

Survey on Digital Twin Edge Networks (DITEN) Toward 6G

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ABSTRACT The next generation (6G) wireless systems aim to cater to the Internet of Everything (IoE) and revolutionize customer services and applications to a fully intelligent and autonomous system. To achieve this, the digital twin edge network (DITEN) is proposed to combine mobile/multi-access edge computing (MEC) and digital twin (DT), thereby improving the network performance such as throughput and security, and reducing the cost of communication, computation, and caching. In DITENs, the network status can be continuously monitored, and based on the obtained network states, the networking schemes, such as routing and resource management, can be studied in the established DITENs from a centralized perspective. In this survey, we present a comprehensive overview of DITEN for 6G. First, we present the fundamental aspects of DITEN, including concept, framework, and potential. Second, a comprehensive design of DITEN is devised, including the DT modeling/updating, DT deployment, key issues, and enabling technologies. Then, the typical applications of DITEN towards 6G are provided, including the Internet of Things (IoT), vehicular network, space-air-ground integrated network (SAGIN), healthcare, wireless systems, and other applications, along with the design of DITEN in each application, such as DT modeling, DT association, incentive mechanisms, and so on. Finally, challenges and open issues are discussed.

INDEX TERMS Digital twin edge networks (DITEN), 6G, DT modeling, DT deployment, applications, challenges.

I. INTRODUCTION

THE SIXTH-GENERATION (6G) wireless systems [1] are designed to cater to the emerging Internet of Everything (IoE) applications, such as brain-computer interaction (BCI), multisensory extended reality (XR), and autonomous systems, to achieve a fully intelligent and autonomous system for customer services and applications in the future [2], as well as to provide users with an immersive experience in a virtual space such as Metaverse [3]. To achieve these, there are some strict requirements on 6G, such as ultra-high throughput and reliability, ultra-low latency, seamless connectivity, and so on. To this end, it is

critical to integrate some advanced technologies to design the 6G wireless system, such as applying Terahertz communications [4] and intelligent reflect surface (IRS) [5] to improve the efficiency of communications [6], [7], and utilizing multi-access/mobile edging computing (MEC) [8] and artificial intelligence (AI) [9] to improve the efficiency of computations [10], [11], as well as employing security-related technologies such as blockchain to avoid the security risk [12]. Furthermore, 6G should also be designed as a self-sustaining wireless system to minimize the intervention from the network operators/end-users [13], and to be developed as a proactive-online-learning-enabled system to

achieve efficient resource management by performing intelligent analysis such as proactive learning before the service request [14].

The advanced wireless communication and computation technologies drive the applications of the digital twin (DT) technology [15]. DT can accurately replicate the physical object in the digital domain, and the physical object interacts constantly and evolves synchronously with its virtual twin throughout its life cycle [16], [17]. With DT, the connection between the physical components and the digital space can be achieved, and the physical system can be simulated, predicted, analyzed, and optimized, by using various technologies in terms of sensing, communication, computation, and analysis [18]. There are three types of DTs based on their functions, namely monitoring DT, simulation DT, and operational DT [19]. Specifically, the monitoring DT is used for monitoring a physical system's status. While, the simulation DT aims at predicting the dynamics of a physical system by utilizing advanced simulation tools and machine learning (ML) technologies. Meanwhile, the operational DT achieves the interactions between system operators and a cyber-physical system, and performs various operations, such as prediction and optimization. DT has been widely applied in different applications, such as the Internet of Things (IoT) [20], and the emerging 6G system [21].

The realization of DT involves many processes ranging from data collection to visualization and service feedback, which requires intensive resource in terms of communication, computation, and storage, so that some resource-limited end devices are hindered to construct and maintain DTs in local. To address this issue, cloud/edge computing can be used to assist with the implementation of DTs. In cloud computing based DT modeling, a cloud server collects real-time information from physical objects, and constructs the physical objects' DT based on the collected information. Thus, high communication overhead incurs since the long transmission distance. In this context, a new paradigm, named digital twin edge networks (DITEN) is emerged [22], [23]. By DITEN, the MEC and DT are integrated to provide service to various applications. In DITENs, edge nodes such as base stations (BSs) and access points (APs) collect real-time operation information of physical objects, and their behavior model can be built along with the dynamical environment based on the collected information. Furthermore, the edge nodes interact with the physical components continuously to keep the consistency between the physical components and their DTs. Thus, by designing and optimizing networking schemes directly in the constructed DITEN, the networking schemes' efficiency can be improved and the cost of communications and computations can be reduced [24], [25]. In the following, DT is used to represent the digital twin technology or a digital twin of a physical object.

Recently, the design of a DITEN has been studied in various scenarios, such as IoT [26], vehicular network [27], space-air-ground integrated network (SAGIN) [28], 6G wireless system [29], healthcare [30], and other applications [31].

Specifically, a DITEN improves the system performance, such as latency and reliability, by accurate DT modeling and intelligent decisions (e.g., DT association, intelligent task offloading, and resource allocation), applying various technologies, i.e., optimization theory, game theory, ML, and blockchain. Although DITEN has some potential on improving system performance, it still faces some challenges considering the limited wireless resource and security concerns [32]. First, how to ensure enough data samples for the edge servers for DT modeling is challenging. The limited wireless resource and traffic congestion in a network hinder the real-time data collection from the physical components. Second, how to motivate the resource rich end devices and edge/cloud servers to contribute their resource to DT modeling and updating is a key issue in DITEN. Third, how to ensure the data privacy and security in DITEN is a challenge, considering the large-scale users and data transmission, and the untrusted and nontransparent wireless network environment.

A. EXISTING SURVEYS AND TUTORIALS

There are a few works that overview the DT technology in various applications such as IoT, industrial applications, wireless communications, etc. The key concepts, applications, and design implications of DT are presented in [33]. The enabling technologies, challenges, and open researches of DT are surveyed in [34]. For IoT applications, in [35], the DT technologies for smart cities including their values, challenges, and enablers are illustrated. In [14], the authors survey DTs in the context of IoT, including technical characteristics, scenarios, and architectural elements. In [36], the key features and definitions of digital twin network (DTN) are presented, along with the key enabling technologies, applications, and open issues. In [37], [38], the authors focus on the DT in smart cities. In [39], the authors study the characteristics of DT, communication technologies and tools for DT modeling, reference models, and standards, and discuss the challenges and open issues. In [40], the existing studies on the cognitive digital twin (CDT) concept are reviewed, along with its definitions and key features. In [41], the authors review the research on DTs, including the key technologies to apply DT, industrial applications, and future directions. In [42], the concept, characteristics, key technologies, application, and future directions of digital twin city (DTC) are illustrated. In [18], the architectures, case study, and challenges for a mobility digital twin (MDT) framework are presented. Although the above surveys and tutorials provide a guideline to apply DT technology, they focus on the application of DT and the integration of DT and MEC is missing. The comprehensive survey on the works on DITEN is still a vacant, and need to be filled up.

B. CONTRIBUTIONS OF THIS WORK

In this paper, we survey the existing works about the DITEN system. The contributions of this work can be summarized as follows,

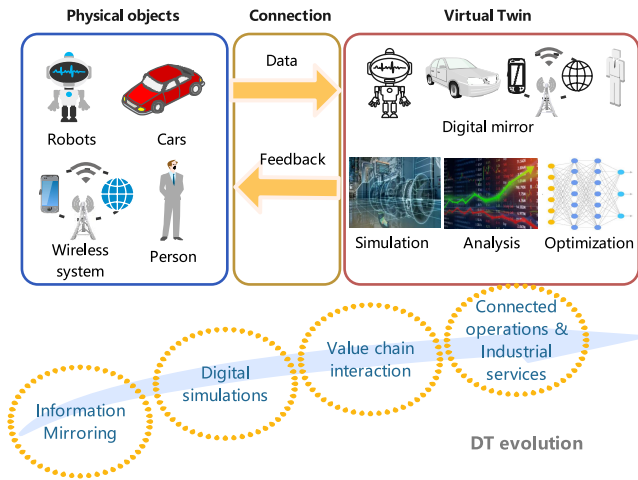


FIGURE 1. The concept of digital twin (DT) and its evolution.

TABLE 1. The three types concept of DT.

Concept	Functions	Physical-to-twin	Twin-to-physical
Monitoring DT	Virtual representation	×	×
Simulation DT	Simulation	✓	×
Operational DT	Co-evolute digital replica	✓	✓

- We present the concept, framework, and potential of DITEN for 6G. (Section II)
- A comprehensive discussion of the design of DITEN is presented, including the DT modeling/updating, DT deployment, key issues, and enabling technologies. (Section III)
- The typical applications of DITEN in 6G are provided, including the IoT, vehicular network, SAGIN, healthcare, wireless systems, and other applications. In addition, the design issues of DITEN in each application are discussed, such as DT modeling, DT association, incentive mechanisms, and so on. (Section IV)
- Several challenges and open issues are discussed. (Section V)

II. DITEN: CONCEPT, FRAMEWORK, AND POTENTIAL

In this section, we present the fundamental aspects of DITEN in 6G, including its concept, framework, and potential.

A. CONCEPT

Before giving the concept of DITEN, we first present some information on DT and MEC.

1) DIGITAL TWIN (DT)

DT is an efficient way to bridge the physical space and digital space [43]. Owing to the advanced communication and computation technologies, the DT has gone through four development processes, i.e., information mirroring, digital simulations, values chain interaction, and connected operations and industrial services, as shown in Fig. 1. To this end, there are three categories of DT definition summarized in Table 1, and the detailed descriptions are as follows,

- Monitoring DT [44]. In this case, DT is used to mirror or virtually represent a physical object. The physical object does not interact with its virtual model, and the changes of the physical object have no effect on its virtual model after it is established, and vice versa.
- Simulation DT [45]. In this case, DT is defined as a simulator or software. By simulating with computers, the physical objects can be understood, predicted, and optimized, so that their performance can be improved. The virtual model evolves with the physical object, but the physical object will not change with the dynamics of the virtual model.
- Operation DT [46], [47], [48]. In this case, the data transmission between physical objects and their twins is bidirectional. Specifically, the physical objects transmit their status information to their twins, based on that information, the twins are constructed and updated, and the conditions of the physical object can be predicted. Meanwhile, the twin will feed back information, such as optimal solutions to a problem, to guide the operations of physical objects.

