Networked Twins and Twins of Networks: An Overview on the Relationship between Digital Twins and 6G

Hamed Ahmadi, Avishek Nag, Zaheer Khan, Kamran Sayrafian, and Susanto Rahardja

Abstract

Digital twin (DT) is a promising technology for the new immersive digital life with a variety of applications in areas such as Industry 4.0, aviation, and healthcare. Proliferation of this technology requires higher data rates, reliability, resilience, and lower latency beyond what is currently offered by 5G. Thus, DT can become a major driver for 6G research and development. Alternatively, 6G network development can benefit from DT technology and its powerful features such as modularity and remote intelligence. Using DT, a 6G network (or some of its components) will have the opportunity to use artificial intelligence more proactively in order to enhance its resilience. DT's application in telecommunications is still in its infancy. In this article, we highlight some of the most promising research and development directions for this technology.

Introduction

As commercial deployments of fifth generation (5G) mobile networks continue in several countries, researchers in industry and academia have started to focus on sixth generation (6G) mobile networks. A range of new technologies such as use of higher frequency bands (THz), orbital angular momentum (OAM) multiplexing, and intelligent surfaces have been proposed for this purpose. In addition, innovative paradigms like integration of terrestrial and satellite networks, massive use of machine learning (ML) and artificial intelligence (AI), and quantum and molecular communications for the physical, medium access control (MAC), and network layers are also under development. All of these upcoming technologies and paradigms can be considered as enablers of 6G [1–3]. However, researchers are still debating on the importance or potential role of each one of the aforementioned technologies in 6G. For example, Viswanathan and Morgensen [1] believe that unmanned aerial vehicles (UAVs) and cell-free communications belong to the 5G era, whereas quantum, visible light, and molecular communications are more long-term technologies that will not be mature enough even for 6G implementation. Since 6G is not fully defined yet, these views are not necessarily shared by other researchers.

Table 1 shows example key performance indicators (KPIs) of 6G in comparison to 5G, which are gathered from [1–3]. These KPIs are generally defined to satisfy the requirements of the driving applications of 6G such as connected robotics, autonomous systems, augmented reality (AR)/virtual reality (VR)/mixed reality (MR), blockchain and trust technologies, and wireless brain-computer interfaces [2]. Some of these applications like connected robotics or AR/VR/MR have been considered in 5G, but their massive use could demand higher levels of KPIs beyond what is achievable by 5G [2]. For example, applications like autonomous driving and immersive AR/VR/MR with high definition 360° video streaming for navigation and/or entertainment are expected to require ultra high reliability and 1 ms latency [4].

The technologies and driving applications of 6G enable an environment where a comprehensive digital representation of the physical world can be created and maintained through digital twins (DTs) of various objects. A DT is a real-time evolving digital duplicate of a physical object or a process that contains all of its history [5]. Its implementation involves massive real-time multi-source data collection, analysis, inference, and visualization. Although DT technology already exists in some industrial applications supported by 5G or even 4G [6], it has not been widely adopted in other sectors, and has not reached its full potential. The need for high throughput (100 Gb/s), reliable and pervasive communication is one of the bottlenecks in realizing DT's potential, requiring beyond-5G technologies. Therefore, 6G can be considered as an enabler for massive adoption of DTs.

The popularity of DT depends on the popularity and necessity of its applications. Potential high-connectivity-demanding and rapidly emerging applications of DT ranging from aerospace, which has very high mobility, to Industry 4.0, which has a very high number of devices in a location, and healthcare, with high reliability requirement, could be a major driver toward the development of 6G [6]. In this article, we also argue that the network itself can have its own DT, which will be an important application of DT. In addition, as discussed in following sections, the DT technology itself integrated with AI could act as a facilitator toward this development.

In this article, we aim to highlight and fur-

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ther explore this relationship between 6G and DT. We further describe DT and its features and requirements. Potential application of DT in future communication networks and in particular 6G are presented. 6G as a facilitator for wide adoption of DTs is then discussed. Finally, a road map for future research directions and some concluding remarks are presented, respectively.

