

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

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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 technologies (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.

Index Terms—Digital twin, 6G, Internet of Everything, artificial intelligence, distributed machine learning.

I. INTRODUCTION

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

- **Self-sustaining wireless systems:** 6G wireless systems will rely on a ubiquitous, intelligent, and seamless connectivity for a massive number of devices to offer various novel IoE services. These IoE services will 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 that can operate with minimum possible intervention from end-users. Such self-sustaining systems can jointly perform efficient network functions adaptation and resource optimization, using emerging techniques in the fields of machine learning, optimization theory, game theory, and matching theory, among others.

- **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]). Digital twin uses machine learning, data analytics, and multi-physics simulation to study of the dynamics of a given system. Digital twins can be categorized into: monitoring digital twin, simulation digital twin, and operational digital twin¹. 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 machine learning 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. In contrast to [5]–[7], we explore the role of the digital twin in enabling 6G wireless systems. For the design of 6G systems, an operational digital twin allows us to enable efficient interaction among various players of 6G. This

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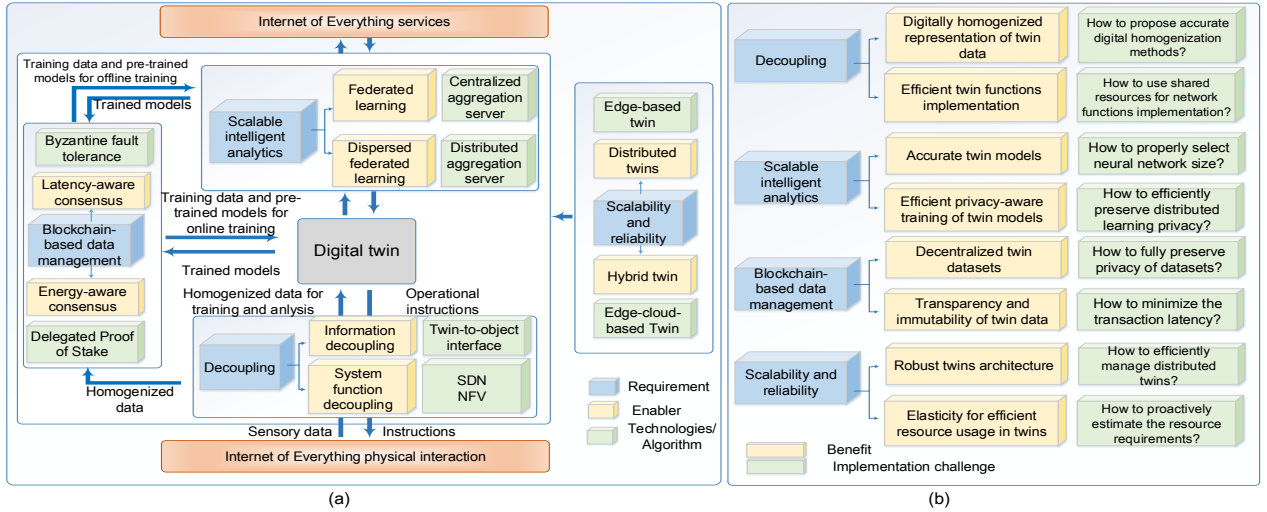


Fig. 1: (a) Key design requirements and (b) Benefits for twins-based architecture.

is not possible without such an operational twin because other twins (e.g., simulation and monitoring twins) can only enable us to 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. In particular, the digital twin will use a virtual representation of the 6G physical system along with communication, computing, security, and privacy technologies to enable 6G-based IoE applications. Meanwhile, to efficiently operate 6G, the digital twin will use machine learning and optimization algorithms for communication and computing resource optimization. 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.

To the best of our knowledge, this is the first work to study digital-twin-enabled 6G systems. In contrast to existing works [1]–[3] on 6G, this paper presents a new perspective regarding the development of intelligent, self-sustaining 6G wireless systems enabled by digital twin.