More recently, based on the above definitions, DT is usually described as “an intelligent and evolving system that accurately digitally replicates a physical object across multiple granularity levels, and monitors, controls, and optimizes the physical objects during its life cycle” [36]. As shown in Fig. 1, DT consists of three parts: i) physical objects, which can be a robot, a car, a complex system, a person, and so on; ii) virtual twins of physical objects; and iii) connection between the physical objects and their virtual twins. With the connection, the physical objects send their states and generated sensing information to the virtual twins for DT modeling and updating, and the virtual twin will also feed back to the physical objects. As such, the dynamic interactions and synchronous evolution between the physical object and the virtual twin can be achieved. To this end, DT is an efficient way to simulate, analyze, predict, and optimize the physical system throughout its life cycle.

2) MOBILE/MULTI-ACCESS EDGE COMPUTING (MEC)

MEC is an emerging paradigm proposed by the European Telecommunications Standards Institute (ETSI) to reduce property constraints on the existing cloud infrastructures [49], [50]. MEC as a kind of distributed cloud architecture forms the backbone technology of the upcoming 6G wireless systems, which transforms the traditional mobile BSs by enabling IT and cloud computing capabilities at the edge of radio access network (RAN) closing to end users, thereby decreasing delay and relieving the burden on the communications [51], and improving the utility of the mobile backhaul and core networks [52]. By applying MEC, the tasks such as computation and caching can be pushed to the network edges, such as BSs and roadside units (RSUs), then be processed locally close to the users [53]. To this end,

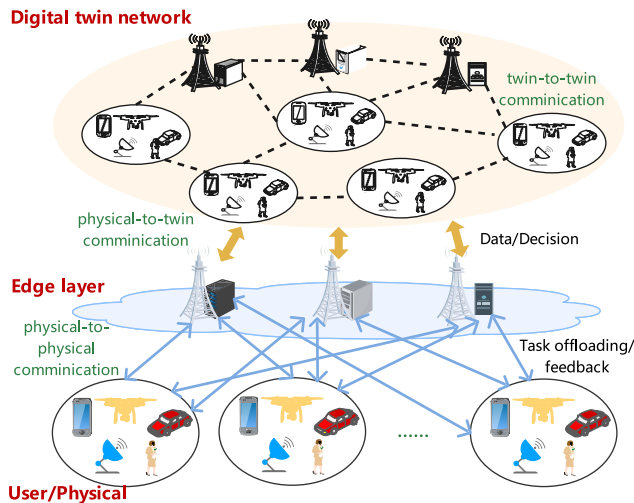


FIGURE 2. The concept of digital twin edge network (DITEN).

the mobile device with the limited resource can also process intensive computation tasks while satisfying ultra-low latency requirement [54].

MEC enhances the existing applications and has great potential to develop a wide variety of emerging innovative applications by authorizing the third parties with computation and storage capabilities at the RAN edge. In addition, thanks to the seamless connectivity provided by cellular networks, MEC becomes a key enabling technology to support mature machine-to-machine (M2M) and IoT services to create vertical services [55]. For example, MEC has been applied in vehicular networks (vehicular edge computing), SAGIN (Aerial edge computing), to empower transport, UAV, and etc. Moreover, by integrating AI in MEC powerfully, edge intelligence can be achieved to further improve the system performance [56].

3) DIGITAL TWIN EDGE NETWORKS (DITEN)

Recently, a new paradigm named DITEN is proposed to bridge the physical MEC system and digital systems [57]. In DITEN, DT models are built and maintained with the assistance of network edge [32]. As shown in Fig. 2, the DITEN consists of three parts, namely the user/physical layer, edge layer, and DTN. In the user/physical layer, local computation and communications are processed, and the real-time state and model parameters information of the user/physical are transmitted to the edge layer via the physical-to-physical communication. In the edge layer, real-time DT modeling and updates are processed. Specifically, the edge nodes such as BSs can collect user/physical components' running status information, and evolve their behavior model based on the collected information along with the time-varying environments. In addition, the edge nodes continuously monitor physical components' states to maintain consistency with their twins. DT can be placed in any edge server, and the edge layer is transparent for users. Meanwhile, the edge resources are shared among all users. In DTN, DTs are virtually connected to form a network with the shared resources

through twin-to-twin communications. In DITEN, the real-time network states can be acquired and are used to obtain the optimal decisions in the network directly from a centralized perspective. To this end, the constructed DITEN can be utilized to design and optimize the network schemes directly, such as task offloading, resource allocation, caching, etc, and the networking schemes' efficiency can be improved and the cost can be reduced. In practice, in the case without DITEN, to perform task offloading and resource allocation decisions, constant communications between edge servers and end users within their coverage are required to obtain real-time information. Therefore, the built of DTs assist with obtaining optimal solutions to resource allocation while minimizing the communication cost. DITEN has the potential to support some computation-intensive services, such as Metaverse and autonomous driving.

The integration of MEC and DT has been studied in several existing works. Lu *et al.* in [58] propose a DTWN, in which the data process tasks are offloaded to the edge servers with the assistance of DT. Sun *et al.* in [22] first consider a DITEN, where DTs estimate edge servers' states and provide training data to DRL agents to obtain the optimal task offloading decisions. Moreover, the deviations between true values and the value of DTs are taken into consideration, and the impacts of such deviations on offloading decisions are also explored. In [28], a DT empowered air-ground network is proposed to represent the network environment virtually for scheme optimization. In [59], DT is leveraged to deal with the resource allocation problem in industrial edge environments.

B. FRAMEWORK

Fig. 3 presents a framework of the DITEN, which can be divided into three layers, namely the physical layer, virtual layer, and application layer. The physical layer contains all the physical devices like end devices and edge/cloud servers, and the wireless communication environment in a MEC system. The end devices have limited computation and storage resources, and need to offload tasks to one or more edge servers for cooperative processing. The network physical entities and the wireless communication environment in the physical layer have their twin mapping in the virtual layer, such as twin end devices, twin edge/cloud servers, and twin communication environment. Data such as the real-time states of the physical entities are collected in the physical layer then be transmitted to the twins in the virtual layer via the physical-to-twin interfaces [60].

The virtual layer contains the DTs that fully copy the physical objects, and manages and controls the physical layer with simulation, prediction, and optimization [60]. The DT system saves the raw data of physical entities, including hardware configuration, user information such as location and available resource, historical data, and real-time operation states of the MEC system, and also keeps monitoring the dynamics of the system. This data is essential to constructing DT models of the physical entities and communication environment

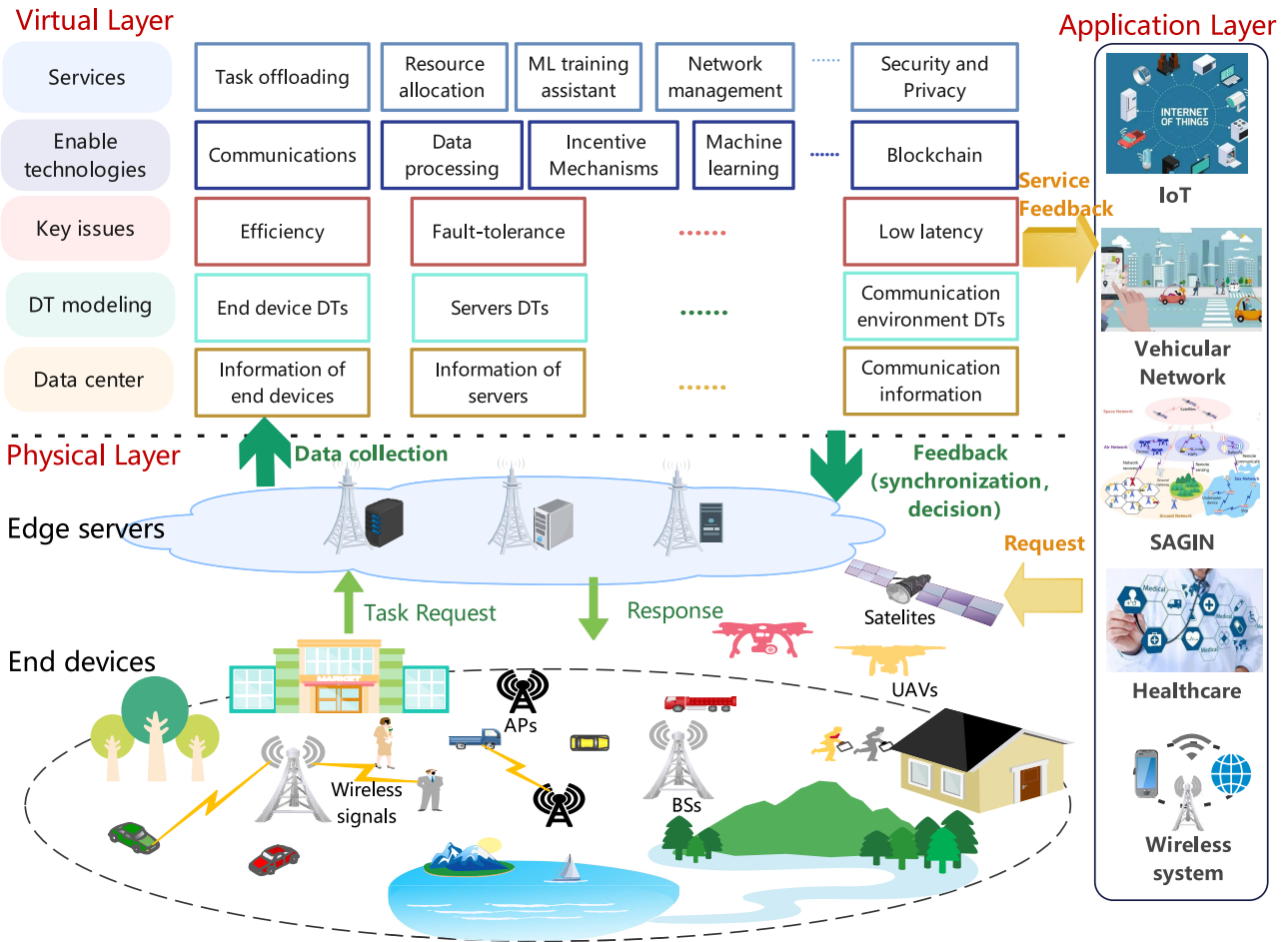


FIGURE 3. Framework of the digital twin edge network (DITEN).

in the virtual layer with high precision. However, in practice, it is challenging to model a physical entity/phenomenon virtually exactly similar to the physical one. Besides, there are some key issues to be addressed, such as efficiency, fault-tolerance, low latency, and security. To solve these issues, various advanced enabling technologies in terms of communications, data processing, incentive mechanisms, ML, and blockchain, can be applied to DT modeling and decision making while protecting the privacy of users. Based on the various formed models and big data, DTs can assist with obtaining intelligent solutions to the problems in the application layer, such as task offloading and resource allocation in IoT, vehicular network, SAGIN, healthcare, wireless system, etc.