Digital Twin

The term "digital twin" was first coined by Grieves in 2003 [7]. The technology became more popular after the emergence of Industry 4.0 (in 2016) as it enabled integration of digital manufacturing and cyber-physical systems.

A DT can be defined as a "virtual representation of an asset, providing both a historical ledger of the asset's previous states, and real-time data on the asset's current state." The asset can be an object, a machine, a process, or even a system. A DT requires a real-time bidirectional connection with its physical twin (PT). It should be clarified that a DT is more than an avatar, a surveillance system, a simulation, or a simple model. An avatar is a limited replica of the physical asset without any possibility of controlling the asset. In addition, the bidirectional connection with the PT makes a DT more sophisticated and capable than a surveillance system. Unlike *simulation*, a DT ideally represents an actual asset with as few assumptions or simplifications as possible (except those that are required to digitally encode the physical asset involved).

While a DT can benefit from AR/VR/MR for visualization purposes, it is different from *augmented virtuality*. The main focus and goal of *augmented virtuality* is representation and human interaction. However, DTs mainly focus on maintaining the full history and up-to-date information of the assets/systems to facilitate intelligent and data-supported decision making [8]. In the following, we briefly discuss key features and specifications of DT as well as relevant standardization activities and challenges.

Key Features of Digital Twin

Pillars: A DT system is composed of three pillars: physical, digital/virtual, and connection pillars [6]. Figure 1 presents an example of a DT system and its pillars. The physical pillar, representing the PT, is the actual asset that is the basis of the digital model and the source of its data. The virtual/digital pillar, or equivalently the DT, is the host of the data models, historical data of the PT, decision support, AI, and visualizations. The DT is capable of sending control commands to the physical pillar. The connection pillar between a PT and a DT is the communication bridge that allows for the exchange of data and control commands among them. The connection pillar is not necessarily symmetric as the flow of data in each direction, PT-to-DT vs. DT-to-PT, requires different levels of quality of service (QoS). In this article, the phrase *DT system* refers to a complete system consisting of all three pillars, while the term *DT* only indicates the digital pillar of the system. It should be emphasized that the DT or digital pillar of any physical asset is only meaningful when it is functioning as part of a complete DT system.

Modularity: Modularity is the key to interoperability and interchangeability. Modularity enables the system to evolve as the technology on each component evolves. In a modular system, the interfaces are standardized, and therefore the components can be replaced due to technology upgrade or seamless maintenance.

KPIs	5G	6G
Data rate	10+Gb/s	100 Gb/s
Delay	1 ms	0.5 ms
Position precision	meter	centimeter
Device intensity	1 Million/Km^2	10 Million/Km^2
Spectral efficiency	–	3x more than 5G
Energy Efficiency	–	10x more than 5G

Table 1. Example KPIs of 5G and 6G [1–3].

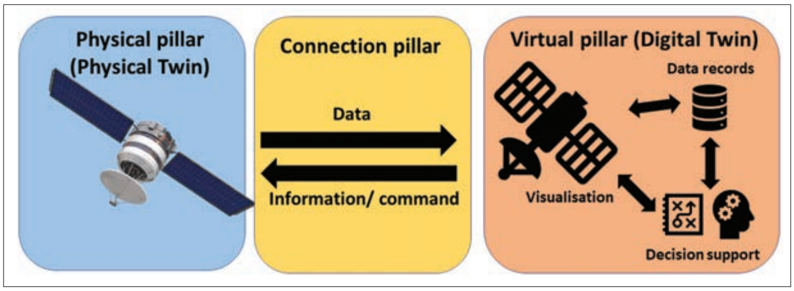

Figure 1. Pillars of a digital twin system.

A DT can be highly modular [9]. It is possible to create a DT for every single component of an asset and create a mega-DT by interconnecting the smaller DTs representing those components. This feature enables rapid reproduction of processes and knowledge transfer. Modularity of a DT allows creating hybrid simulation and prototyping systems. In such systems, the DTs of existing physical subsystems are combined with a simulation of subsystems that still do not have a corresponding PT. A hybrid system can accelerate the design, development, and prototyping of new products and services. It can also enable performance testing of the physical subsystems in a virtual replica of the target application environment (within the boundaries of the data model used to represent the related PTs).

