that keep learning and improving their approximation of the physical world, and hence their decisions, over time. In particular, these digital twins could leverage learning agents and use prior decisions and feedback to enhance the modeling accuracy of the 3D maps, the processing and integration of the multi-modal sensing data, and the approximation fidelity of the ray tracing. These true digital twins can, therefore, be used to make decisions that are both real-time and accurate for the various wireless communication and sensing tasks. However, achieving the true digital twin still requires investigating several important challenges. Later, we highlight some of the open research directions.

Three Digital Twin Levels

Constructing and utilizing digital twins requires interaction with the devices that are contributing to the digital twins with their sensing data and that are leveraging the digital twins in making decisions. This raises questions about the required level of coordination between these devices for both the sensing and communication tasks. For that, we envision that digital twins will evolve through three main levels of coordination as the computation, synchronization, and communication capabilities develop over time. Next, we briefly present these operating modes (levels) and highlight their considerations and challenges in deployments (Fig. 2).

Local Information and Individual Decisions

We envision the first level of the digital twin to incorporate local sensing and individual decisions. In particular, each device exploits its sensors to collect local sensing information. The acquired local data is then projected onto a 3D map to generate a real-time local digital twin, which can facilitate the sensing and communication decision-making process for the device.

Shared Information and Individual Decisions:

The first level of the digital twin is limited by its local view of the environment. To that end, in the second operation level, we propose to fuse the local information collected across devices to generate a detailed and thorough digital twin. Even though information is shared across devices, each device is envisioned to undertake its own sensing and communication decisions.

Shared Information and Joint/Cooperative Decisions

With the increased computation and communication capabilities, we envision that digital twins will evolve into a more global and cooperative form. On the third level, the devices share their sensing information to form a global and comprehensive real-time digital twin. In addition, the sensing and communication decisions are jointly optimized in a central or distributed way.

As the level increases, the digital twin gets more powerful in their decision capabilities, higher in computation and coordination, and more likely to be centralized. We take the beam management task between one BS and multiple users as an example to illustrate the considerations of the digital twin levels in deployments. In the first level, the BS can perform beamforming utilizing its local digital twin, which may be effective for LoS users. However, this local digital twin may not be able to model the non-line-of-sight (NLoS) users that are not captured by the local sensors. This partial view of the digital twin limits its decision-making capability. In the second level, the BS utilizes a global digital twin constructed by sensory data from all devices. This global digital twin can model all devices and the surrounding geometry, enabling NLoS beamforming decisions. However, sharing the sensing data and constructing a more comprehensive digital replica increase computation and communication overhead. In the third level, the global digital twin is used for joint beam management to align the BS and user beams and reduce interference. While the joint decision increases system performance, it requires more overhead. In deployment, the digital twin level should be carefully designed considering the application requirements, computation and communication capabilities, and implementation cost.

Digital Twins in the O-RAN Architecture

The three digital levels can align with the O-RAN architecture. For example, in the second and third digital twin levels, communication devices may share their information with an O-RAN application that runs on the edge and/or cloud. This application can then use the information from these communication devices to construct and host a global digital twin. In the case of the second level, communication devices may obtain useful information from the global digital twin via this application, and make individual decisions. For the third level, the O-RAN application may use the global digital twin to make joint decisions and feed them to the communication devices.

Constructing and utilizing digital twins requires interaction with the devices that are contributing to the digital twins with their sensing data and that are leveraging the digital twins in making decisions.

Applications

The proposed digital twin can infer various information about the wireless channels, such as the propagation path parameters (path loss, delays, angles, etc.), channel and covariance information, link quality, and blockage status. Moreover, by utilizing the temporal and spatial consistency of the channels, the digital twin can predict future channel information in dynamic environments. The digital twin can enable real-time and proactive decisions that can potentially improve the communication system operations in the physical, access, network, and application layers (Fig. 3).

Physical Layer

The physical layer operation has, by definition, a clear dependency on wireless channels. Many physical layer tasks, for example, MIMO precoding and link adaptation, directly rely on partial or full knowledge about the communication channels. However, channel acquisition is typically associated with high overhead, especially in large-dimensional systems, which degrades the overall system efficiency. Real-time digital twins open novel opportunities to revolutionize the channel acquisition process: When the real-time 3D maps and ray tracing computations are sufficiently accurate, the digital twin could be directly used to accurately infer the channels, reducing or even eliminating the channel acquisition overhead. Further, in scenarios where the approximation is insufficient to accurately estimate the full channels, the digital twin may still be used to predict the dominant channel subspaces and reduce the channel acquisition overhead [11, 12]. These digital twins can also be used to estimate the signal-to-noise ratio (SNR) of the communication links and improve the modulation and coding scheme selection. Another interesting physical layer application of the digital twin is to generate a massive amount of data for a given site in the real world. This site-specific data can then be utilized to optimize the traffic beam sets and the channel feedback compression codebooks.

