Digital-Twin-Enabled 6G: Vision, Architectural Trends, and Future Directions

Latif U. Khan, Walid Saad, Dusit Niyato, Zhu Han, and Choong Seon Hong

Enabling IoE applications over 6G requires a new framework that can be used to manage, operate, and optimize the 6G wireless system and its underlying IoE services.

Abstract

Internet of Everything (IoE) applications such as haptics, human-computer interaction, and extended reality, using the sixth-generation (6G) of wireless systems have diverse requirements in terms of latency, reliability, data rate, and user-defined performance metrics. Therefore, enabling IoE applications over 6G requires a new framework that can be used to manage, operate, and optimize the 6G wireless system and its underlying IoE services. Such a new framework for 6G can be based on digital twins. Digital twins use a virtual representation of the 6G physical system along with the associated algorithms (e.g., machine learning, optimization), communication technologies (e.g., millimeter-wave and terahertz communication), computing systems (e.g., edge computing and cloud computing), as well as privacy and security-related technologists (e.g., blockchain). First, we present the key design requirements for enabling 6G through the use of a digital twin. Next, the architectural components and trends such as edge-based twins, cloud-based-twins, and edge-cloud-based twins are presented. Furthermore, we provide a comparative description of various twins. Finally, we outline and recommend guidelines for several future research directions.

Introduction

The wireless research landscape is rapidly evolving to cater for emerging Internet of Everything (IoE) applications such as extended reality (XR), haptics, brain-computer interaction, and flying vehicles [1]. To meet the diverse requirements (e.g., latency, reliability, and quality-of-experience) of these IoE applications, the sixth generation (6G) of wireless systems must possess several key properties [2–4]:

- *Self-sustaining wireless systems:* 6G systems will rely on a ubiquitous, intelligent, and seamless connectivity for a massive number of devices to offer novel IoE services. These services require true adaptation to the dynamically changing environment and optimization of scarce computation and communication resources. Therefore, to enable IoE services using 6G, there is a need to propose self-sustaining wireless systems. Such self-sustaining systems can jointly perform efficient network functions adaptation and resource optimization, using emerging techniques in the fields of machine learning (ML), optimization theory, game theory, and matching theory, among others, to autonomously (i.e., minimum possible assistance from users/network operators) maintain 6G key performance indicator [2].
- *Proactive-online-learning-based wireless systems:* 6G-based IoE applications must meet highly dynamic and extreme requirements in terms of latency, reliability, data rate, and user-defined performance metrics. To meet these highly dynamic requirements, 6G will use high frequency bands (e.g., millimeter wave, sub-terahertz, and terahertz), emerging computing technologies (e.g., cloud and edge computing), and security related technologies (e.g., blockchain), among others. Therefore, to successfully enable interaction among these technologies, one cannot rely on classical offline learning systems, but, instead, there is a need for online solutions that can proactively adapt to the 6G system dynamics.

To efficiently enable the aforementioned properties of 6G wireless systems, we can explore the concept of a digital twin. A digital twin is a virtual representation of the elements and dynamics of a physical system (e.g., see [5] and [6]). Note that digital twin for 6G can be used to emulate a single entity/function (e.g., IoE device, edge server), single IoE service (i.e., XR-based healthcare), and multiple IoE services (e.g., healthcare, industry 4.0). Digital twin uses ML, data analytics, and multi-physics simulation to study the dynamics of a given system. Digital twins can be categorized into: monitoring digital twin, simulation digital twin, and operational digital twin. A monitoring twin supports monitoring the status of a physical system (e.g., autonomous car dashboard), whereas a simulation twin uses various simulation tools and ML schemes to provide insights about future states. Meanwhile, an operational twin enables system operators to interact with a cyber-physical system and perform different actions in addition to analysis and system design. Several works considered digital twins for enabling Industry 4.0 [5–7]. In [5], the authors devised a taxonomy of blockchain in enabling digital twins. Meanwhile, the authors in [6] reviewed digital twins for Industry 4.0, whereas the work in [7] proposed digital twin architecture for Industry 4.0. On the other