Furthermore, effective interfaces between different layers of the DITEN system are required to bridge the physical objects, twins, and applications [61]. Specifically, through the twin-to-physical object interface, the real-time interaction between the DT layer and the physical layer can be achieved. The global information of the system can be obtained through the communications between twins with the twin-to-twin interfaces. Moreover, through twin-to-application interfaces, the applications such as IoT, vehicular networks,

and healthcare, request a service from the DITEN system, and the virtual layer feeds back the optimal decisions to the application layer.

C. POTENTIALS OF DITEN TOWARDS 6G

The DITEN has some potential to support various applications towards 6G [61], such as communication, computation, and simulation. The details are given in the following.

1) COMMUNICATIONS

Communications are fundamental to a network, and directly impact the performance of the network, including the throughput, transmission latency, security, etc. Usually, the communication resource in a network is limited. It is infeasible to attempt different options in a real network. Fortunately, with DITEN, we can process various communication operations in a virtual edge network, and then obtain the optimal operation parameters to feedback to the real network to gain the optimal network performance, such as communication rate, bandwidth usage, security, etc. Several researches are focusing on applying DT to improve the communication quality in a network. In [62], DITEN is applied to obtain the optimal communication resource allocation to alleviate the

traffic congestion. In [63], the authors apply DT to connect the physical and network layer in the optical communication system, to improve the communication reliability and efficiency, and make the network management scheme better match the real physical situation. In [64], DT is employed to design an intelligent clock synchronization method in an industrial IoT scenario. By predicting the clock behaviors to reduce time stamp exchange related to the synchronization, thereby improving the clock accuracy and decreasing the cost of communication.

2) COMPUTATION

Although MEC can be used to process some computation tasks and relieve stress on computation resources in a network, the computation resources in the network are limited and still hard to handle intensive tasks to support the emerging applications such as VR and Metaverse. Recently, by integrating AI with MEC, the intelligent edge has emerged, where different AI models are trained using various ML methods, such as deep learning, and transfer learning, which requires many computation resources to train and update the model. DITEN can be utilized to improve the computation efficiency [27], [65]. In particular, by constructing a DITEN for a network, the physical object and AI models are digitized in the virtual domain to process task computation and model training, then the results will be fed back to the corresponding physical objects. To this end, with DITEN, resource-limited devices and servers can also process intensive computation tasks and AI model training.

3) SIMULATION

DITEN can be applied to simulate various tasks in different scenarios, especially for the areas involving a large workforce or intensive resource consumption, such as anomaly detection and autonomous driving. As mentioned before, DITEN has some potential for reliable and efficient communication and computation to achieve accurate and real-time data transmission and results feedback. Thus, DITEN can be applied to simulate the physical environment, obtain the optimal decisions, and predict the development trend of the system. Employed DT to simulate a system has attracted much attention in industry and academia. In [66], the DT constructs a cellular automata-based road traffic simulator and an LTE-V MEC network simulator, which is applied to evaluate and verify the obtained strategy to guide the lane-changing of the automated vehicles. In [67], DT is utilized to develop a security framework, which can guarantee the security of the physical system in the smart grid intelligently. The proposed framework evaluates the system behavior and simulates the complex attacks using the real-time collected information. In [68], the authors utilize DT to simulate the healthcare era, such as body physical indicator detection and disease prevention. By constructing a DT of a human body, the medication can be simulated and the body reaction can be monitored, which can promote the area of drug research, epidemic treatment, disease prediction, etc.

Based on the above potentials, DITEN can be applied to assist in the deployment and operation of a network for various applications. A network can be deployed, tested, and verified with the DTs of physical components in the digital domain using AI. In addition, after the network deployment, the operational parameters of a network can be optimized in the digital domain based on the real-time information and prior knowledge stored in the DITEN. The system performance can be optimized by checking all possible scenarios and conditions in the digital domain. Meanwhile, with DITEN, a network's disruption can be predicted, such as the failure of components in a network, then protect them before happening, and respond to them proactively.

III. THE DESIGN OF DITEN

In this section, we discuss the basic aspects of the design of DITEN. We first present the DT modeling/updating. After that, the deployment of the DT in the DITEN is illustrated. Then, the key issues to be addressed during the design of a DITEN is discussed. Finally, we introduce the enabling technologies to overcome those issues.

A. DT MODELING/UPDATING

DT modeling and updating are the essential parts to design a DITEN. Based on the real-time status of the physical objects, the DT of the physical object can be constructed in the resource-rich end devices, and edge/cloud servers. Meanwhile, the DTs will be updated synchronously by interacting with the physical objects, and feeding back information to the physical objects, thereby achieving the synchronization between the physical objects and DTs.

The construction of the DT model has been widely studied in different applications, such as manufacturing [69], product quality monitoring [70], etc. The pilot methods and techniques to build DT models are presented in [69], [71]. Digital simulation models of different service levels can be built in the DT space. Moreover, model methods include mathematical model, 3D model, and data-driven model [30], [38]. Using a mathematical model to represent a physical object requires several assumptions [72], and the model accuracy is limited, so as to 3D models. To this end, physical objects can be efficiently modeled using ML based on data-driven models [73], [74]. While, it is a challenge to choose an effective ML model, which consumes a significant amount of time [75], [76].

To construct a DT model, large-scale data should be transmitted from physical objects to DTs, which poses a high burden on communications and incurs data leakage in many applications and also increases communication risks for the physical object. To this end, recently, federated learning (FL) has been utilized for DT modeling, which consists of three steps. First, each physical object trains a local model based on its local database. Then, the physical object transmits its model parameters to the server. After that, the edge server yields a global model based on the received local model parameters, and then shares the global model parameters

to physical objects for local model updating. The above processes will continue until convergence performance is achieved.

B. DT DEPLOYMENT

In DITEN, DTs can be deployed on various locations including cloud, edge, and physical entity [61], depending on the distinct requirements for different applications, such as latency, physical experience quality, computing resource requirement, and reliability, etc.

1) DEPLOYMENT ON THE CLOUD [79], [80]

The first way to deploy DTs is on the cloud, which has been applied in most cases. Cloud has large coverage and rich available resource, it can ensure the stability of the data transmission between the physical entities and DTs, and satisfy the intensive computation requirements for DT modeling and updating. As such, deploying DTs on the cloud suits the case where the physical entities move constantly, and the DTs are called by multiple devices, such as vehicles, wearable devices, etc. However, although the cloud has rich computing resources than the edge, it will lead to high latency and low context awareness.

2) DEPLOYMENT ON THE EDGE [81], [82]

The DT system can be also deployed at the network edge. Since the limited coverage of the edge servers, this DT deployment way more suits the case where the physical entities are relatively fixed and have the requirement of latency, such as some large-scale types of equipment. Moreover, deploying a DT system at the edge, the performance of AI models for data processing and analysis is improved with the localized edge environment, and the security and synchronization of data transmission can be guaranteed with the fast and inexpensive edge connections [38]. Low latency and more context awareness such as location and mobility of end devices can be achieved by deploying DT at the network edge compared with deploying DT at the cloud. Although edge-based twins have many advantages to enable a variety of applications, they are constrained by limited computing resources.

3) DEPLOYMENT ON THE PHYSICAL ENTITY [83]

The third way is to deploy the DT system on the physical entities directly. This way does not require the data exchange between the edge/cloud servers and physical entities, thereby relieving the burden on communications, and improving security by protecting the physical entities from malicious communications. In this case, external communication access to the inter-twin communications through DTs, and private intra-twin communications are used to forward the verified and secured data from the DT to the entities' execution units. While, the physical entities always have limited computing capability and storage space, which may hinder the DT modeling and updating.

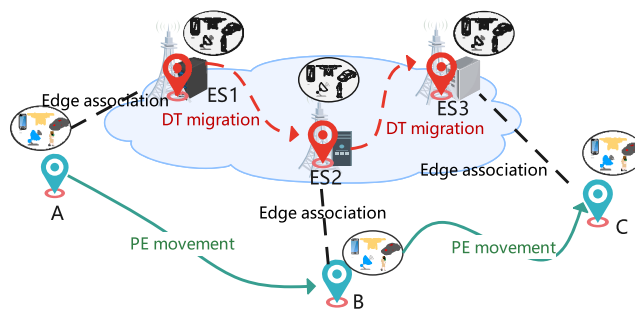


FIGURE 4. Digital twin migration in DITEN.

4) HYBRID DEPLOYMENT [26], [27]

The above three DT deployment methods have different characteristics. To obtain the optimal system performance, the above three DT deployment methods can be integrated to yield a hybrid DT deployment, such as deploying DTs both in edge and cloud. For example, in the DT based infotainment system for autonomous cars, DTs are deployed both at the edge and cloud for efficient caching. The DTs deployed at the edge make caching decisions for the users with critical latency requirements. In addition, the cloud is used to cache the information with relatively low usage frequency to address the limited caching capacity at the edge. Cloud DTs are used to manage the caching in the cloud.

5) DT MIGRATION

DT migration has the potential to provide constant services for end devices by deploying DTs on the edge. Due to the mobility of end devices, a device connected to a small BS may move to the coverage area of another BS, where the BS is installed with an edge server running DTs. The mobile device can connect with the original edge servers via the core network with the assistance of a newly associated BS. But it may lead to high inherent latency, and is not applicable for many applications with strict latency constraints. In addition, constructing a new DT system on the edge server on the newly associated small BS is time-consuming and resource cost. To this end, it is promising to migrate the DTs to the newly associated small BS. Based on the location of the mobile device, DTs should be migrated dynamically [82]. As shown in Fig. 4, the physical object moves from location A to C through B, the DT of the physical object is migrated from edge server ES1, ES2, and ES3 accordingly. The DTs migration can be achieved efficiently by exploring ML schemes. However, the heterogeneity of edge servers makes the model migration challenging. The interoperability among different edge/cloud servers may hinder the migration of DTs from one edge/cloud server to another. To simplify the migration of DTs to address end device mobility issues, interoperable must be considered in the design of the servers. Easier migration can be achieved utilizing common architecture, such as a unified cloud interface/cloud proxy, and open cloud computing interface [83].

C. KEY ISSUES

There are some key issues to be addressed during the design of the DITEN, including efficiency, fault-tolerance, low latency, and security. We will discuss these four issues in detail in the following.