II. KEY DESIGN REQUIREMENTS

In this section, we present the key requirements that are indispensable for creating a digital twin for wireless 6G systems, as shown in Fig. 1. These key requirements are decoupling, scalable intelligent analytics, and blockchain-based data management. To fulfill the aforementioned requirements, one must use scalable and reliable architecture and algorithms. A digital twin will use a virtual representation

of the system to analyze the system dynamics. For example, in 6G, the digital twin will virtually represent: a) the physical wireless system (e.g., intelligent reflecting surfaces with backhaul links), b) a typical 6G application physical system (autonomous driving car, Industry 4.0 plant, and e-healthcare system), and c) specific module (e.g., edge caching module, computational offloading module at the edge). Based on the analysis performed by digital twin for a user requested IoE service, necessary actions will be performed to serve the 6G service requesting user. To carry out analysis and control actions, there is a need to efficiently deploy digital twin models with other technologies to enable easier network management (more details about architecture will be given in Section III). To train digital twin models, one can use the data generated by IoE devices. In addition to the IoE devices data, the blockchain network will store pre-trained twin models. These pre-trained models can be employed for training other twin models using newly received data for better performance. This way of updating the twin models will improve the overall performance over time by using newly added data. Next, we discuss the requirements for enabling digital twin for 6G in detail.

A. Decoupling

The transformation of a physical system into a digital twin is primarily based on *decoupling*. Decoupling in the context of digital twins can be of two types: information decoupling and system functions decoupling, as shown in Fig. 1a. Information decoupling allows the transformation of physical system information (i.e., system state) into a homogenized digital representation that will offer generality and ease the implementation of digital twins. Moreover, homogenized digital representation helps digital twins to easily realize the dynamically changing states of a physical interaction space. A 6G physical interaction space consists of base stations (BSs), intelligent reflecting surfaces, smart devices/sensors, and edge/cloud servers. Examples of 6G physical interaction

TABLE I: Comparison of edge-based, cloud-based, and edge-cloud-based twins.

	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 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
Robustness	Robustness refers to seamless operation of digital-twin-enabled 6G application in case of failure one of the twin objects.	Highest (for multiple edge-based twins)	Lowest	Medium

space information include industrial process control sensory data and holographic images, haptics sensors, 6G spectrum usage data, edge servers resource management data, among others. On the other hand, in order enable a flexible operation of a digital twin-based wireless system, it is necessary to effectively decouple the system functions (i.e., mobility management, resource allocation, edge caching, etc.) from hardware to software. The decoupling of system functions will allow us to make the digital twin-based system operate efficiently and adaptively as per the network dynamics (i.e., network adaptability to enable self-sustainable 6G networks). To enable digital twin for 6G with functions 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 network slicing, digital-twins-enabled 6G will be different than the classical network slicing. In contrast to network slicing, digital twin-enabled 6G will use a digital representation of the physical system to enable 6G services. The digital representation with machine learning will enable us 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 in Section II-C). 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 stored data on a blockchain) and real-time control. However, network slicing will enable real-time resource management in response to the end-users requests. Therefore, we can say that 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.

B. Scalable Intelligent Analytics

6G must be able to sustain heterogeneous system requirements, network structures, and hardware architectures.

Therefore, digital-twin-enabled 6G wireless systems should be based primarily on effective machine learning schemes for large datasets [3]. However, training twin models for large datasets faces many challenges, such as the need to deal with a complex machine learning 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 [8]. Therefore, we must define new scalable machine learning schemes to overcome this limitation. Federated learning with sparsification can be a promising solution to enable scalable, distributed machine learning-based twin model. Sparsification-enabled federated learning sends only the important values of a full gradient, and thus further reduces the communication overhead. Although federated learning offers scalable machine learning, it has robustness issues due to its dependency on a single centralized server for global model computation. The centralized aggregation server might fail due to an attack or physical damage. To

address this limitation, we can use dispersed federated learning based on distributed aggregations [9].

C. Blockchain-Based Data Management

Digital-twin-enabled 6G will be based mostly on decentralized network architectures using machine learning to offer extremely low latency services. To manage the decentralized datasets in a transparent and immutable manner, blockchain is a promising candidate. This is because blockchain allows us to store data that cannot be altered without collusion of the network majority and a retroactive change of all subsequent blocks. Moreover, blockchain can offer a seamless transfer of data without losing data integrity. Specifically, blockchain can be used to store the twins pre-trained machine learning models for various scenarios which can further use performance improvement in terms of learning accuracy and reduced training time. Additionally, it can store the data required for the training of digital twin machine learning models. For example, a blockchain can be used to store pre-trained models for medical imaging applications developed by different hospitals and healthcare centers. Moreover, blockchain can store additional datasets from new clinics as it can be considered as a trusted data management platform.