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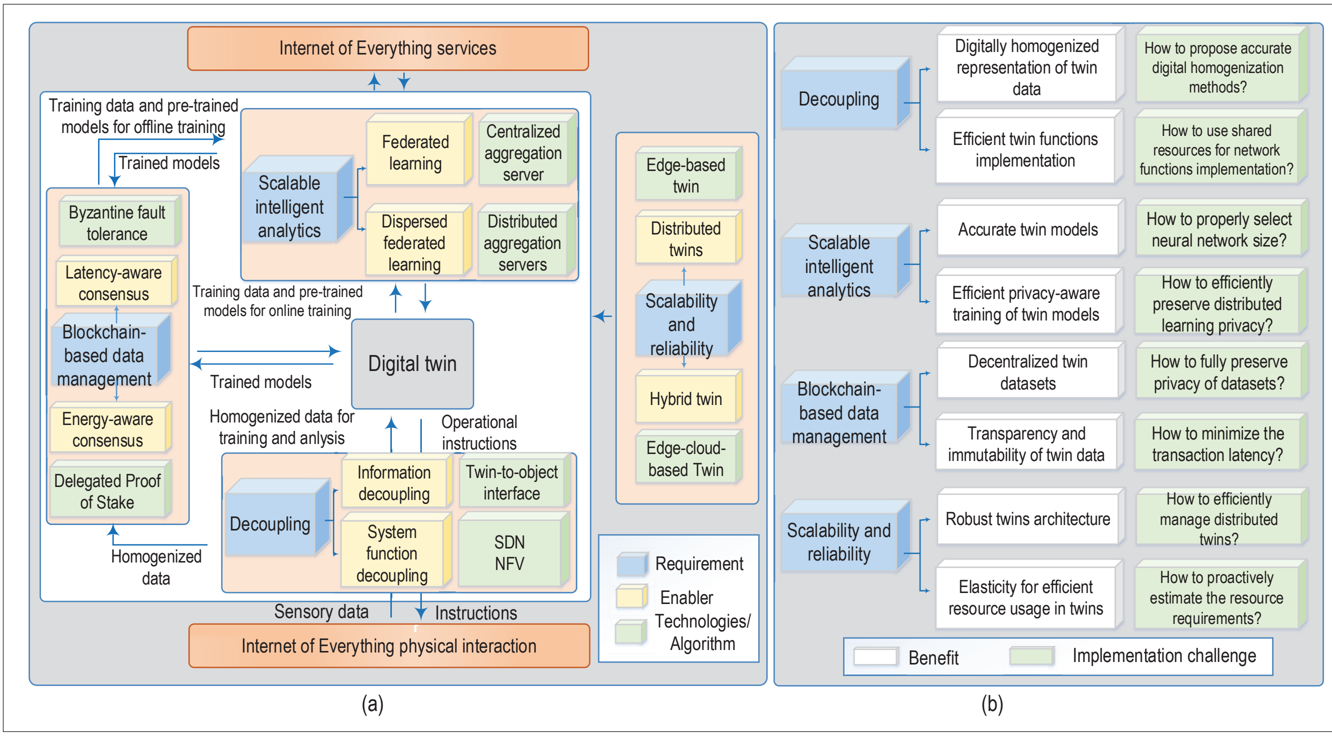

FIGURE 1. a) key design requirements; b) benefits for twins-based architecture.

hand, the work in [8] proposed the use of digital twin for 5G. In contrast to [5–8], we explore the role of the digital twin in enabling 6G wireless systems. To design 6G systems, an operational digital twin allows us to enable efficient interaction among various players of 6G. This is not possible without such an operational twin because other twins (e.g., simulation and monitoring twins) can only enable us to monitor or analyze the cyber physical system without controlling the system in real time. As such, our focus will be on the use of an operational digital twin for 6G. Unless stated otherwise, hereinafter, the term digital twin refers to the operational twin. Our main contributions are as follows:

- We present the key design requirements to realize the vision of digital-twin-enabled 6G systems. These requirements are decoupling, scalable intelligent analytics, blockchain-based data management as well as scalability and reliability.
- We propose an architecture for digital-twin-enabled 6G and present its various trends based on deployment fashion of twins.
- Finally, we provide an outlook on future research directions.