1) EFFICIENCY

The first key issue is efficiency, including communications efficiency and computation efficiency. In terms of communications, as mentioned before, is fundamental to design the DITEN. Large-scale data generated from the physical layer need to be transmitted to the virtual layer for DT modeling and updating, which increases the burden on the wireless communication link and the risk of congestion and data leakage, thereby affecting the efficiency of the communications. Meanwhile, processing such large-scale raw data and constructing and updating DT models requires intensive computation resources. To solve this issue, FL can be applied to improve the efficiency of the design of DITEN [23], where end devices train their model based on the local data set, and only need to transmit the model parameters to servers. To this end, the data transfer volume can be greatly reduced, compared with transmitting all raw data.

There are three steps for the FL-enabled DITEN design. The first step is computation, in which each node makes the local training and builds model. The second step is communications, where each node transmits model parameters to the server. The third step is aggregations, e.g., the edge server aggregates all parameters to yield a global model. Taking constructing DT model at the edge server with FL as an example [23]. The main purpose of FL is to build an ML model that evolves with the physical devices' rules and states. Let $f(\omega)$ be the loss function to quantify the distance between the estimated value by DT and the true value. Users participating in FL train their model locally with the objective of minimizing the local loss. The BS collects and aggregates local model parameters to yield a global model with the objective of minimizing the global loss.

There are two processes for users participating in FL for model training, namely local training and parameters transmission. The execution time varies for different users due to their heterogeneous resources in terms of communication and computation. To aggregate the local models of all users, a BS with the MEC server acting as an aggregator, needs to wait for all the users including the slowest one to finish their execution, which slows down the whole synchronous scheme. With regard to this, we can improve the FL efficiency through communication, computation, and incentive mechanism, i.e.,

- *Communication efficient:* To improve the communication efficiency, we can further reduce the size of model parameters to be transmitted to the aggregator to relieve the communication burden and to improve the update efficiency of FL. In addition, we can improve communication efficiency by optimizing resource allocation in terms of communications.

- *Computation efficient:* The computation efficiency can be improved from the following two aspects: i) Select the nodes with relatively high computation speed for DT modeling to improve the update efficiency; ii) Optimize computation resource allocation to improve the computation efficiency.
- *Incentive mechanism:* Efficient incentive mechanisms are also another way to improve efficiency. By motivating the resource-rich end devices and edge servers to contribute their resource to model training, the model accuracy can be also improved.

2) FAULT-TOLERANCE [22], [86]

In practice, the DT model may not perfectly reflect the physical objects, so the DT mappings have a bias from the actual values, and the performance of the service provided by DITEN, such as optimization, prediction, and analysis, can be affected by the bias. In this case, we can improve the DT modeling method and increase the update frequency to minimize the bias. However, it is difficult to completely eliminate the bias due to the constraints on technologies and the limited available resource in terms of communication, computation and caching. To this end, to relieve the impact of bias on the system performance, another way is to take the bias into consideration during the design of the system to enable that the system is fault tolerant.

In [84], a DITEN with fault tolerance is studied, where different reputation values are endowed for devices based on the bias of their DTs from the true values. The industrial devices' DTs are constructed and maintained at the edge servers, and the DT of device i can be denoted as $DT_i(t) = \{F(\omega_i^t), f_i(t) + \hat{f}_i(t), E_i(t)\}$, where ω_i^t , $F(\omega_i^t)$, $f_i(t)$ and $E_i(t)$ are the model parameter, training state, computational capability and energy consumption of device i within time t , respectively. It is worth noting that $\hat{f}_i(t)$ is the mapping bias in terms of CPU frequency. In practice, different devices have different mapping biases, and the resource-constrained industrial devices are collaborative to complete a complex task, such as applying FL. In this case, by setting beliefs for different devices based on their mapping bias, the effect of the bias can be relieved. Specifically, the belief value is negatively related to DT error. A lower belief is set to a device with greater DT error, and a higher weight is set to the parameters uploaded by a device with lower mapping bias during the aggregation process.

3) REAL-TIME [27], [59]

In DITEN, DT models are constructed and updated at edge servers in many cases. The data exchange and processing are time- and resource-consuming, especially for the large-scale data for constantly synchronization between the physical and virtual. Due to the heterogeneity of the end devices and edge servers, their available resource for communication, computation, and caching are various. To this end, it is necessary to optimize the usage of the limited resources in the wireless network to improve the resource utility and decrease

TABLE 2. Requirements of different communications.

Communications	Definition	Reliability	Latency	Capacity	Connectivity
P2P	Communications among physical objects	High	High	High	Low
P2T	Communications between physical objects and digital twins	High	High	High	High
T2T	Communications among digital twins	Low	Low	High	Low

the latency for DT modeling and updating. To this end, it is necessary to optimize the usage of the limited resources in the wireless network.

An efficient way to improve the resource utilization is to optimize the association between end devices and edge servers based on their computation capabilities and communication channel state. By establishing and updating DTs at the associated edge servers, the data and tasks for model training can be adaptively distributed to different edge servers. The edge association jointly considers end devices' datasets, the computation capability of edge servers, and the communication states between end devices and edge servers. Meanwhile, the learning accuracy can be improved by increasing the training batch size of DTs. However, the large-scale training batch size requires more time to process more computation tasks, thereby resulting in long latency. Moreover, the optimal resource allocation, such as bandwidth, should also be studied to improve the efficiency of communications. In [58], the edge association problem is researched to balance the learning accuracy and the learning time cost, where the associations between DTs and edge servers, the training data batch size, and the bandwidth allocation are optimized.

4) SECURITY

Security is also a key issue in DITEN, including the security and privacy of the physical objects and data privacy preservation in DT. With the large scale of physical objects and their distribution, how to resist unauthorized access to the physical objects, servers, DTs, and so on is one of the key problems in the design of DITEN. Moreover, how to guarantee the security of interfaces between different layers of the DITEN is also a key issue to be addressed, since large-scale data transmission is required for the DT modeling and updating, and physical-virtual synchronization.

Besides, security and privacy issues during data transmission for model training are also needed to be considered. In the distributed model training case, some malicious physical objects may transmit error information to mislead the behavior of the edge server for global model training. Conversely, some malicious edge servers may transmit mistake global model parameters to mislead the updating of the local model in each physical object. To this end, privacy leakage will be caused and need to be considered during the design of the DITEN [85], [86], [87].

D. ENABLE TECHNOLOGIES

In this subsection, we present some technologies to enable the DITEN, including communications, data processing,

machine learning, blockchain, and incentive mechanisms, which are discussed in the following.

1) COMMUNICATIONS

Communications are fundamental to realize a DITEN, where large-scale data exchange is required to achieve DT modeling/updating and the synchronization between the physical objects and their virtual twin in the entire DITEN system. There are three kinds of communications in DITEN, namely physical-to-physical (P2P) communication, physical-to-twin (P2T) communication, and twin-to-twin (T2T) communication, which are summarized in Table 2.

The P2P communications achieve the interaction and sharing of information among physical objects, which include the communications among end devices, communications among edge/cloud servers, and communications between end devices and edge/cloud servers. The P2P communications have strict requirements for their performance of reliability, latency, and capacity. The P2T communications refer to the information transmission between physical objects and DTs through wireless communication technologies. With P2T communications, the physical objects transmit their real-time information to DTN for DT model construction and updating, and the DTN will feed back the results and instructions to the physical object. In P2T communications, a physical object first accesses the network through a BS, then connects to the DT on the Internet. To achieve the real-time data exchange between the physical object and the DTs, there are some strict requirements for P2T communications, including robust communication infrastructure, high reliability, low latency, high capacity, and guaranteed transmission privacy and security. The T2T communications achieve the data transmissions between DTs of physical objects in DTN, aiming to mirror the communication behavior in the practical physical communication system. The T2T communications rely on the DT servers' computation ability to model the data transmission behavior and do not need to consume any communication resources such as spectrum and radio power. In addition, compared with the P2P communications that need to consume a certain amount of time, the T2T communications only require a very short time to complete the same transmission behavior. To this end, T2T communications can be utilized to imitate the long-term transmission process in a relatively short period of time, and the results will be sent to the physical communications to guide the schedule of the practical applications.

Due to the different communication environments, the above three communications have different requirements for their performance, such as reliability, latency, capacity, and connectivity, which are summarized in Table 2. First, for

reliability, since the real-time status information from the physical object to its DTs, and the results feedback from DTs to the physical object, are the essential information to realize and maintain the DITEN, which poses strict requirement for reliability for P2P and P2T communications. However, the data and model sharing among DTs are not the key information for DT modeling and results feedback, so the requirement for reliability in T2T communications is relatively low. Second, for the transmission latency, the DT modeling and the synchronization between physical objects and DTs all require real-time data transmission, there are strict requirements on latency for P2P and P2T communications. As mentioned before, T2T communication can complete a long period of transmission behavior in a short time period, so the latency requirement on T2T communications is low. Third, for the capacity, the large-scale data transmission is required in DITEN, which poses strict requirements on the capacity for the three communications. Finally, for the connectivity requirement, considering the requirements for the quickly model updates, real-time predictions, and feedback, the P2T communications have a high requirement for connectivity. Since the P2P and T2T communications are mainly used to transmit collaborative information, which poses relatively low requirements on the network connectivity although a large amount of information.

2) DATA PROCESSING

In DITEN, the raw data from the physical objects are large-scale, multi-source, and heterogeneous. Meanwhile, the amount of data will increase at an exponential rate, as the expansion of the scale of DITEN. Those data are transmitted to edge/cloud servers for DT modeling/updating and decision making, and it is necessary to fully use those data to improve the performance of the DITEN and to reduce the cost of communication and computation. Moreover, the congestion will cause if a large amount of data is transmitted directly through the wireless communication system, especially for the high volume of data. To address the above problems, and fully use the data, it is necessary to process the data efficiently, such as data cleaning and data fusion, to handle data redundancy, data missing, data conflicts, etc. Specifically, since the data always has spatiotemporal correlation, which causes data redundancy. As such, processing data fusion to aggregate the redundant data is necessary to reduce the scale of the transmitted data and to improve the robustness and reliability of the data.