Remote Intelligence: The capability to apply remote intelligence to enhance the operation of the PT is another important feature of a DT. A resource-limited physical device or an old machine can become more efficient or intelligent by running data analysis, AI algorithms, or even conventional optimization and/or analysis algorithms on its DT, which can be located at the edge or in the cloud.

Standardisation

The modularity feature of DT enables creation of mega-DTs by rapid reproduction of processes from DTs of different components. This necessitates interoperability among these components and therefore highlights the importance of DT standardization. The current activities on DT standardization are focusing on data collection, storage, and exchange [10]. Microsoft[1] is developing a programming-language-independent data management model based on JavaScript Object Notation for Linked Data (JSON-LD) called Digital

[1] Commercial products and companies mentioned in this article are merely intended to foster understanding. Their identification does not imply recommendation or endorsement by the National Institute of Standards and Technology.

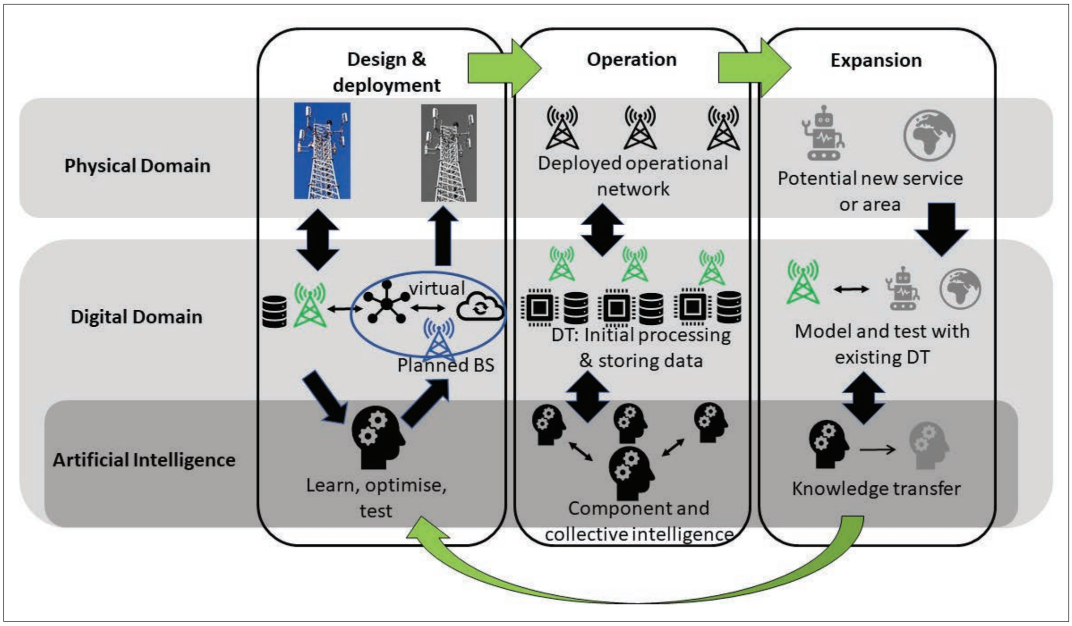

FIGURE 2. A network's life cycle using DT. The grey icons like base stations indicate that they have not been deployed yet, and the action results of the other side of the arrow leads to their existence.

Twin Definition Language (DTDL). DTDL is used for data management of DTs that are deployed using Microsoft Azure. Although DTDL addresses the interoperability challenges on Azure-based DTs, lack of comprehensive standardization could affect DT adoption, especially for their deployment at the edge [9].

Another candidate for widespread standardization of DTs could be the functional mockup interface (FMI) (https://fmi-standard.org/). It is currently a free standard that enables building DTs of different PTs using combinations of XML and C codes.