Key Design Requirements

Decoupling

The transformation of a physical system into a digital twin is primarily based on decoupling that refers to management/operation of twins independent (i.e., for generality) of the underlying physical system, as shown in Fig. 1a. Decoupling in digital-enabled 6G can be mainly performed using information decoupling that allows the transformation of physical system information (i.e., system state) into a homogenized digital representation. A 6G physical interaction space consists of base stations (BSs), intelligent reflecting surfaces, smart devices/sensors, and edge/cloud servers. Next to data homogenization, it is necessary to effectively decouple the system functions (i.e., mobility management, resource allocation, edge caching, and so on) from hardware to software for flexible operation. The decoupling of system functions will allow us to make the digital twin-based system operate efficiently and adaptively as per the network dynamics. Examples of such 6G functions are link adaptation and mobility management. To enable digital twin for 6G with function decoupling, software-defined networking (SDN) and network function virtualization (NFV) can be the promising candidates. SDN offers separation between control plane and data plane, whereas NFV offers system cost-efficient implementation of various network functions using virtual machines running on generic hardware. Although SDN and NFV are key enablers of classical network slicing, digital-twins-enabled 6G is different. For instance, digital twin-enabled 6G will use a digital representation of the physical system. Additionally, it will use ML to proactively analyze and model various system functions. These trained models will be stored in a blockchain network for further use (will be discussed in more detail later. Overall, the digital twin-based 6G system can be seen as a complex concept that performs offline analysis (e.g., proactive analytics, such as data analytics and pre-training of twin models, using blockchain-stored data) and real-time control. However, network slicing will enable real-time resource management in response to the end-users requests. Therefore, a digital twin-based 6G system will use network slicing in addition to other technologies (e.g., data decoupling, interfacing, blockchain, proactive analytics, optimization) for efficient control.

	Description	Edge-based twin	Cloud-based twin	Edge-cloud-based twin
Scalability	Scalability refers to fulfilling latency requirements for massive number of 6G devices. Furthermore, the addition of new nodes should not significantly degrade the system performance in terms of latency.	High	Lowest	Low
Latency	This metric represents the overall delay that accounts for latency from service request until service provision in providing 6G services.	Low	High	Medium
Geo-distribution	This metric tells us about the geographical distribution of twin objects for enabling a 6G service.	Distributed	Centralized	Hybrid
Elasticity	This metric refers to on-demand dynamic resource allocation for digital twins operation in an elastic way in response to highly dynamic requirements.	High	Low	High
Context-awareness	Context-awareness is the function that deals with the knowledge about the end-devices location and network traffic.	High	Low	Medium
Mobility support	Mobility support deals with the ability of digital twins to seamlessly serve mobile end-devices.	High	Low	Medium
Twins Robustness (reliability)	Robustness refers to seamless operation of digital-twin-enabled 6G application in case of failure of twin objects.	Highest (for multiple edge-based twins)	Lowest	Medium

TABLE 1. Comparison of edge-based, cloud-based, and edge-cloud-based twins.

Scalable Intelligent Analytics

6G must sustain heterogeneous system requirements, network structures, and hardware architectures. Therefore, digital-twin-enabled 6G wireless systems should be based primarily on effective ML schemes for large datasets [3]. However, training twin models for large datasets faces many challenges, such as the need to deal with a complex ML model of large size and the high computing power needed for training. For instance, shallow neural networks can have better scalability in terms of computing power for training large datasets, but their performance will degrade for highly dynamic scenarios (e.g., for mobility management, resource allocation, and edge caching). Although one can consider a deep learning-based twin model for highly dynamic scenarios with large datasets, training of a deep learning-based twin model at a centralized location might not be feasible due to a high training time. Moreover, the inference will also be slow for large datasets. To address these challenges, we can use distributed deep learning-based twin models. In distributed deep learning models, multiple models can be trained at various locations to reduce the model training time. After the computation of multiple twin models at different locations, all the trained twin models are combined at a centralized location. This process continues in an iterative manner until convergence. Generally, twin model computing time and communication time have an inverse relationship: When the number of distributed machines is increased, the model computing time decreases while the communication time increases. However, there is some saturation point, beyond which the training cost (i.e., the sum of computation time and communication time) shows no significant change for an increase in the number of machines [9]. Therefore, we must define new scalable ML schemes to overcome this limitation. Federated learning (FL) with sparsification can be a promising solution to enable scalable, distributed ML-based twin model [10]. Sparsification-enabled FL sends only the important values of a full gradient, and thus further reduces the communication overhead. Although sparsification-enabled FL reduces communication resources consumption, it will result in a loss of global accuracy. Therefore, a trade-off must be made between communication resources consumption and global accuracy. Furthermore, FL has robustness issues due to its dependency on a single centralized server for global model computation. The centralized aggregation server might fails due to an attack or physical damage. To address this limitation, we can use dispersed FL based on distributed aggregations without relying on centralized global aggregation [10].