To run a blockchain consensus algorithm, edge servers can be used as miners. 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 concerns [5]. Generally, blockchain has a slower transaction speed with an increase in the number of nodes. Therefore, we must resolve this bottleneck of the blockchain to enable it for digital twins-enabled 6G. The consensus algorithm used in blockchain adds a significant amount of delay and consumes energy before reaching a consensus. Furthermore, it has privacy concerns because of its distributed design. Every node in a blockchain has access to the blockchain transaction data itself, and thus privacy leakage can occur in the presence of a malicious user. 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).

D. Scalability and Reliability

The expected massive number of devices in 6G motivates us to design a scalable and reliable architecture based on digital twins. Specifically, digital twins will suffer from a scalability and reliability issue, when it comes to implementing 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 in Section III). 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 tradeoff 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.

III. ARCHITECTURE OF DIGITAL-TWIN-ENABLED 6G

We propose the notion of virtual twin objects-based architecture for digital-twin-enabled 6G to enable various IoE applications, whose overview is given in Fig. 3. The twin objects interact with IoE devices and other twins to enable 6G services. We next present a detailed discussion on digital-twin-based 6G architecture components and its deployment possibilities.

A. Twin Objects

To efficiently deploy digital-twin-enabled 6G wireless systems, we can use the notion of virtual twin objects. Twin objects will be responsible for performing optimization, training of a machine learning model, and control to enable a given 6G service. A typical 6G service can be deployed either using a single or multiple twin objects. These twin objects can be created and terminated dynamically to enable 6G services based on requests [10]. Twin object can be implemented using transient-based virtual machines (TVM). TVM-based twin objects will offer us the proactive customization of resources and post-use cleanup. The proactive customization of resources can be enabled by proactive intelligent analytics based on emerging machine learning schemes [3]. Later, the resources assigned to the TVM should be released after executing the service. It must be noted 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.

B. Twin Object Deployment Trends

Twin objects can be deployed either at end-devices, edge, or cloud. Depending on the deployment of twin objects, 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. 2. Edge-based twin objects are more suitable for 6G applications with strict latency constraints (e.g., massive URLLC), whereas cloud-based twin objects can be used for delay tolerant, high computational power applications. Meanwhile, edge-cloud-based twins can use both edge and cloud resources to offer a tradeoff between latency and computational power. Edge-based twins are characterized by lower computational power

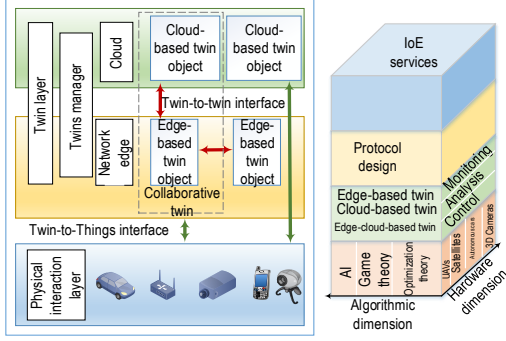


Fig. 2: Twin objects deployment trends.

and lower storage than cloud-based twins. 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). For instance, consider a cooperative intelligence-enabled transportation system using edge-cloud-based twins. For designing traffic congestion control in 6G, we can employ twins that are installed at the cloud [11], whereas for reporting accidents between autonomous cars, we can use edge-based twins due to the instant reporting requirement of such events [12]. Comparison of twins for various performance metrics is given in Table I. Considering scalability, an edge-based twin will have the highest value due to the fact that it has the lowest latency compared to both cloud and edge-cloud-based twins. We can add more end-devices in 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 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. Furthermore, elasticity for both edge and edge-cloud-based-twins is much higher than for a cloud-based twin because of low context-awareness (i.e., less information about the network edge dynamics). In terms of mobility support, edge-based twins and edge-cloud-based twins have higher support than a cloud. Also, edge-based twins and edge-cloud-based twins have more information about end-user network dynamics, and thus can easily handle mobility than the remote cloud.

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. Using a twin interface, we can add and remove twins designated for specific applications without affecting the other twins' operation [13]. Furthermore, 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 [14]). For instance, to implement distributed machine learning-based systems, various twin objects can be used to train machine learning models at network edges. Next, to get an ensemble

machine learning 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).

C. Digital Twin Operational Steps

Mainly, we can divide the twin operation into two types: training and operation as shown in Fig. 3. For training, one can use distributed machine learning (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 process of learning 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 machine learning 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.

Now we explain the operation of digital twin in response to the end-users request for 6G service (XR is used as 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 must 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. Upon the end-user request for services, the on-demand twin objects can use these pre-trained models (i.e., either use them directly for instant XR operation and perform further training for future use). The instantiated twin object will serve the XR requesting end-user by enabling efficient communication and computing resource management with other controls (steps 6, 7, and 8).