Access Layer

Current and future communication systems, especially at higher frequencies, employ large antenna arrays and highly-directional beams to achieve sufficient SNR and realize high data rates. Aligning these beams, however, typically requires large beam training overhead that scales with the number of antennas. The real-time and future channel information predicted by the digital twin can facilitate the initial access (initial beam alignment) and beam management for these systems and reduce the beam training overhead. Further, due to the increased penetration loss, high-frequency communication links experience sudden disturbance

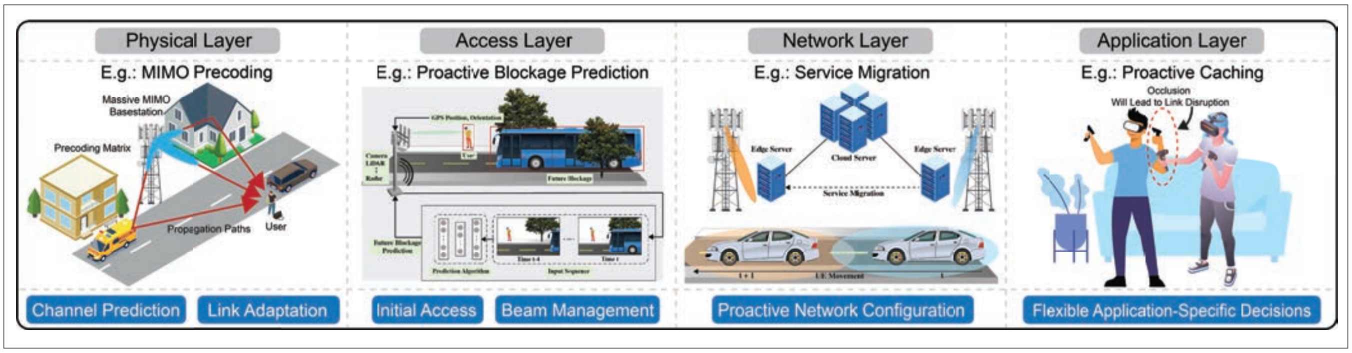

FIGURE 3. Example communication applications that digital twins can facilitate across various layers. For example, in the access layer, the digital twin can proactively predict blockages and initiate hand-off.

due to blockages. By tracking the motion of the user and other objects in the environment, the digital twins can proactively predict the occurrence and duration of incoming blockages before they happen. This enables seamless handover control and improves network reliability and latency performance. Digital twins can also enhance the access layer resource allocation, user scheduling, MU-MIMO user pairing, and interference management, among many other applications.

Network Layer

In prior work, digital twins have been used to optimize the network layer operations and applications such as device and traffic monitoring, resource allocation, and edge computing. We refer to this type of digital twins as the network-level digital twins since they typically focus on monitoring network status and modeling the network-level entities, services, and dynamics. Differently, the envisioned physical-level digital twins can provide fine-grained information about the communication links, which can also be used to improve the accuracy of the radio access network (RAN) modeling. This accurate RAN modeling can enhance the efficiency and reliability of various network-level operations. Further, the physical-level digital twins can provide real-time and future information about the user position and mobility characteristics, which could be leveraged to improve several edge computing operations. For instance, when a user is moving out of the service area of the in-use edge server, proactive service migration can be triggered to improve the service quality. The physical-level digital twins can also work cooperatively and in an integrated manner with the network-level digital twins to enhance the end-user experience.

Application Layer

Emerging applications pose more stringent reliability and latency requirements to advanced communication systems. The 6G aims to deliver 9-nine reliability with 0.1ms latency for safety-critical applications. Moreover, different applications with varying needs for data throughput, reliability, and latency require different strategies when handling link instability. The digital twin can simulate the physical signal propagation and channels, which can offer fine-grained information on the communication link quality, both in real-time and proactively. This link quality information provides more flexibility for making efficient application-layer decisions in a way that respects this application diversity. For example, if a video streaming application knows ahead of time about the communication link disruption and blockage status, this application can pre-load a certain portion of the video, considering the duration of the cut-off, and achieve a seamless user experience with efficient usage of communication resources. While the digital twin provides low-level and fine-grained information about the communication links, how to efficiently utilize this information is still to be investigated.

Essential Considerations for Digital Twins

Here, we discuss some essential considerations for the construction and operation of digital twins, and how they impact different applications, layers, and systems.

Data Requirements

Constructing and leveraging digital twins require capturing, transferring, and processing different types of information. This includes information about the physical communication environment and the communication service. The necessary information varies for different tasks. For example, to infer LoS mmWave beams, it may be sufficient to have information about the device position, beamforming codebook, and latency requirements. NLoS mmWave beam prediction, however, also needs the geometry information of the surrounding static and dynamic objects.