Blockchain-Based Data Management

Digital-twin-enabled 6G will be based mostly on decentralized network architectures using ML to offer IoE services. To manage the decentralized datasets in a transparent and immutable manner, blockchain is a promising candidate. There are two goals for using blockchain in a digital twin-enabled 6G network: storing pre-trained models, and immutable, decentralized management of training data for ML models. The twins pre-trained ML models for various scenarios can be used by a twin-based architecture to enable real-time services. It can additionally be assisting further training on newly added data for performance improvement in terms of learning accuracy and reduced training time. For example, a blockchain can be used to store pre-trained models for medical imaging applications developed by different hospitals and healthcare centers. To run a blockchain consensus algorithm, edge servers can be used as miners in 6G. Although blockchain can offer several benefits, it has a few challenges. These challenges are scalability, the high latency associated with a blockchain consensus algorithm, high-energy consumption, and privacy issues [5]. In 6G, there will be a large number of IoE devices and miners that will suffer from scalability issues for a blockchain-based architecture. Generally, the speed of a blockchain transaction decreases when the number of nodes. Therefore, we must resolve this bottleneck to enable the use of a blockchain for digital twin-based 6G. Additionally, blockchain consensus algorithms will use significant energy and suffer from high latency. To efficiently operate digital-twin-enabled 6G, we must propose blockchain consensus algorithms that will offer low-latency (e.g., Byzantine fault tolerance) and low energy (e.g., delegated proof of stake) compared to Proof of Work.

Scalability and Reliability

The expected massive number of devices in 6G motivates us to design a scalable and reliable architecture based on digital twins. Digital twins face scalability and reliability challenges pertaining to the implementation of massive ultra-reliable low latency communication (mURLLC) services [2]. Although cloud-based twin implementation can offer a low design complexity pertaining to management and design, it will suffer from high latency issues for networks with a large number of devices. To address this issue, one can use a distributed twin architecture (as detailed below). Distributed architectures (i.e., edge-based twins) reduce latency and increase scalability. However, distributed digital twins will suffer from higher management complexity compared to centralized digital twins. A centralized digital twin may have more computational power and storage than the distributed one, but it has high latency. Therefore, we can use a hybrid approach by combining the features of both centralized and distributed digital twins to offer a trade-off between computational power, storage capacity, and latency. For instance, consider collaborative caching for extended reality. One can deploy edge-based twin objects using deep reinforcement learning at the network edge and cloud-based twin object at a cloud. Edge-based twin objects will update themselves using their own data and send their learning updates to the cloud-based twin. Finally, cloud-based twin object can share the updated learning updates with all edge-based twin objects. Note that there are two main aspects of reliability, such as twin reliability and twin-based service reliability. Twin reliability refers to the operation of a twin with minimum possible interruption due to a malfunction of the edge/cloud server running the twin objects. Additionally, the twin signaling (e.g., training of distributed learning model to yield pr-trained machine learning models) over wireless access channel required for various services is affected by channel uncertainties. To ensure reliable twin signaling, there is a need to employ channel coding schemes (e.g., URLLC codes) and other techniques (e.g., multi-connectivity, packet duplication). Table 1 explains the twin reliability under malfunctioning of edge/cloud server running twin objects. On the other hand, twin service reliability mainly depends on wireless channel reliability and reliable/cloud edge computing. For service wireless channel reliability, similar to twin signaling we can use channel coding schemes and other techniques for communication. Additionally, digital twin can be used for predictive maintenance of 6G systems to avoid system malfunctions and cyber attacks through AI analytics and simulation.