Several other relevant existing standards, such as Object Linking and Embedding for Process Control (OPC) Unified Architecture (OPC-UA), which is a standard for machine-to-machine communication, can be leveraged toward DT standardization. OPC-UA can be used to connect the components of the PT, and then the communication links between the PT and the DT can utilize existing application programming interfaces (APIs) like the REpresentational State Transfer (REST) API. All these standards along with newly defined ones can be brought together to define a unified set of standards for DTs.

Digital Twin of Communication Networks

So far, the DT technology has been adopted in manufacturing, healthcare, and aviation [9]. In the telecommunications industry, companies like Spirent Communications and British Telecommunication (BT) have started developing DTs for 5G network components. These activities will pave the way for full adoption of DT in 6G.

Similar to its application in other industries, using a DT of a telecommunication network or any of its components can significantly improve network design and maintenance. This directly affects the network's life cycle, as discussed in the remainder of this section.

Network and DT's Life Cycle

The evolving digital replica of a network that is provided by its DT can assist in the design, deployment, operation, and expansion phases of a network. This is shown in Fig. 2 and further illustrated in the following.

Design and Deployment: In the era of DTs, simulation and model-based network design is replaced by an analytics-supported design process. Modularity of DTs enables network designers to exploit the existing knowledge on DTs of various networks' components. Engineers will then be able to design the communication network by creating a hybrid-simulation environment using the modularity feature. As observed in Fig. 2, the design and deployment phase starts with a physical component of the network such as a base station (BS) (shown in blue highlight) and its DT. The rest of the network is designed in the digital domain using AI. Once the design process, test, and verification are completed through analytics in the hybrid system, the deployment phase starts (the BS is highlighted in grey). As different sections (or subsystems) of the network are deployed, their DTs will be created and merged with the hybrid simulation environment. By the end of the deployment phase, the hybrid system becomes a complete DT. The key difference in this methodology compared to existing network simulation and planning tools used in 5G and earlier generations, including general ones and proprietary tools, is that DT-based systems are connected to deployed physical subsystems, and the whole system evolves as the deployment proceeds.

Smart Operation, Maintenance, and Resilience: Phase two deals with the operation of the network as shown in Fig. 2's operation phase. Here, an AI-enabled DT optimizes the operational parameters of the network based on the real-time data and the knowledge generated through prior experience. Resilience is the ability of the network to maintain an acceptable level of service in the event of various faults and challenges appearing during normal operation [11]. *Resilience* cannot be achieved if the network is not prepared for potential disruptions. AI can check all possible *what-if* scenarios and choose the network configuration that guarantees operation with the highest QoS. This is a step beyond what is known as the self-organizing network (SON). To achieve real resilience, the AI in the DT acts beyond self-optimization and self-healing, and performs prediction and strategic planning. In the SON, questions like placement of the required intelligence and the coordination with legacy systems still remain unclear. DT modularity supports intelligence at the edge, federated learning, and transfer learning to provide maximum resilience [4]. Basically, modularity will bring the flexibility to add and remove crucial components at different locations and essentially provide the redundancy as and when needed. It is true that redundancy improves resilience, but it also increases cost and overhead. Our point is that with DT modularity, intelligence is supported, and intelligence predicts potential disruptions. Predicted disruptions can be taken care of before happening, and the system will be resilient without the need of having costly redundant copies for each and every component. Also, additional sensors and edge computation can be used to create DTs for legacy equipment.

Maintenance, prediction, and strategic planning can be better clarified with the following toy example. The equipment used in a network has a certain lifetime beyond which they need either maintenance or replacement. The estimated lifetime is normally provided by the manufacturer. However, in practice, the actual lifetime could differ from this estimate based on the workload and physical condition of the operating location. The AI on the network's DT or each of its components' DTs are capable of learning each component's lifetime from the manufacturer data, the real-time data received from the PT, as well as other external factors. As a result, the DT can modify the network's working conditions to maximize the lifetime of different equipment and/or efficiently schedule maintenance time. In real scenarios, other than this toy example, the optimization should consider optimal service and other important criteria too. Using AI facilitated by DT to support a network's operation enables the network to predict its disruptions caused by components' failure or other sources, proactively respond to them, and/or prevent them before happening.