3) MACHINE LEARNING

ML is one of the key enabling technologies of the DITEN. Recent advances in ML enable the capabilities to achieve environment sensing, make decisions, and deal with unsolved ever-complex problems in various applications, such as vehicular networks [88], SAGIN [89], [90], [91], and others [11], [92]. ML makes the DITEN intelligent for information collection, decision making, and smart and efficient system management. Specifically, various ML

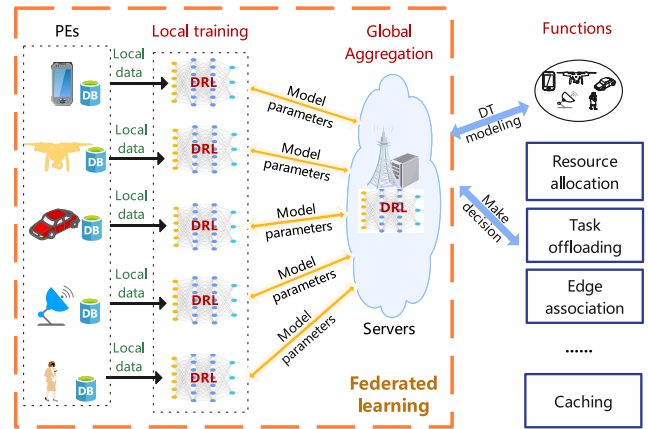


FIGURE 5. Machine learning in digital twin edge network (DITEN).

technologies, such as deep reinforcement learning (DRL), FL, and transfer learning (TL), have been used for DT construction/updating, DT deployment, physical-virtual synchronization, and decision making in DITEN, as shown in Fig. 5.

DRL: Deep learning (DL) algorithms are able to obtain the near-optimal solutions in real-time as the problem scale increases [93]. DL algorithms require to acquire optimal solutions from a simplified model first, which may be impracticable in a practical system. To this end, some technologies, such as DRL, are applied to enable DL algorithms [94]. DRL learns from the feedback of the real environment, does not need any labeled training samples, and has been applied to solve a problem modeled as a Markov Decision Processes (MDP). DRL can also be used to solve the problems with the characteristic of time-varying [95], [96]. DRL has been widely applied to optimize the task offloading problem in a wireless network. Specifically, in [97], the authors employ a deep-Q network (DQN) to propose a task offloading scheme in a vehicular network to optimize the edge server selection and transmission model, aiming at achieving the maximum task offloading utility. In [98], a double DQN is applied to obtain the optimal task offloading scheme to minimize the energy consumption for communication. With the same subjective, in [99], a deep deterministic policy gradient (DDPG) is utilized for task offloading and resource allocation.

DRL has been also applied in DITEN for DT modeling/updating, and to find the optimal solutions, such as edge association, task offloading, and resource allocation. In [84], a DQN-based adaptive global aggregation frequency calibration method is designed to increase the learning accuracy of FL with a limited resource budget and to achieve the dynamic balance between the energy consumption on computation and communication in a dynamic wireless communication environment. In [93], a DRL in terms of asynchronous actor-critic (AAC) based algorithm is developed to obtain the optimal decisions on task offloading. In [26], a DRL in terms of proximal policy optimization

(PPO) is applied to obtain the optimal task offloading and resource allocation decision in a distributed blockchain environment. In [27], DRL is applied to solve the task offloading problem in a DT-enabled vehicular edge computing (VEC) network. In [79], DQN with experience replay and target network is employed to solve the service offloading problem in a DT-enabled Internet of Vehicles (IoV) network. In [80] Double Deep Q-learning Network (DDQN) is utilized to solve the resource allocation problem at the cooperative edge servers.

FL: The centralized ML algorithms have a high risk of data leakage since it requires data exchange between the edge servers and end devices. In addition, in various application scenarios, synchronizing all raw data to DTs will result in over-communication load and data leakage, as such the end users may have communication risk. To this end, FL as a promising decentralized ML framework is applied to strengthen data security and protect user privacy [32]. FL does not require the end devices to transmit their raw data to the server. In FL, the end devices train their ML model locally based on their database and only need to transmit their local model parameters to the server, thereby alleviating users' privacy concerns and providing an ML framework for distributed users [100]. FL is a key technology to enable the development of IoT [101], [102] and 6G [103] due to its distributed and privacy-preserving features. Recently, in [23], FL is applied to promote privacy and security in DT modeling. Clients train their model and transmit their trained model to the BS. After that, the BS builds DTs of client devices.

However, during DT modeling, a BS that has DTs of all physical devices may mislead users' behavior models. In addition, malicious physical devices may affect DT modeling by propagating fake data or low-quality models to the BS. Moreover, signal distortion and aggregation errors occur since the constrained resource of the edge devices and the random wireless communication environment, which affects the convergence speed and prediction accuracy of FL. To this end, in [104], the authors minimize the loss function of ML by selecting the users participating in FL and allocating resources optimally. In [105], to motivate more users to join in FL, an incentive mechanism is proposed based on an auction game. In [28], the dynamic DT and FL in an air-ground network is studied. An incentive scheme based on Stackelberg game is developed to motivate customers to join in model training collaboratively. In [106], an incentive scheme combining reputation and contract theory is proposed to motivate mobile users with high reputations to join in FL. In [32], cooperative FL is designed to build DTs for resource-limited devices at the edge of the network, and consortium blockchain is employed to secure model updates both in global and local. Moreover, an iterative double auction is developed to motivate APs to train local models and verify updates.

TL: TL is a promising ML approach in which an agent solves a problem with the help of prior knowledge gained

from others performing similar or related tasks. TL minimizes the statistical distance between the source and target domains in the feature space, by sharing model parameters between the source and target domains and considering the transferability of the learned parameters. In [107], deep transfer learning is applied in DT-assisted fault diagnosis. To achieve this, a virtual model is built for the system first, and then when the built virtual model reaches acceptable performance, based on the real-time states of the physical object and knowledge learned from the virtual model, a diagnostic model is constructed and updated applying deep transfer learning.

In [29], TL is exploited to address the DT migration problem. Considering the mobility of devices in DITEN, the efficiency of service provided from edge servers to end devices is reduced, so it is challenging to construct and maintain DTs. When end users move from one location to another location, synchronization of the original DT model deployed in the edge server will incur high resource consumption, while communication over long distances will lead to high latency. To this end, it is necessary to transfer the DT model from the original edge server to the newly selected edge server after users' mobility, like DT mobility in the Metaverse. By migrating DTs among servers based on the location of end devices applying TL, guaranteed and high-quality services are provided to users while preventing resource consumption and latency for new model training. Applying TL for DT migration, the knowledge in original servers can be reused to construct a DT of users in a target server immediately.

4) BLOCKCHAIN

Blockchain can be considered as a tamper-proof distributed database, which guarantees the security of a system in a distributed way by using cryptography. Blockchain has the advantage of decentralization, tamper-proof, anonymous, publicly verifiable, and traceable. When distributed learning is utilized to train DT models, blockchain has the potential to store the pre-trained models in an immutable and transparent manner, so that those pre-trained models can be used to serve to request users in the future. Thus, blockchain can be integrated with DITEN to achieve guaranteed security, immutability trust, accessibility, and traceability of transactions [108].

There are several works that apply blockchain in DT. In [109], blockchain is utilized for DT construction, where the transactions initiated by participants involved in DT construction are managed and tracked with smart contracts. In [110], a reference model is proposed to authorize the owners of home appliances' DT located on fog to its owner, and apply blockchain and clouds to facilitate human-centric services and applications. In [108], blockchain is applied in DTs' reshape and transformation process, aiming at achieving secure manufacturing with traceability guarantees, authenticity, compliance, quality, and safety. It is difficult to sustain a conventional blockchain in MEC since

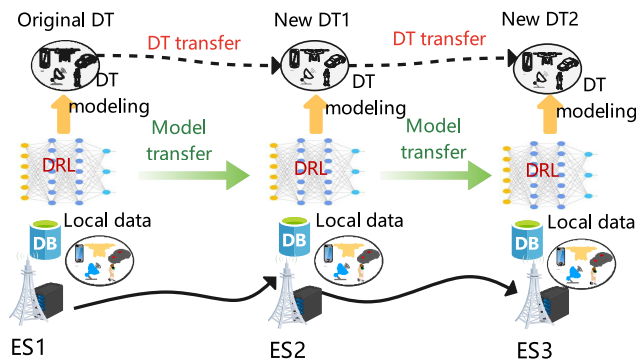


FIGURE 6. Transfer learning for digital twin migration.

the traditional blockchain schemes with the characters of high latency and resource cost.

Currently, blockchain has been applied to DITEN to achieve a security system. In [32], blockchain is exploited to achieve a new DITEN framework to support secure DT establishment. In [77], the permissioned blockchain is applied in an industrial IoT scenario to configure decentralized, traceable, and secure intelligent manufacturing systems (IMS). In [26], blockchain is introduced to manage edge nodes and enable real-time computation with security and reliability. In [58], a blockchain empowered FL framework is presented to relieve the burden on real-time data process and security on the edge. In [60], blockchain is utilized to select the mobile edge servers. In [57], a light blockchain scheme is proposed for DITENs, which is further improved to integrate with the FL process efficiently. It is known from the above mentioned that the blockchain has the potential to conquer the current shortcomings in DITEN. However, applying blockchain in DITEN is still needed to be studied. Researchers are working to achieve scalable and deployable blockchain-based DITEN platforms. There are still some challenges to be addressed, like distributed consensus methods and data analysis with privacy protection.

5) INCENTIVE MECHANISMS

In DITEN, incentive mechanisms are required for various tasks, such as pre-training of DT models, physical object control, and blockchain mining. Various physical entities acting as players, such as network operators, end devices, and servers, are motivated to contribute their available resources to drive different services.

As mentioned before, distributed learning has been applied for DTs, where end devices participate in local models training, and edge/cloud servers run DTs and aggregate local models for global model training [86]. To this end, it is necessary to reward them for their contributions to model training, so that to motivate more devices and edge/cloud servers to participate in distributed learning to improve the learning accuracy. Note that specific incentive mechanisms should be designed for different players for various tasks.

In DITEN, the servers cooperate with end devices to construct DTs applying distributed learning. Specifically, the end devices train models locally, and then transmit their model parameters to the servers for aggregation and to obtain a global model. Then, models in end devices will be updated based on the global model. Finally, continue the above process until reaching a convergence. In this case, incentive mechanisms can be designed with the Stackelberg game following a leader-follower manner. Specifically, the servers act as leaders aiming at maximizing the global accuracy, and the end devices act as followers aiming at maximizing the reward in terms of money while minimizing the cost of communication and computation [111]. The more monetary reward should be provided to the device with high local accuracy, considering that more computation resources are consumed to obtain better accuracy for the local model. In addition, contract theory and auction theory can be also used to design incentive mechanisms to pre-train DT models [106], [112].