Architecture of Digital-Twin-Enabled 6G

Twin Objects

We propose the notion of twin objects-based architecture for digital-twin-enabled 6G to enable various IoE applications, whose overview is given in Fig. 2 Twin objects use the virtual model of a physical system (i.e., IoE service) and will be responsible for performing optimization, training of an ML model, and control to enable a given 6G service. To virtually represent a physical system, there are many challenges, such as true reflection of attributes, entanglement, and composability. Entanglement refers to truly complete information exchange between physical objects and logical twin objects, whereas composability deals with using the existing twin objects of various entities for enabling a complete twin-based service. A typical 6G service can be deployed either using a single or multiple twin objects. In our framework, the twin objects can be used to emulate a single entity (e.g., edge server, cloud server, end-device, wireless channel), single service (e.g, augmented reality), and multiple services. For a single entity, twin can be used to optimize resources (e.g., energy for various tasks). Twins can also be used for emulation of a complete service by end-to-end resource management and planning. Another way of emulating a service can be combining the existing single entity twins (e.g., edge server twin, devices twin, cloud server twin) to enable a complete service. On the other hand, one can use twins for various services on a single network by optimizing overall resources and the quality of service.

The twin objects can be created and terminated dynamically to enable 6G services based on requests [11]. Twin objects can be implemented using transient-based virtual machines (TVM) to offer the proactive customization of resources and post-use cleanup. The proactive customization of resources can be enabled by proactive intelligent analytics based on emerging ML schemes [3]. Twin objects can enable proactive intelligent analytics either using pre-trained ML models for synchronous communication or newly trained ML models for asynchronous communication. Later, the resources assigned to the TVM should be released after executing the service. Note that the TVM for a particular service should be isolated from the TVM of another service. Furthermore, the TVM must be separated from the host node software. The host node software must interact with the TVM seamlessly and ubiquitously to enable us with the efficient implementation of multiple TVMs.

Twin Object Deployment Trends

Twin objects can be deployed either at end-devices, edge, or cloud. Depending on this deployment, we can divide the architecture of digital twin into three categories: *edge-based digital twin*, *cloud-based digital twin*, and *edge-cloud-based collaborative digital twin*, as shown in Fig. 3. Edge-based twin objects are more suitable for 6G applications with strict latency constraints (e.g., massive URLLC) due to their nearby locations to end-devices, whereas cloud-based twin objects can be used for delay tolerant and high computational power applications. Generally, the available computing power at the cloud is higher than