Knowledge Transfer and Robust Expansion: The last phase of most products in manufacturing is dismissal phase and release of a new product according to changes in the market and the lessons learned from the existing product. In the telecommunications domain, we can translate it to network expansion to new domains, geographical locations, and/or providing new services; for example, using the DT of a 5G network to transfer knowledge for the design phase of 6G. Disconnected twins of components or the complete network can be used for the design of new networks and testing new services. Additionally, operators can monetize their experience by selling the data and the created knowledge via disconnected twins [12]. As shown in Fig. 2, this phase closes the network life cycle loop.

DT of the Next Generation of Networks

As 5G has already reached its deployment phase and its standardization has been almost completed, DT-based design and operation of networks can show its benefit mostly in 6G. Using a DT-based approach, 6G can be designed and standardized in a more data-oriented fashion. In the operation phase, 6G will be able to handle its own DT, while the massive overhead created by the DT of the network cannot be handled by 5G while supporting its high throughput and/or ultra delay-sensitive usual services. 6G's high KPIs in addition to its synergy with AI will enable it to support the additional overhead to have its own DT. In the next section, we present how 6G can support other DTs.

6G as an Enabler of Digital Twin

As discussed so far, a DT is implemented using a combination of a simulation of the physical system and a means to *communicate* all the data generated by the physical system to its DT and the AI-processed command and control from DT to the physical system. The *communication* part involved in the successful synergy between a DT and its corresponding PT has to support ultra-reliable, real-time (or semi-real-time depending on the application), and high QoS communication.

At present, DT technology is mainly used in industrial plants, and it is supported by 5G or earlier generations of communication protocols. It is quite conceivable that wide adoption of this technology results in higher capacity demands as well as new scenarios beyond the capabilities of 5G.

Among the early adopters, General Electric is one of the pioneers in using DT technology in manufacturing. According to the company $1.6 billion has been saved by early detection of industrial component failure through continuous remote monitoring of assets [13]. In such scenarios, network reliability is extremely important, and full wired connection is not an option due to its complexity of installation and high cost. Therefore, for future massive-scale industrial Internet of Things (IoT) applications facilitated by DTs, a 6G network is more advantageous than its 5G counterpart.

Figure 3 gives a schematic detail of how a PT in an industrial IoT use case can have different DTs for each of its components distributed over the cloud and the edge, supported by a 6G network infrastructure. The PT, a factory with different physical systems, is modeled as a combination of several DTs. The DTs are distributed in various cloud and edge servers. The red dotted lines represent logical bidirectional connections between the PT and the DTs. The network infrastructure as depicted in Fig. 3 has a fully automated control plane. This control plane can orchestrate the network using AI algorithms that are continuously trained by the network data. AI-supported autonomous operation of this complex system (mega-DT) requires near-perfect connection between the DTs on the edge and the cloud servers. 6G can support this mega-DT with millisecond latency, 100 GB/s data rate, and ultra high reliability.

A DT system can benefit from integrated modern virtualization technology in order to display

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DT ownership is a challenging issue with technical, financial, and legal aspects. The challenge is mainly caused by the potential difference in the ownership of the physical entity and the DT platform.