Besides, incentive mechanisms for network operators need to be designed with game theory and auction theory. The goal of the network operators is to serve more users to maximize their profits, the end users aim to optimize their performance such as throughput. For twining operations, incentives for the edge/cloud servers running DTs are essential. In addition, blockchain is applied to store the pre-trained twin models for future use in the DT-based architecture [113]. To this end, attractive incentives need to be provided for miners to perform blockchain consensus algorithms and storage [114]. Moreover, attractive incentives need to be also offered to the software-defined network (SDN) for efficient twinning [115].

IV. THE TYPICAL APPLICATIONS OF DITEN

In this section, we first present the typical services provided by DITEN, such as edge association, task offloading, resource allocation, and security. Then, the typical applications of DITEN are discussed, including IoT, vehicular network, SAGIN, healthcare, wireless system, and other applications.

A. TYPICAL SERVICES OF DITEN

As mentioned in the previous sections, we know that the DITEN can mirror the physical MEC system, monitor the network parameters and models, such as the variety of the available resources, and task arriving process, the DITEN can also make predictions, simulate the physical system, and contributes optimization and analysis. In DITEN, the historical information and the current system status can be obtained. Based on this information, the optimal decisions in a system can be made from a centralized viewpoint. Hence, the networking schemes, such as DT modeling/updating, edge association, task offloading, resource allocation, security mechanism, etc, can be directly designed and optimized, thereby promoting network performance and reducing cost.

- DT Modeling/Updating [32], [119], which mainly aims to improve DT modeling/update performance, such as the model accuracy, latency, and cost.

TABLE 3. DITEN applied in IoT scenarios.

Ref.	Issues	Methods	DT location	DT functions	Main contributions
[57]	DT modeling	FL, DNN	Edge	Not mentioned	i. DT model construction ii. Asynchronous model update scheme iii. Communication efficiency
[84]	Fault-tolerance	FL, DQN	Edge	Not mentioned	i. Trust-weighted aggregation strategy ii. Adaptive global aggregation frequency calibration iii. Asynchronous federated learning framework iii. Learning accuracy, convergence rate, and energy saving
[93]	Task offloading Resource allocation	Lyapunov optimization, AAC	Edge	Decision making	Minimize the long-term energy efficiency
[26]	Security, Resource allocation	Blockchain, DRL (PPO)	Edge, Cloud	Decision making	i. Data and knowledge dual-driven learning model ii. Computation and communication allocation policy iii. Minimize the system delay and energy consumption, iv. Improve system reliability (Learning accuracy)
[77]	System design	Blockchain	Cloud	Reference model for evaluation	i. MBCoT architecture for IMS ii. MBCoT prototype system
[116]	Network design	Not mentioned	Edge	Mirror for evaluation	Realistic setup for DT of IoT deployment
[117]	Network design	Not mentioned	Edge	Digital mirror, Simulation	i. Semantic DT based IoT model ii. Enhances the interoperability of heterogeneous devices.
[118]	Smart manufacturing	Not mentioned	Cloud	Control, Optimization	The concept of MEC based smart manufacturing

- Edge Association [60], [94], [120], which includes the association between end devices/DTs and edge servers.
- Task Offloading [60], [94], [120], which aims to decide whether to offload a task and the proportion, thereby improving the task processing efficiency.
- Resource Allocation [94], [119], [120], which includes the allocation of resources in terms of communication, computation, caching, and so on.
- Security Mechanism [32], [60], [119], [121], [122], which aims to guarantee the security while satisfying the performance requirements.

Recently, some existing works are focusing on designing and optimizing the network schemes. In [120], the authors apply DITEN to study the computing tasks in the industrial automation scenario. By jointly optimizing the task offloading and resource allocation, the end-to-end latency is minimized. In [121], the authors aim to promote data security in industrial applications by utilizing DT and the corresponding trusted architecture. In [122], the security system and mechanism are designed based on DT to guarantee the profit of the edging computing, such as low latency, flexibility, and self-organization.

In [32], the authors exploit blockchain to develop a new DITEN framework to enable flexible and secure DTs establishment. First, to construct the DTs of the resource-constrained devices at the network edges, a cooperative FL method via AP is developed. Then, a model update chain is proposed by applying a directed acyclic graph (DAG) blockchain to ensure the security of local/global model updates. In addition, a joint cooperative FL and local model update verification scheme is proposed based on the iterative double auction, aiming at motivating APs to contribute their resource to local model training and updating verification for resource-constrained devices. Meanwhile, social welfare is maximized by optimizing the

unified time for cooperative FL and local model update verification.

In [119], the authors focus on DT construction and DT-assisted resource allocation. To balance the delay and accuracy performance, the iteration latency and DT's loss function are jointly optimized. In addition, abnormal model recognition (AMR) is leveraged at the servers to protect the edge aggregation from malicious devices, thereby improving the security of DT. A two-stage algorithm is proposed based on DQN, which learns the optimal computational resource allocation, device access management, and power control scheme, by interacting with the environment constantly. Furthermore, DT can improve the learning performance by predicting some key state information for intelligent DQN-based resource scheduling, such as the available resource of devices and edge servers, and communication status.

In [60], DT is applied to assist the mobile users in edge server selection and task offloading. An edge cooperative node selection scheme is proposed to guarantee data security and provide high-quality communication links so that to settle the security problem of cooperative edge servers selection in DITEN. The security of the edge servers is verified using the blockchained data stored in DTs. The reliable edge cooperative nodes can be the ones that passed data consistency authentication, or the ones with superior communication link quality, which can be measured by the real-time communication environment data in DT. Moreover, DT can obtain the real-time status of the network, so that the mobile users can offload the task to the selected edge server with low power expenditure and latency. In addition, the decision tree algorithm (DTA) and DDQN are applied to solve the formulated mathematical optimization model to optimize the energy consumption and network delay.

In [94], the authors propose a DL framework to minimize the energy consumption on per bit data transmission of URLLC and delay tolerant services in a MEC system,

by jointly optimizing the task offloading and resource allocation. An optimal user association scheme is proposed based on DNN, which instructs the physical entity after it is trained at a central server off-line. When the user association scheme is known, each AP optimizes the resource allocation and task offloading policies. Moreover, to explore labeled training samples, a DT of the MEC system is constructed to mirror the real system, including the network topology, wireless communication environment, and resource states. Various user association strategies can be evaluated in the DITEN to obtain the corresponding network performance, and the scheme with the optimal performance is stored in the memory as a labeled training sample. In addition, a global and low complexity resource management algorithm is proposed along with the user association policy. The proposed resource management algorithm is also used for performance evaluation in the DT.

In the following, we present the services of DITEN in its typical applications.

B. IOT

Recently, DITEN is leveraged to tackle various problems in IoT networks, including task offloading and resource allocation, DT modeling, security, and network deployment. In [123], an end-to-end DT conceptual model is proposed to represent the physical objects from the ground to the air, which includes multiple layers from down to up, such as the physical layer, communication layer, virtual layer, etc. The characters of each layer are presented, and the hardware and software technologies used for model construction are discussed. In [47], the authors present the overarching framework for developing DTs combined with industrial IoT technologies to advance the autonomy of aerospace platforms. In addition, the function of data fusion in the DT framework in predictive maintenance for aircraft is also discussed and identified.

In [57], an architecture of DITEN is proposed to optimize the industrial IoT network efficiently and appropriately, by integrating DT with MEC. The DT models of the industrial IoT devices are constructed based on their running data exploiting FL. Furthermore, an asynchronous model update policy is proposed to improve communication efficiency during the DT model's construction. In [84], the estimation deviations of DTs from their true values are seriously considered. The authors first introduce DTs to map the physical objects to the digital world in real-time, including their operation states and behaviors. Then, in the trust-weighted aggregation strategy, the estimation deviations are considered to quantify the contribution of each device to the global aggregation of FL, so that to promote the reliability and accuracy of training models. Furthermore, an adaptive global aggregation frequency calibration is designed based on DQN, which minimizes the loss function of FL with constraints on resource budget, and balances the energy consumption on computation and

communication in an ever-changing communication environment. Moreover, an asynchronous FL framework is proposed to adapt to the heterogeneous industrial IoT environment. The proposed framework uses clustering nodes to overcome the straggler effect and employs a time-weighted inter-cluster aggregation scheme to improve the learning efficiency.

In [93], a DTN is proposed to map the industrial IoT and its digital system. Based on the real-time state information of IoT devices and BSs, the virtual model of IoT entities can be constructed, which contains the network topology and random task arrival process. The edge association, and resource allocation in terms of bandwidth, transmit power, and computation resource are jointly optimized to maximize the finished computation tasks with the minimum energy consumption. The optimal solutions to edge association and resource allocation are acquired by employing the Lyapunov optimization technique and DRL-based algorithm in terms of AAC.

In addition, blockchain technology is integrated into DITEN to address the security issue in IoT networks. In [26], the authors employ blockchain technology to develop a hierarchical digital twin IoT system, where DT and MEC are combined, and blockchain technology is introduced to manage edge servers. The proposed system aims to address the problems in IoT applications including security, accuracy, reliability, and sustainability. A data- and knowledge-enabled learning method is proposed to achieve efficient optimization and real-time interaction among the physical and the digital worlds. Meanwhile, the computation and communication allocation policy is designed based on PPO to minimize the delay and energy consumption of communication and computation, and improving the reliability of the system and the learning accuracy in the system. In [77], permissioned blockchain is integrated into the IoT scenario and a novel manufacturing blockchain of things (MBCoT) architecture is designed to configure a traceable, secure, and decentralized intelligent manufacturing systems (IMS). A data-driven and knowledge-driven DT of the system is constructed to guide the operation of the IMS. Finally, an MBCoT prototype system is implemented.

Besides, in [116], a realistic setup for a DT of IoT deployment is designed to measure the impact of IoT networks and compute slices on the physical resources of edge computing hosts. The proposed DT setup can emulate the broker's behavior, and massive real and emulated devices, thereby measuring the network resource utilization and its variation over time. In [117], a semantic DT-based IoT model is proposed, which mimics the IoT devices and enhances the interoperability of the heterogeneous IoT devices with the support at the edge with container technology. With DT, the processing power and storage capacity at the edges through docker images of connected IoT devices can be enhanced. Meanwhile, the interoperability among devices and applications can be improved. The semantic DT model, along with microservices, can simplify the orchestration of various

IoT devices and applications. In [118], the concept of edge computing based smart manufacturing with distributed control structure is demonstrated. The physical entities act as edge devices, the concepts of holons and digital agents are combined with local DTs to achieve local control, decision making, and optimization. The global digital agent connected to a global DT globally controls the network of manufacturing nodes, which can be used for the optimization of the production order and logistics, local digital agents, and DTs.