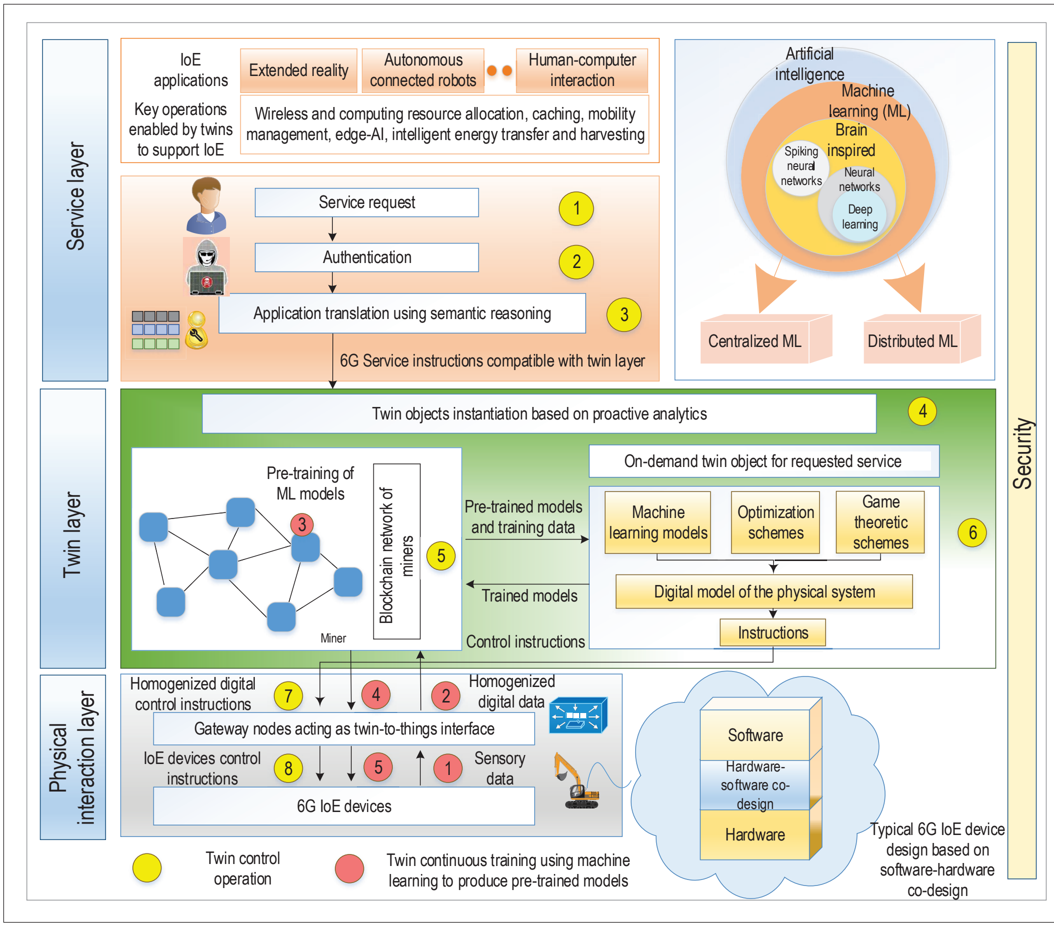

FIGURE 2. Digital twin sequence diagram.

that of the edge, but with larger latency and more communication cost. Meanwhile, edge-cloud-based twins exploit the advantages of both cloud-based twins (i.e., high computational power) and edge-based twins (i.e., instant analytics with low communication cost). One thing must be noted that for real-time applications, twin objects will use pre-trained models for instant use. For non-real-time applications, twin objects can further train the pre-trained ML model for performance improvement. For instance, consider a cooperative intelligence-enabled transportation system using edge-cloud-based twins. For designing 6G traffic congestion control, we can employ twins that are installed at the cloud [12], whereas for reporting accidents using prediction between autonomous cars, we can use edge-based twins due to the instant reporting requirement of such events [13]. Additionally, if we want to deploy intelligent caching based on deep reinforcement learning for infotainment services in autonomous driving cars, we can use multiple edge-based twins that will act as agents for optimal caching decisions [14]. Comparison of twins for various performance metrics is given in Table 1. Considering scalability, an edge-based twin will have the highest value because it has the lowest latency compared to both cloud and edge-cloud-based twins. We can add more end-devices in the case of edge-based twins until their maximum serving limit without significantly increasing the latency. However, a cloud-based twin will suffer from low scalability due to an increase in latency when the number of devices increases. Therefore, depending on the 6G application nature, we should deploy the twin object at an appropriate location.

Various interfaces such as twins-to-things, twin-to-twin, and twin-to-service interfaces must be proposed for seamless, isolation-based, complex interaction in a scalable and reliable manner. Twin-to-object interfaces allow us to efficiently decouple the IoE devices from the twin layer, thus proving us with easier management. A twin-to-twin interface enables the communication between various twin objects to implement a distributed system (e.g., federated learning-based vehicular edge computing [15]). For instance, to implement distributed ML-based systems, various twin objects can be used to train ML models at network edges. Next, to get an ensemble ML model, a twin-to-twin interface will be used. Furthermore, a twin-to-twin interface will be used for communication among various twins at different levels (i.e., cloud and edge levels). Here, we note that digital-twin-enabled 6G architecture must have necessary security against various security attacks. Blockchain-based data management can enable sufficient security for data at distributed nodes. End-devices, edge/cloud servers, and twin objects must be provided with lightweight and effective authentication schemes.

Digital Twin Operational Steps

We can divide the twin operation into two types: training and operation as shown in Fig. 2. For training, one can use distributed ML (step 1). Next, the local learning models are sent to the twin layer for aggregation at the blockchain miner (steps 2 and 3). After the computation of the global model, the global model updates are sent back to the IoE devices for updating their local learning models (steps 4 and 5). This iterative learning process can take place either in a synchronous or asynchronous fashion. In an asynchronous fashion, a device will send its local learning model only when getting a connection to miners, whereas the devices, must send their local learning models within a predefined time to the miner for global aggregation in case of synchronous fashion. Therefore, we must appropriately select the fashion of aggregation depending on connectivity conditions. On the other hand, there are some scenarios such as autonomous driving cars in which devices can generate up to 4,000 gigaoctet of data every day, which must be considered in the training of the considered learning model. Although one can use centralized ML for such scenarios, it has the downside of using more communication resources to transfer the end-devices data to a centralized server. To address this challenge, we should use federated learning to continuously update the global model for better performance.