Accuracy

The accuracy of a digital twin is directly determined by the accuracy of the 3D maps, sensory data, and ray tracing used to construct it. This accuracy is particularly critical for systems and applications that require CSI knowledge than those that rely more on large-scale information, such as beam power and channel covariance.

Latency

Due to the data sharing and processing time overhead, the real-time digital replica may have a slight latency offset (e.g., tens of milliseconds) relative to the physical world. Although this offset may be acceptable for some higher-layer tasks, it may pose challenges for the physical and access layer tasks that are often more sensitive to latency and system dynamics. In these cases, it might be interesting to still leverage the digital twins to make proactive decisions that can help compensate for the latency.

Synchronization

The interactions between the digital and physical worlds, including data-sharing and decision-making, need to be synchronized. The mis-synchronization of the digital twin may degrade its modeling accuracy and decision-making performance. The impact of that depends on the system dynamics and application requirements. In particular, a higher synchronization rate may be required for scenarios with high mobility and for applications that are sensitive to modeling accuracy.

Digital Twin Research Platform

Here, we present a digital twin research platform based on the DeepSense 6G [13] and the DeepVerse 6G [14] datasets that can be used to investigate various digital twin research directions. Next, we briefly present these digital twin datasets and show how they can be used to investigate an example application of digital twin-assisted beam prediction.

Digital Twin Datasets

The digital twins rely on co-existing real-world data and high-fidelity synthetic data generated using accurate 3D maps and ray tracing. For that, the DeepSense 6G and the DeepVerse 6G datasets are well-suited to facilitate the research and development of digital twins. The DeepSense 6G is a large-scale multi-modal sensing and communication dataset collected in real-world scenarios; the DeepVerse 6G is a synthetic dataset that can simulate high-fidelity multi-modal sensing and communication data from ray tracing. Combining real-world scenarios and their synthetic replicas from the two datasets, we present a research platform for digital twins.

Example Application

Reference [15] considers a digital twin-assisted system. In particular, the digital replica is used to generate a site-specific synthetic dataset for a real-world system. This synthetic dataset is leveraged to train an ML model that can solve the beam prediction task using real-time 3D maps. Then, the digital twin utilizes this ML model to infer optimal beams for the real-world system. The considered digital twin-assisted system operates on the second level, that is, shared information and individual decision. In this system, the user shares its position with the global digital twin. The global digital twin leverages the ML model (trained on the synthetic dataset) and the real-time 3D maps (containing user positions) to infer optimal beams. These beams can aid applications such as initial access and beam management. When the ML is trained solely using the digital replica, it is limited by the impairments in the 3D map and ray tracing. A small amount of real-world data can be utilized to fine-tune this ML model (i.e., transfer learning) to transcend the digital replica.

Experimental Setup

Scenario 1 of DeepSense is adopted as the real-world scenario, where a BS serves a mobile user vehicle on the 60 GHz band. The BS employs a uniform linear array and adopts a beam-steering codebook with 16 beams spanning 90° in the horizontal dimension. The user carries an omni-directional antenna array and a GPS sensor, and passes in front of the BS in an urban area. At each synchronized time instance, the BS measures the received power of the 16 beams, and the user measures its GPS position. The digital replica of this scenario is constructed and simulated. For simplicity, the latency of the digital twin is not modeled.

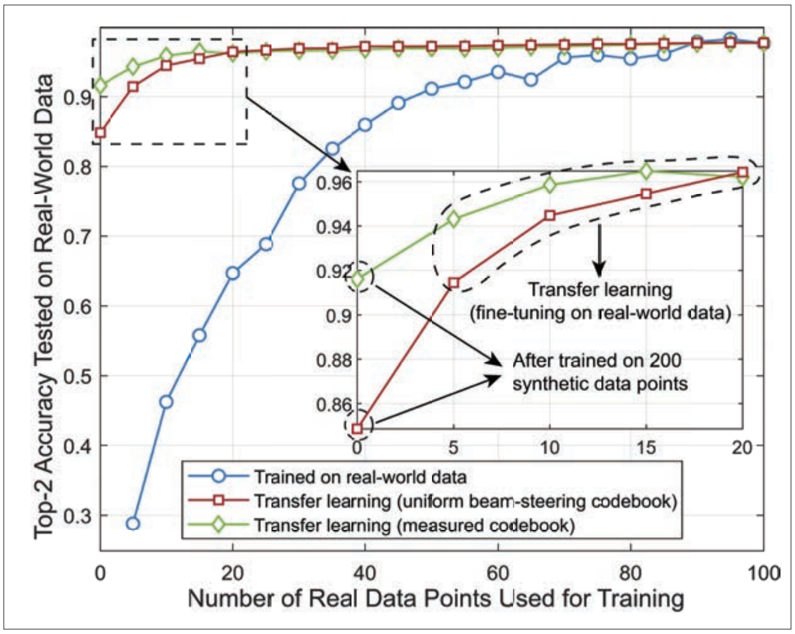

FIGURE 4. Top-2 accuracy obtained by training the NN on the synthetic data generated by the digital twin and/or the real-world data.