C. VEHICULAR NETWORK

DITEN is a promising technology to achieve autonomous vehicles, which has attracted much attention from academia and industry. For task offloading, authors in [65] employ DT technology and AI to design an vehicular MEC system. Cooperative task offloading strategy for vehicles is proposed to minimize the offloading costs. An edge management framework is developed to improve the learning efficiency of multi-agents with DT while enhancing the synchronization between DT and the physical system. Moreover, the potential cooperation among vehicles can be revealed by leveraging DT, and multi-agents learning groups can be formed adaptively, thereby improving resource utilization and reducing learning complexity. In addition, a distributed strategy based on multi-agents learning is proposed to minimize the task offloading costs of vehicles under strict delay constraint and adjusts the mapping mode of the DT network's state dynamically.

In [27], the authors first introduce the framework of the VEC network and the key issues such as task offloading, communication, and caching in the VEC network. Then, an adaptive DT-based VEC network consisting of two AI-empowered closed loops is proposed for DT construction and VEC network management. In addition, a DRL-based intelligent method is designed to obtain the optimal VEC offloading decisions to minimize total task execution time. In [79], the authors propose a DRL-based service offloading method in a multiuser offloading system to minimize services response time. The authors first analyze the response time in a multiuser offloading system, and then model the edge devices as the agent. Finally, the optimal services offloading strategy is obtained by applying a DQN to minimize the response time. In [80], the latency minimization in a DT-IoV framework is studied. The edge servers are modeled as M/M/1/N queues, and the expression of the response time of offloading tasks is formulated mathematically. Then, the optimization model is constructed to minimize the response time, and DDQN is employed to train the edge server to get the optimal solutions to the task offloading action.

The above works provide a variety of useful and promising task offloading solutions in the IoV era. However, some of the existing solutions consider a static environment and do not consider the task arrival in the coming time. In [62], the authors apply DT technology to predict the

real-time traffic data in IoV applications, aiming at optimizing network resource allocation and alleviating the potential traffic congestion during peak periods. Applying DT to the task offloading problem in IoV is also studied in [78], and the optimal solutions are acquired by applying DRL. DT can be considered as a software agent located in the cloud, with which the global network information can be obtained through the information exchange between DTs, and the historical states of a vehicle can be obtained through the communications within the twin. In [78], the system states are captured and analyzed by employing DT and DRL. The cost of renting cloud servers and bandwidth, time-varying communication conditions, and the available computation resources of MEC servers are jointly considered. A task prediction module is designed to predict the task arriving process, so that to reserve computation resources for the upcoming tasks, thereby solving the task queue overflow problem. The task offloading process is modeled as an MDP, where the state is obtained through the DT, and then as the input of DRL. The subjective is to optimize the system utility in terms of latency, energy consumption, and rent cost.

Besides, in [124], DT is applied to obtain the optimal caching strategy in a VEN. By leveraging DT technology, the edge caching system is mapped into virtual space, which facilitates the construction of social relation model to cater to the complex and dynamic social characteristics of vehicles. Based on the social relation model, a vehicular cache cloud concept is proposed to incorporate the content cache dependencies among different vehicles in various traffic environments. Then, an optimal social-aware caching strategy is proposed, which dynamically coordinates the caching capabilities of RSUs and vehicles based on the similarity of user preferences and service availability, and jointly considers social model establishment, cache cloud formation, and cache resource management.

In [125], a DT framework is proposed for connected vehicles with vehicle-to-cloud (V2C) communication, to enable the driver to control the vehicle more smartly. In [126], a sensor fusion method is proposed to prevent potential dangers, which draws and matches the bounding box of the target vehicle by combing the camera images and DT knowledge. In [66], DT is employed in MEC framework designed to achieve safety and intelligent connections among vehicles, and the lane-changing of automated vehicles (CAV). The DT of a MEC network enables the network information to be mapped to a coupled road traffic and wireless network simulator. To this end, the CAVs can learn the optimal solutions to lane-changing through a visionary smart method, where self-interest and traffic flow efficiency improvement are jointly taken into consideration. The established DT can be used to evaluate and verify the obtained strategy and then apply the strategy in the physical system for CAVs to make decisions on lane-changing. In addition, the authors present a case study, in which the DT is composed of a cellular automata-based road traffic simulator and an LTE-V MEC network simulator. The lane-changing strategy

TABLE 4. DITEN applied in vehicular network.

Reference	Issues	Methods	DT location	DT functions	Main contributions
[65]	Task offloading	Multiagent learning	RSUs	Decision making	i. Coordination graph-driven vehicle task offloading scheme ii. Edge management framework iii. Minimizing offloading costs with delay constraint iv. High edge resource utilization and low learning complexity.
[78]	Task offloading	DRL	Cloud	Prediction, Decision making	i. Task arrival prediction module ii. Minimize the latency, energy consumption, and rent cost.
[27]	Task offloading	DRL	Edge, Cloud	Network manage, Decision making	i. Adaptive DT-based VEC network for DT construction and network management ii. DRL-based intelligent algorithm for task offloading iii. Minimize the task execution time.
[79]	Task offloading	DRL	Edge	Decision making	Minimize the response time
[80]	Task offloading	DDQN	Edge	Decision making	i. the expression of the response time of offloading tasks ii. DDQN based task offloading scheme iii. Minimize the task response time.
[124]	Caching	DDPG	RSU	Decision making	i. Social-aware vehicular edge caching mechanism ii. Maximize the system utility.
[62]	Resource schedule	-	Not mentioned	Prediction	i. DT-assisted real-time traffic data prediction method ii. Optimal resource scheduling iii. Alleviate traffic congestion.
[125]	Smart control	-	Cloud	Simulation, Decision making	i. DT framework for connected vehicles.
[126]	Safety	CNN	Cloud	Decision making	i. Sensor fusion method to prevent potential dangers.
[66]	Lane-changing	DRL	Cloud	Simulation, Decision making.	i. DT empowered MEC framework for CAV lane-changing.

is trained with DRL based on the aggregated lane state information.

D. SAGIN

In [81], the authors apply DT to catch the network dynamics in air-ground networks. The drones acting as aggregators collaboratively complete the model training with the ground clients such as vehicles and smartphones in FL. In addition, the stackelberg game based incentive strategy is designed for FL, where the drone’s DT acting as a leader sets the preferences of the client based on their reputation values, and the clients acting as followers decide the training rounds for the global model in the game after trading off profits and costs. In addition, another incentive mechanism is proposed to adjust the optimal client selection and its participation degree in each global update, thereby adapting to the varies of air-ground networks. There are some advantages to the drone acting as the leader. First, since DTs hold the clients’ state information such as available resources so that clients with high performance can be chosen to join the FL. Second, the direct communications between the clients and the drone and the corresponding communication costs can be reduced by selecting the drone’s DT as the leader of the Stackelberg game. Third, the state information of each client is not required during the curator making decisions, by deploying the client’s DT on the resource-rich ground clients. Finally, the leader’s DT captures the real-time status and the training rounds of the participating clients, which can make sure the clients finish the training rounds.

In many existing works, it is assumed that the device mobility and service requests are predictable. As such, In [28], DT is utilized in an aerial-assisted IoV network, to catch the dynamics of the resource requirements. A Stackelberg game based incentive mechanism is developed

for resource allocation, in which the leader is the DT of vehicles or roadside units, and the followers are the RSUs, and the objective is to jointly optimize the vehicles’ satisfaction and roadside units’ overall energy efficiency. By establishing the dynamic DT for an aerial-assisted IoV, the dynamics of resources in terms of requirements and provide in the network can be captured. The computation task of vehicles that out coverage of ground network can be offloaded to the equipment like RSUs with rich resources, with the assistance of UAV. By establishing the DTs of vehicles and RSUs at UAV, and keeping updating when the vehicles and RSUs are out of UAV’s coverage, the unified and efficient resource management can be achieved in an aerial-assisted IoV network.

In [127], the authors focus on the task scheduling strategy in a UAV-assisted MEC system. The system dynamics and time-varying task arrivals due to the mobility of UAVs and mobile users (MUs) are jointly considered. The interactions among MUs are modeled as a stochastic game, and a proactive DRL scheme is derived to obtain a nash equilibrium (NE), which only uses the local information of each MU for local and remote computation scheduling. The homogeneous behaviors of MU enable to train the proposed scheme offline using DT. In [128], the military large-scale UAVs are presented including their characteristics and advantages, and the basic problems currently encountered. Then, based on its design, manufacturing, and application, the urgent to construct a cloud computing based DT framework for military large-scale UAVs is analyzed, which is further discussed from test cost, integrated sensing, centralized control, business prediction, and mission planning.

E. HEALTHCARE

DT is an important technology in the health domain. The application of IoT makes it possible to monitor a patient’s

TABLE 5. DITEN applied in SAGIN.

Reference	Issues	Methods	DT location	DT functions	Main contributions
[81]	Model training	FL Stackelberg game	PE, Edge	Decision making	i. Incentive strategy for FL
[28]	Resource allocation and scheduling	FL Stackelberg game	Edge	Decision making	i. Incentive mechanism for RSU ii. Incentive scheme for resource allocation iii. Vehicles's satisfaction and RSUs' energy efficiency.
[127]	Computation scheduling	DRL	Not mentioned	Decision making	i. Stochastic computation scheduling policy
[128]	Military	-	Cloud	Simulation, Decision making	i. DT framework for military large-scale UAVs.

health status comprehensively by deploying massive intelligent human body monitoring equipment and environment sensors. A patient twin can be established to gather the time-varying information of the patient, including the physiological status and lifestyle, medication information, and emotion, to enable the doctors to provide comprehensive medical care for patients and to predict the disease condition changes to prevent disease worse in advance. For example, by constructing a DT for a patient, a personalized recovery plan can be tailored based on the patient's real-time physical signs, which can improve the patient's physique and faster the recovery time.

Apart from detecting patient signs continuously, DT has some potential for remote surgery. Experts can operate on DTs of patients and control the surgery based on real-time body information. Meanwhile, based on the real-time information, emergencies that may arise during operation can be predicted, and the corresponding optimal solutions can be obtained in advance. In this case, ultra-fast and ultra-reliable communications are required to ensure information exchange. Furthermore, DT can be applied to develop twin organs with high precision and sensitivity.