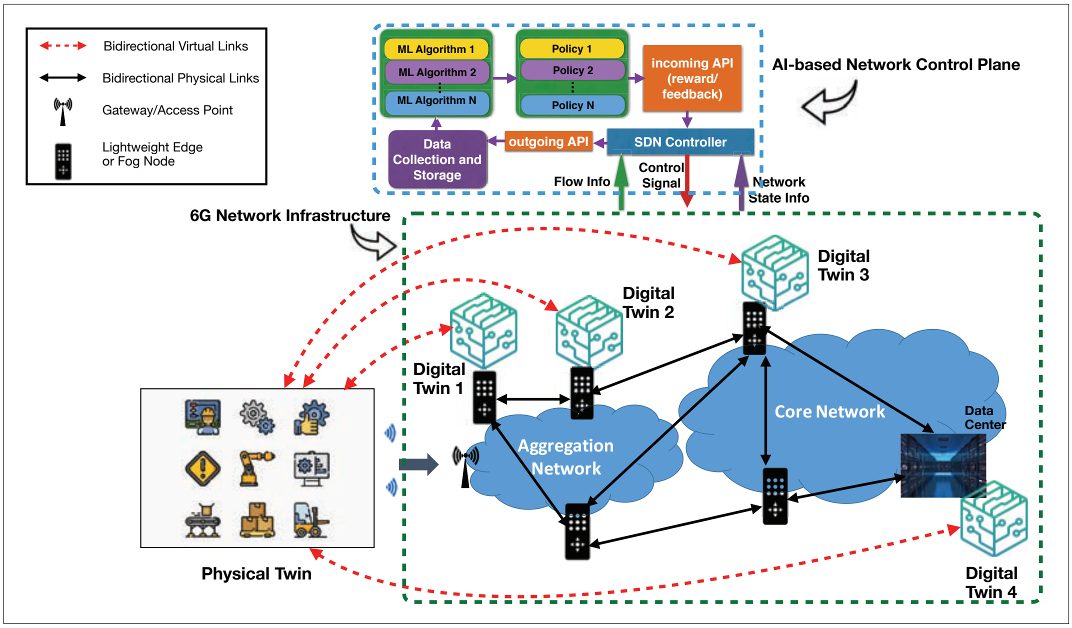

FIGURE 3. Communication of PT and DT over a 6G network.

complex data types to the users. To enable that, many networked data-collection devices (e.g., high-resolution cameras) are required, and this has to be enabled in the edge networks [5]. Processing ultra-high-definition videos along with complex AI algorithms like deep learning would require significant processing power localized in a single node or a few nodes. A more feasible solution is to enable federated AI, where different components of the AI algorithms can be distributed over the network nodes [4]. For example, a deep neural network can have some of its inputs/outputs in the low-complexity edge nodes, while hidden neurons reside in the cloud with more processing power. These spatially distributed components of the neural network require ultra-reliable communication to avoid erroneous training and output. Although federated AI has been implemented using 5G in small scale, its larger and more complex deployment could require ultra high reliability and 1 ms latency of 6G [4].

Furthermore, due to the modularity feature of DTs, they may not be localized in either a single node or a small subset of nodes [9]. As a result, the data associated with the DTs and the AI that operates on these data may have to be distributed over the cloud and/or several edge servers across the network. Seamless communication among these distributed DTs, computation associated with the distributed AI operating on these DTs, and maintaining security and integrity of these data is a challenge. One solution is using blockchain-based transactions between these nodes. However, high transaction throughput requirement (i.e., 10,000 transactions per second and millisecond latency) of private and consortium blockchains can only be satisfied by 6G-level QoS [1].

Future Research Directions

Having introduced the concept of DT in telecommunications and its potential roles in setting up and transforming 6G networks, as both an enabler and a use case, in this section we enumerate several key research directions related to this combined field.

DT Ownership Issues

DT ownership is a challenging issue with technical, financial, and legal aspects. The challenge is mainly caused by the potential difference in the ownership of the physical entity and the DT platform. A simplified example of this scenario is common fitness trackers. A fitness tracker device is owned by an individual, while the generated data is owned by and stored on the application provider's cloud. Normally, the individual can only access the data via a specific application interface without the option of exporting the data. However, the individual can disconnect the fitness tracker or simply stop using it at any time. Since a DT contains more detailed information and needs to be always connected with the physical object, ownership issues must be clarified. This is especially important considering the General Data Protection Rules (GDPR) introduced in the European Union. In [2], the authors considered home appliances in an IoT scenario. The owner of an appliance, if also interested in full ownership of the data, can buy, install, and maintain its DT on his/her home gateway. While this is a viable option, it requires owning a gateway with sufficient storage capacity and security. Alternatively, the appliance owner can rent cloud/fog/edge services to install and maintain the DT. Therefore, the ownership issue will go hand in hand with cloud/fog/edge computing and placement challenges. In [12], the IoT devices are connected to the home network, and the ownership scenario will be more complicated in industrial settings with the use of 6G. The investigation of more complicated ownership-related scenarios, especially for process or system DTs with multiple components owned by different entities, remains open for further research.