Experimental Results

We adopt a neural network (NN) as the ML model utilizing its strong function-approximation capability. The NN employs a fully connected architecture with two hidden layers. Each hidden layer has 256 nodes with the ReLU activation. The model takes in the user position and infers the one-hot-encoded beam (more details in [15]). The NN is first trained on the synthetic data from the digital replica and then fine-tuned on the real-world data (Fig. 4). After training on 200 synthetic data points, the NN achieves a top-2 beam prediction accuracy of 91.4 percent when tested on real-world data. Note that this digital twin approach does not need any real-world training data. Moreover, with transfer learning, a small number of real-world data points (less than 20) can quickly improve the NN to achieve near-optimal performance. Next, we compare the transfer learning performance with a uniform beam-steering codebook (that doesn't exactly match the codebook implemented in the hardware) and a measured codebook. The codebook with a mismatch leads to lower performance. However, when fine-tuned with only 20 real-world data points, the performance approaches the measured codebook one. This shows that the digital replica mismatch can be calibrated with a small real-world dataset.

Future Research Directions

Realizing the potential of the envisioned digital twin requires overcoming several fundamental challenges and thoroughly investigating important design aspects. Next, we present some open research directions toward digital twin-aided next-generation wireless communications.

Impact of Digital Twin on Communication Tasks

Deploying digital twin-aided solutions in the real world requires revisiting all the problem statements, such as LoS/NLoS beam prediction and hand-off, to evaluate the efficacy of these solu-

With access to a comprehensive digital twin, the question arises: How will it be utilized in the sensing and communication decision-making process? Users can make individual decisions in a distributed manner or adopt a centralized way. Both approaches have advantages and limitations.

tions accurately. In particular, it is necessary to investigate how much performance gain can be achieved by utilizing the real-time digital twins compared to conventional and sensing-aided approaches. Therefore, the DeepVerse 6G synthetic dataset was created to mimic the real-world scenarios of the DeepSense 6G dataset, making them a digital twin of each other. These two datasets combined can enable the development and evaluation of digital twin-aided applications.

Communication-Sensing Trade-Off

To generate an accurate real-time digital twin with minimal latency, the sensing data collected across different devices need to be transferred quickly to a central unit for further processing (digital twin levels 2 and 3). The data transfer rate depends on the available bandwidth of the communication system. As the amount of sensing data increases (e.g., with the increase in sensors and devices), so does the requirement for communication bandwidth. While access to diverse and detailed sensing information may improve the modeling accuracy and decision-making capability of the digital twin, transferring that sensing data consume communication resources, potentially offsetting any gains. A promising solution to overcome this challenge is to first process the sensory data locally and extract relevant features, and then transfer the low-dimensional extracted features across devices. Investigating this trade-off and the possible solutions is an interesting open problem.

Sensing Fusion and Coordination

In the third digital twin level, devices communicate and coordinate to make joint sensing and communication decisions. For instance, multiple devices in the same area may capture similar sensing data. Since some of this data may be redundant, transferring this data over the limited communication bandwidth for further processing will only increase the computational cost overhead without significantly improving the digital twin system. One solution to improve resource utilization can be to sense and transfer the optimum data required to generate a complete and accurate digital twin. Realizing such a solution requires devices to communicate with each other and adopt efficient protocols for cooperative sensing. These challenges highlight the need for further investigation.

Central and Distributed Decision

With access to a comprehensive digital twin, the question arises: How will it be utilized in the sensing and communication decision-making process? Users can make individual decisions in a distributed manner or adopt a centralized way. Both approaches have advantages and limitations. For example, distributed decisions made on the edge can minimize any latency resulting from networking and data transfer. However, this typically requires intensive computations which increases the overhead on these resource-constrained devices. Developing robust and efficient solutions that can be deployed in the real world requires detailed investigations.

Conclusion

This article presented a vision for future wireless communication and sensing systems that would leverage precise 3D maps, multi-modal sensing, efficient ray tracing, and advanced ML/DL to construct, update, and utilize real-time digital twins. As computation, communication, and synchronization capabilities evolve over time, we expect devices to gradually coordinate in building and updating global digital twins using their sensing information and potentially make joint sensing and communication decisions. The article also presented a research platform, based on the real-world DeepSense 6G dataset and its digital replica, DeepVerse 6G, to investigate various digital twin research directions, and showed how to use this platform for one example application.

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