In [30], a DT framework is proposed for an intelligent context-aware healthcare system, to improve the healthcare process of patients and healthcare operations. The proposed DT framework constructs a patient twin with IoT devices, data analysis, and AI, and can collaborate healthcare professionals effectively. Accordingly, an electrocardiogram (ECG) heart rhythms classifier model is proposed applying ML to process heart disease diagnosis and heart problems detection with high accuracy. In [129], a Cardio Twin architecture runs on the Edge is designed to detect ischemic heart disease.

F. WIRELESS SYSTEMS

DT technology has been applied to wireless systems to improve the network performance [22], [131]. In [113], key requirements for implementing DT to design 6G are presented firstly. Then, the authors introduce the architecture components and trends for different types of twins, such as edge-based twins, cloud-based-twins, etc. In addition, various types of twins are compared, and providing some potential directions and the corresponding guidelines. In [58], DT

is integrated into a 6G wireless system, and a blockchain-enabled FL framework is proposed to relieve the burden of edge servers on real-time data processing and privacy risk. In [29], a DT model for a 6G network is designed, where the DT is employed to ease the unreliable long-distance communication between the end devices and edge servers. The authors formulate an adaptive DT deployment problem to associate DTs with edge servers, the objective is to reduce the average latency and improve the user utility in DT-enabled edge networks. Then, a DRL-based algorithm is proposed to obtain the optimal solutions to the formulated problem, where the DT placement scheme and the system delay are jointly considered. Furthermore, a TL based DT migration method is proposed to adapt to the user mobility.

DITENs can be also applied to support interoperability in the network era, and reduce heterogeneity by designing an application drive layer on the top of physical equipment. In [59], the Application-driven digital twin networking (ADTN) middleware is designed to support the interactions among the simplified, distributed, and heterogeneous industrial equipment, and to manage the network resource dynamically in a distributed industrial environment from an application point of view. In particular, the interactions among various equipment are simplified by enabling DTs to use IP protocols, and the network resource is managed dynamically by applying software defined network to develop communication mechanisms that suit application needs [132]. To this end, the management of the industrial network can be improved greatly, and then configure the topology structure faster and safer, so that the same production site can be exploited for different industrial applications.

In [130], the congestion control strategy is proposed for DTENs applying Lyapunov optimization, which does not require the prior information of the system, and converts the long-term congestion control problem to multiple online edge association problems in each time slot. Then, a long-term incentive mechanism is proposed based on contract theory, which jointly considers the service delay, individual rationality (IR), and incentive compatibility (IC) of physical entities. The optimal contracts are derived to maximize the profit of the service provider. In [22], DT is applied to estimate the edge server status and to provide training data for DRL agent, during the task offloading of mobile

TABLE 6. DITEN applied in wireless systems.

Reference	Issues	Methods	DT Location	DT functions	Main contributions
[58]	Security	Blockchain, FL	Edge	Decision making	i. Migrate computation pressure and privacy risks on the edge plane.
[29]	DT-edge association, Security	Blockchain, DRL	Edge	Simulation, Decision making	i. DT placement and mitigation ii. Latency and user utility
[130]	Congestion control	Lyapunov optimization, contract theory	Edge	Simulation, Decision	i. Adaptive long-term congestion control scheme; ii. Incentive mechanism; iii. Maximize the profit of the service provider.
[22]	Task offloading	Lyapunov optimization, DRL	Edge	i. State estimation ii. Provide training data	i. Task offloading scheme to minimize latency.
[59]	Hardware design	-	Edge	Simulation	i. ADTN middleware; ii. Support interactions among devices, iii. Manage resource allocation.

users in DITEN. In addition, the impact of estimation deviations of DTs from their true value on task offloading is explored. Then, the optimal solutions to the task offloading are obtained by applying Lyapunov optimization and DRL, to minimize the offloading latency with the constraints on the total migration cost.

G. OTHERS APPLICATIONS

In [31], the authors apply the DT technology to a battery management system (BMS). First, a cloud collaborative architecture is proposed to break through the constraints on computation capability and storage space in the conventional BMS, by exploring the massive computing and storage capacity of cloud-based servers. Then, the DTs of the batteries are constructed in the cloud based on the real-time data of the batteries, and the two-way dynamic mapping between the batteries and their DTs can be achieved. The refinement of safety management of the battery life cycle can be realized, by online learning and model updating to overcome the shortage of using fixed model parameters in traditional BMS. In addition, based on the accumulated data of batteries and their DTs, the optimal system performance upgrade route is constructed based on the intelligent on-the-air remote program upgrade technology.

In [133], an intelligent edge-based DT model is proposed for Robotics, where robots offload computation and analysis models to the edge, and even towards the cloud. The proposed model requires the support of 5G connectivity and facilitates the enhanced automation and control by a set of intelligent functions, such as task learning, prediction, and optimization. In [134], a concept of edge-based DT is presented to assess the ecological sustainability of a cross-company production network. The sustainability indicators are computed locally, which can reduce the data communications. To this end, the sustainability of a manufactured product can be traced and does not require suppliers to publish sensitive data or domain knowledge. Besides, in [135], DT is applied to proposed a cloud-edge collaborative architecture for FDM additive manufacturing. The system development and architecture components of the system are elaborated, thus providing a guideline for other manufacturing resources in cloud manufacturing.

V. CHALLENGES AND OPEN ISSUES

In the following, the challenges and open issues are presented, including high-precision modeling, physical-virtual synchronization, DT migration for mobility, and security and privacy.

A. HIGH-PRECISION MODELING

In DITEN, the precision of the DT modeling directly decides the services provided by the DITEN, such as task offloading, resource allocation, network management, and so on. It is challenging to model the physical objects in high precision due to the communication and computation constraints. To overcome this issue, a large scale of real-time information on the objects should be provided and further processed, and it is also required to design some efficient modeling methods, which poses some challenges to communications and computation. On one hand, it has strict requirements for wireless communication systems in terms of ultra-high capacity and reliability, to support the large-scale data transmission in P2T communications. To do so, some advanced technologies, such as Terahertz communication, communication with an IRS, and AI, can be integrated into the design of the wireless communication system. On the other hand, the computation capability is constrained by the available resources. Thus, it is urgent to design some lightweight and tiny compute methods to process the computation task.

Recently, distributed learning such as FL-based DT modeling has been widely investigated, in which the end devices train the model locally, and then send the local model parameters to the server for aggregation to train the global model, thereby decreasing the scale of transmitted data. In this case, how to incentive the physical objects and servers to contribute their resource to DT modeling is a challenge. Another challenge is to balance the modeling precision and cost in terms of latency. Since the end devices have different communication and computation time, it will cost a long time on waiting for local model parameters of all physical objects for global aggregation. A promising method is to select a part of physical objects for model training. To this end, how to select the participating physical objects [104], thereby balancing the modeling precision and waiting time is a challenge, which requires a lot of careful follow-ups research work.

B. PHYSICAL-VIRTUAL SYNCHRONIZATION

In DITEN, the virtual twin receives data and controls its corresponding physical object. Since the real world environment is dynamic, the state of physical objects is always time-varying. It is essential to synchronize the physical objects and their virtual twin to provide services in different applications. Real-time and reliable two-way communication for large-scale data is the foundation to achieve physical-virtual synchronization. The latency during DT building and updating includes three parts, namely data transmission over wireless links, data transmission between edge servers, and DT model computation/training. To reduce the latency during the transmission, apart from the advanced communication technologies mentioned before, routing algorithm, congestion control, and communication resources allocation are also significant to improve the communication efficiency, and need to be further investigated to cater to the DITEN.

C. DT MIGRATION FOR MOBILITY

Due to the mobility of the physical objects and the limited coverage range of BSs/edge servers, when a physical object moves from one location to a new location, it will cause high latency during the physical object communicates with the original connected BS/edge server, or even cause connection outage when out of the coverage range. In this case, some DTs are deployed on the edge server installed on the BS in DITEN, thus the mobility of the physical object will have impact on the real-time interaction between the physical object and its DT. A feasible solution to this issue is to place a DT of the physical object on a new BS/edge server near the physical object. However, constructing a new DT is time-consuming, the physical object may move to another new location when its DT is constructed. Meanwhile, DT modeling costs intensive communication and computation resources, and frequent construction of new DTs will pose great pressure on wireless communication systems. Thereby, it is a challenge to migrate DTs to cater to the mobility of physical objects.

Recently, TL is applied in DT migration to save time and network resources [29]. However, the heterogeneous hardware/software designs of different edge servers may hinder the transfer learning designed in DITEN. Transferring an ML model from one server to another may face interoperability problems. Besides, the selection of a new BS/edge server is another issue to be addressed. To achieve the optimal performance, such as the service time for the physical object, the achieved profit, the complex system conditions, the mobility and operation states, and the availability of various BSs/edge servers should be jointly taken into consideration, which is an open issue need to be further investigated in the further researches.

D. SECURITY AND PRIVACY

In DITEN, it is challenging to guarantee the security and privacy of physical objects and data privacy preservation in DT. Due to the large scale of physical objects and their distribution,

it is challenging to design an efficient authentication scheme to resist unauthorized access to the physical objects, servers, DTs, and so on. In addition, the DT modeling and updating, and the physical-virtual synchronization, require large-scale data exchange between the physical objects and DTs through the interfaces. How to guarantee the security of interfaces between different layers of the DITEN is also a challenge.

Apart from the interfaces, there are still some other security and privacy issues during the DT modeling. In the centralized model training case, all physical objects transmit their information to a centralized server for model training, which will cause security and privacy issues during data transmission, and model training and integrating blockchain into the DITEN is a promising method. In the distributed model training case, physical objects train their local model based on their local information and then transmit their local model parameters to a server for aggregation to train a global model. Since the physical objects do not need to transmit their raw data to the server, the distributed method can improve the security and privacy problem to some extent compared with the centralized case. However, there may be some malicious physical objects that transmit error information to mislead the behavior of the edge server for global model training. Conversely, some malicious edge servers may transmit mistake global model parameters to mislead the updating of the local models in each physical object. To this end, privacy leakage will be caused and need to be considered during the design of the DITEN, which is challenging and need further investigated in the further research.

VI. CONCLUSION

This paper has comprehensively surveyed the research in the area of DITEN. In particular, we first gave the basic aspect of DITEN towards 6G, including its concept, framework, and potential. Then, the aspects of the design of DITEN were presented, such as DT modeling, DT deployment, key issues, and enabling technologies. After that, we comprehensively discussed the typical applications of DITEN towards 6G, including IoT, vehicular network, SAGIN, healthcare, wireless systems, and other applications. Finally, some challenges and open issues related to DITEN were elaborated.

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