Ultra-Low-Latency and Reliable Communication between DT and PT

As mentioned previously, a seamless real-time data exchange between the DT and the PT is a necessary condition to define a DT system. A significant amount of data has to be continuously and reliably exchanged between the pair. The software tools, data analytics modules, and data that make the DT an appropriate clone of the PT should mostly be stored in the cloud. However, for some critical use cases (e.g., the DT of a remote-surgery system), implementation in the edge might be preferred [14].

Whatever the scenario, it is anticipated that most DT implementations would require ultra-low-latency and reliable communication between the DT and its PT. Recent research studies have established the importance of ultra-low-latency and reliable communication for some future applications, and reported the development of technologies and algorithms that could make that achievable [1, 2]. However, further breakthroughs across all protocol layers of the network are still needed to achieve strict latency and reliability requirements.

Federated DT in the Cloud/Edge

Resources such as power, storage, and high-speed memory are sometimes constrained in today's networks. Therefore, significant resource management is necessary to sustain a technology like the DT, which includes communication, data analysis, and AI-based computation. To accommodate various use cases of 6G and beyond networks, it is anticipated that a large percentage of the computation (including AI algorithms) and storage is moved to the edge of the network [4]. The trend will be similar if 6G and beyond networks have to support massive adoption of DT technology. Having said that, it will be almost imperative that several backend solutions enabling a DT for a particular PT need to be hosted in multiple data centers in the cloud and/or edge.

There are several reasons for the need to do this distribution or even replication of DTs. First of all, the storage and computing facilities of the servers in the cloud or the edge may pose system-level limitations to host a DT in one place. This might create unnecessary performance bottlenecks. Second, there might be failures in the servers or network links that might hamper the seamless connectivity between a PT and its DT. Therefore, it is pragmatic to distribute multiple copies of DTs all over the cloud and/or the edge servers, as illustrated in Fig. 3.

Several components of the cloud and/or edge distributed DTs need to communicate with one another to exchange data and/or train AI models to establish automated and intelligent operations. This can be referred to as *federated DT* similar to the concept of federated learning as proposed in [4]. It is a challenging task to run such forms of synchronized and collaborative AI algorithms over the nodes of the network. This is still an open research area.

DT of an Entire Network

As mentioned before, DT technology has not been utilized much for telecommunication networks. Today's telecommunication networks are getting softwarized due to new trends like software defined networking (SDN) and network function virtualization (NFV). The advent of AI in addition to network softwarization is further pushing the drive toward automated and autonomous telecommunication networks. Therefore, apart from the physical infrastructure (i.e., transceivers, antennas, optical fibers, filters, etc.), most of the other network components can be implemented as cloud-native software.

This would constitute a paradigm shift in terms of how future networks can be managed and used if a composite DT of an entire network can be created. If the DTs of the physical components of the networks (i.e., transceivers, switches, links) can be implemented, they can be nicely intertwined along with the other softwarized components of the network to form a composite DT of the network. Just like a massive manufacturing unit or a giant space shuttle can be troubleshot and managed by tuning several parameters on their DTs, an entire network can also be managed, upgraded, and troubleshot using its DT. Several network services and new technologies pertaining to networks can also be tested and pre-implemented on these massive-scale network DTs before deployment in the real networks.

Figure 4 captures our vision toward enabling the DT of an entire network. It also highlights some of the related research issues like network monitoring and troubleshooting using AI-based analytics and ownership issues using *smart contracts* hosted in a blockchain.

Experimental Investigation of DTs

The development of a complete LTE network using commercially available software components such as Amarisoft™ LTE 100 eNodeB, UE from software radio systems (srsUE™), and a generic RF front-end was documented in [15]. This network was entirely switched ON/OFF using a Python and Linux-based code. The code would turn on the LTE network, stream a YouTube video, collect data from the video for analysis in real time, and plot various performance curves. A similar type of setup can prove to be a suitable starting point for an experimental investigation of the DT of a network. More developments would still be required to build a graphical user interface (GUI) to visualize the operations of all components, and to set up real-time connections between the graphical representations of the DTs and PTs.