IV. FUTURE DIRECTIONS

A. Isolation Between Twins-Based Services

To allow 6G to use twin objects for various IoE applications, efficient utilization of network resources is necessary. To

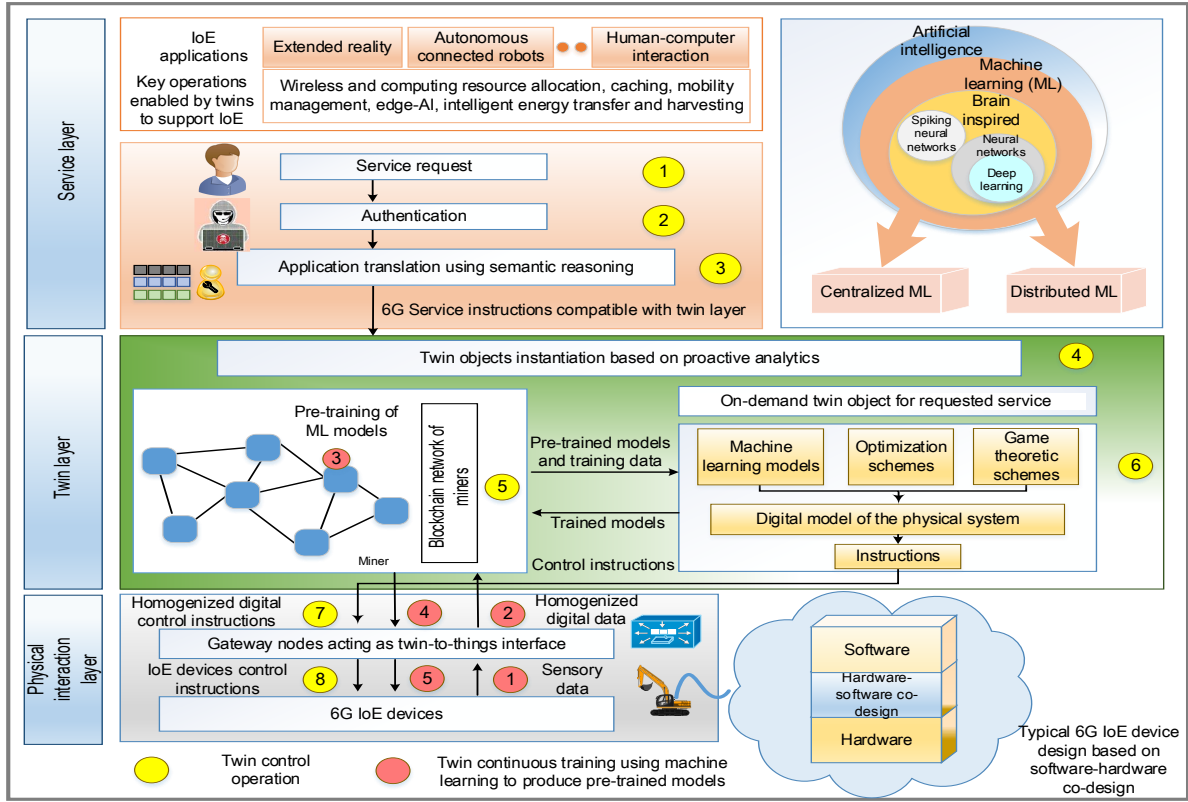


Fig. 3: Digital twin sequence diagram.

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 optimization schemes for twin objects that will enable the efficient use of resources by sharing them among many twin-based services while fulfilling their isolation requirements.

B. 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, migrating the service to new twin object/s will be based on the prediction of user mobility to proactively find the new twin objects for service migration. Therefore, we must propose effective

prediction schemes to find the locations of newly twin objects for service migration.

C. 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. Evidence identification is the first and difficult to find out due to the proliferation of devices and data, device mobility, heterogeneity in devices, and their software. Other than evidence identification, evidence acquisition, and preservation pose challenges to implement forensics techniques. Acquiring evidence from the devices suffers from data encryption and hardware/software heterogeneity. Next, preserving the evidence for investigation in cases of limited memory devices. One possible solution to preserving evidence is to save it in another location (e.g., edge computing servers). The final step in forensics is how to present the data to enable efficient forensics analysis.

V. CONCLUSIONS

In this paper, 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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