We now explain the operation of a digital twin in response to the end-users request for 6G service. XR is used an example here to provide a concrete understanding of the digital twin operation. For instance, consider a 6G system in which an XR device requests a service from the BS (step 1). In response to the user request, first of all, authentication takes place (step 2). After validation of the end-user XR request, the XR request must be translated using semantic reasoning techniques, into a form understandable by the twin objects (step 3). Next, we instantiate twin objects at the BS based on TVM and associate them with blockchain miners (step 4). The miners will store and run a blockchain consensus algorithm to enable trustworthy sharing of data for twins' operations (step 5). Moreover, miners will store the data required for twin proactive analytics. Additionally, miner will store the pre-trained models for XR service. To serve the end-users, the on-demand twin objects can use these pre-trained models (i.e., use them either directly for instant XR operation or perform further training for future use). The instantiated twin object will serve the XR end-user by enabling efficient communication and computing resource management with other controls (steps 6, 7, and 8).

Future Directions

Isolation Between Twins-Based Services

To allow 6G to use twin objects for various IoE applications, efficient utilization of network resources is necessary. Additionally, to guarantee the performance of a twin-based IoE service without affecting the performance of other twin-based services, there is a need to explicitly allocate resources (i.e., computation and communication resources) for various twin-based services. One way can be to use a dedicated allocation of resources to various twin-based services. However, dedicated allocation of resources (e.g., edge server) to a digital twin-based service will result in an inefficient use of resources. Therefore, we must propose novel resource optimization schemes for twinning over a shared network.

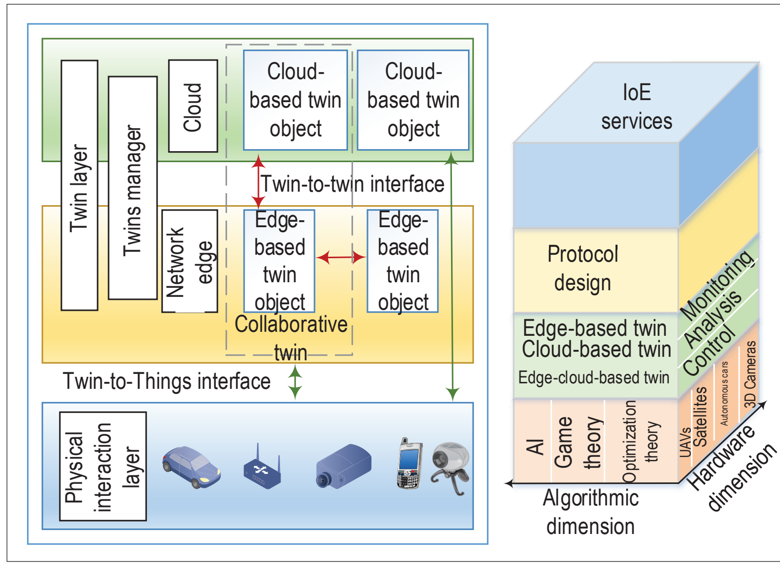

FIGURE 3. Twin objects deployment trends.

Mobility Management for Edge-Based Twins

An end-user must be served seamlessly by the digital-twin-enabled 6G system during the service period. A mobile device associated with a twin object might suffer from service interruption due to moving outside the coverage of the access point/BS associated with the twin. One way is to enable the end-user with the service via communication with its twin object/s using a backhaul link. But, this approach will suffer from the issues of slight interruption of the service and high latency. To cope with these issues, one can migrate the service to the newly associated twin objects. However, the migration of services depends on user mobility that can be proactively predicted using ML schemes.

Digital Twin Forensics

A typical digital-twin-enabled 6G system will have a variety of players (e.g., end-devices, TVM-based twin-objects, communication interfaces). Therefore, it will be vulnerable to various security threats. To enable the successful operation of the twin-based system, there is a need to propose effective forensic techniques to investigate these security attacks. Based on the analysis of attacks, there is a need to develop new security mechanisms. The main challenges that will be involved in digital-twin-enabled 6G forensics are attacks evidence identification, evidence acquisition and preservation, and evidence presentation.

Conclusions

In this article, we have presented a vision of digital-twin-enabled 6G.We have proposed a digital twin-based architecture for 6G. Furthermore, we have provided an outlook on future research. We have concluded that a digital twin will serve as a key enabler of 6G services. Our proposed edge-based digital twins will offer key features scalability and reliability by using distributed deployment. We have also provided a roadmap for future research to truly realize the vision of a digital twin for 6G.

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Biographies

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