Conclusions

In this article, we discuss the application of DT in networking and present its potential relationship with 6G. While 6G can facilitate realization and adoption of DT in several industries by providing the required levels of reliability and speed, DT integrated with AI can also facilitate 6G network design, deployment, and operation. This approach can have significant impact on achieving high network resilience. Additionally, demanding applications of DT, ranging from aerospace to Industry 4.0 and healthcare, could be a major driver toward the development of 6G. Potential DT-related research directions have also been highlighted in the article.

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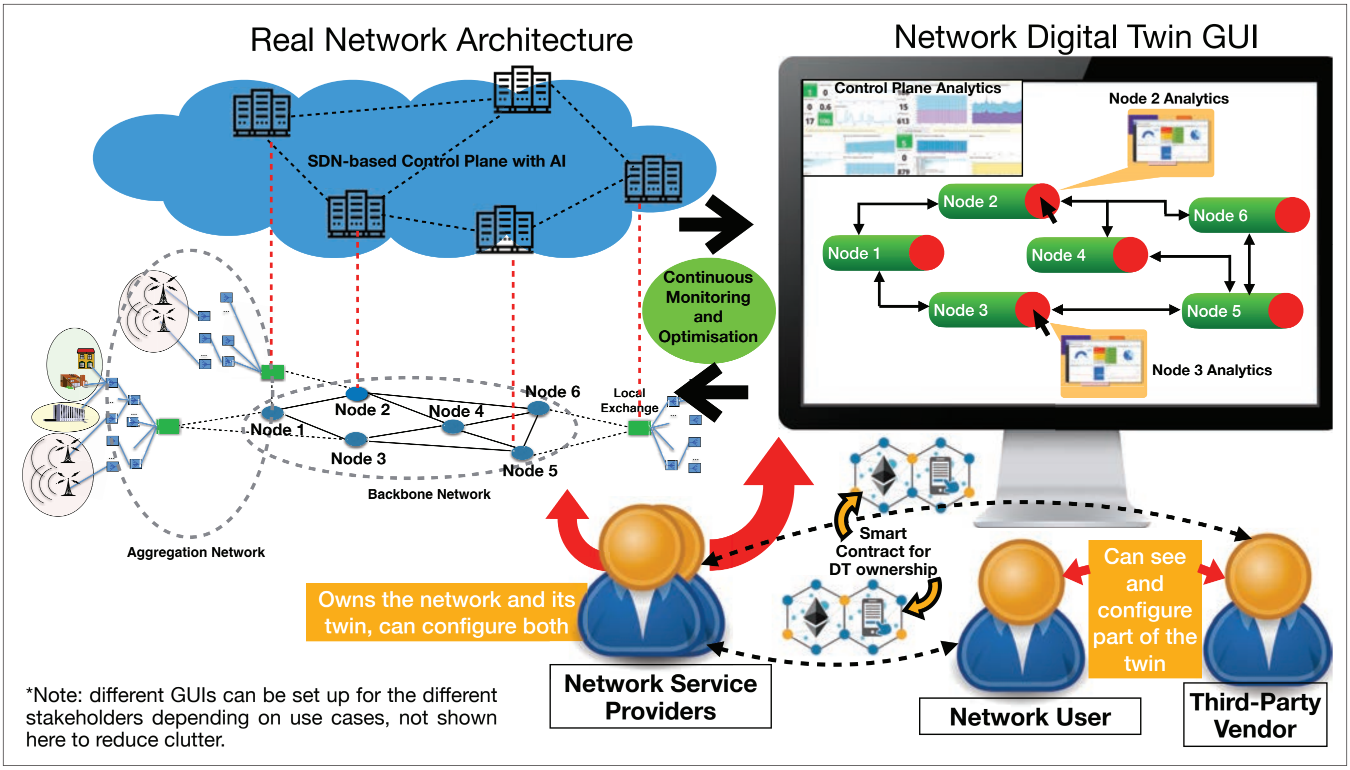

FIGURE 4. Digital twin for an entire network.

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