Digital Twin Networks: A Survey

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***Abstract*—Digital twin network (DTN) is an emerging network that utilizes digital twin (DT) technology to create the virtual twins of physical objects. DTN realizes co-evolution between physical and virtual spaces through DT modeling, communication, computing, data processing technologies. In this article, we present a comprehensive survey of DTN to explore the potentiality of DT. First, we elaborate key features and definitions of DTN. Next, the key technologies and the technical challenges in DTN are discussed. Furthermore, we depict the typical application scenarios, such as manufacturing, aviation, healthcare, 6G networks, intelligent transportation systems, and urban intelligence in smart cities. Finally, the new trends and open research issues related to DTN are pointed out.**

***Index Terms*—Digital twin (DT), digital twin network (DTN), DT modeling.**

I. Introduction

IN RECENT years, both the academia and industry have shown great interest in the development of the digital twin (DT) technology, which benefits in many domains, such as real-time remote monitoring and control in industry, risk assessment in transportation, and the smart scheduling in smart city. It is envisioned that DT will significantly reshape cyber application paradigms in terms of efficiency and intelligence in the near future.

Fig. 1 shows the development timeline of DT. The DT concept is first introduced by Michael Grieves in his presentation about product life-cycle management (PLM) with the title "Conceptual Ideal for PLM" in 2002. Thereafter, Framling *et al.* proposed "an agent-based architecture where each product item has a corresponding virtual counterpart or agent associated with it" [1]. Shafto *et al.* [1] indicated that an effective PLM system should keep a faithful view of the product status and information, from when it is planned and manufactured, through its time of use and until the time of disposal. In 2010, NASA developed two identical space vehicles for the Apollo project, which simulates and reflects space status in flight training. This is the first time to put the concept of DT into practical applications. Tuegel *et al.* [2] introduced a conceptual model to explain how DT can be utilized as a virtual sensor in predicting the structural life and integrity of an aircraft. Based on the aforementioned work, the U.S. Air Force proposes the concept of Digital Thread, where digital refers to the communication framework used to link all product data in a virtual and logical way [3]. The formal definition of DT is given in Grieves and Vickers white paper [4]. This definition encompasses three primary elements, namely, a physical object in physical space, a virtual object in virtual space, and the data link between the two spaces. Recently, much attention has been paid on DT and its applications in a large variety of domains, such as manufacturing, aviation, healthcare, 6G networks, intelligent transportation systems, and urban intelligence in smart cities.

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Despite the promising benefits brought by DT, there are only few survey reports focusing on this technology. For instance, [5] mainly reviews the construction of virtual twins from a modeling perspective. Barricelli *et al.* [6] investigated the main characteristics of DT and explored its application domains. These studies mainly focus on a physical object and its virtual twin. In the literature, the detailed study of the network which utilizes the DT technology are missing. Furthermore, the discussion about challenges and research trends in technologies that support DT has not been investigated.

In this article, we present a comprehensive survey of the DT network (DTN). We will provide in-depth insights of the key technologies of DTN as well as applications, critical challenges, and evolution trends. The main contributions of this article are provided as follows.

1) We present the key technologies in DTN, including communications, physical data processing, DT modeling, cloud computing, and edge computing. We also outline the challenges and potential solutions.
2) We investigate DTN applications in manufacturing, aviation, healthcare, 6G networks, intelligent transportation systems, and urban intelligence in smart cities.
3) We further point out the new trends and open research issues in the future.

The remainder of this article is organized as follows. Section II elaborates the definition of DT and DTN and clarifies the difference between DT, DTN, and CPS (CPS, a physical and engineered system). Section III presents key technologies in DTN. Technical challenges are discussed in Section IV. DTN applications are listed in Section V. The new trends are discussed in Section VI. The open research issues are outlined in Section VII. Finally, we conclude this article in Section VIII.

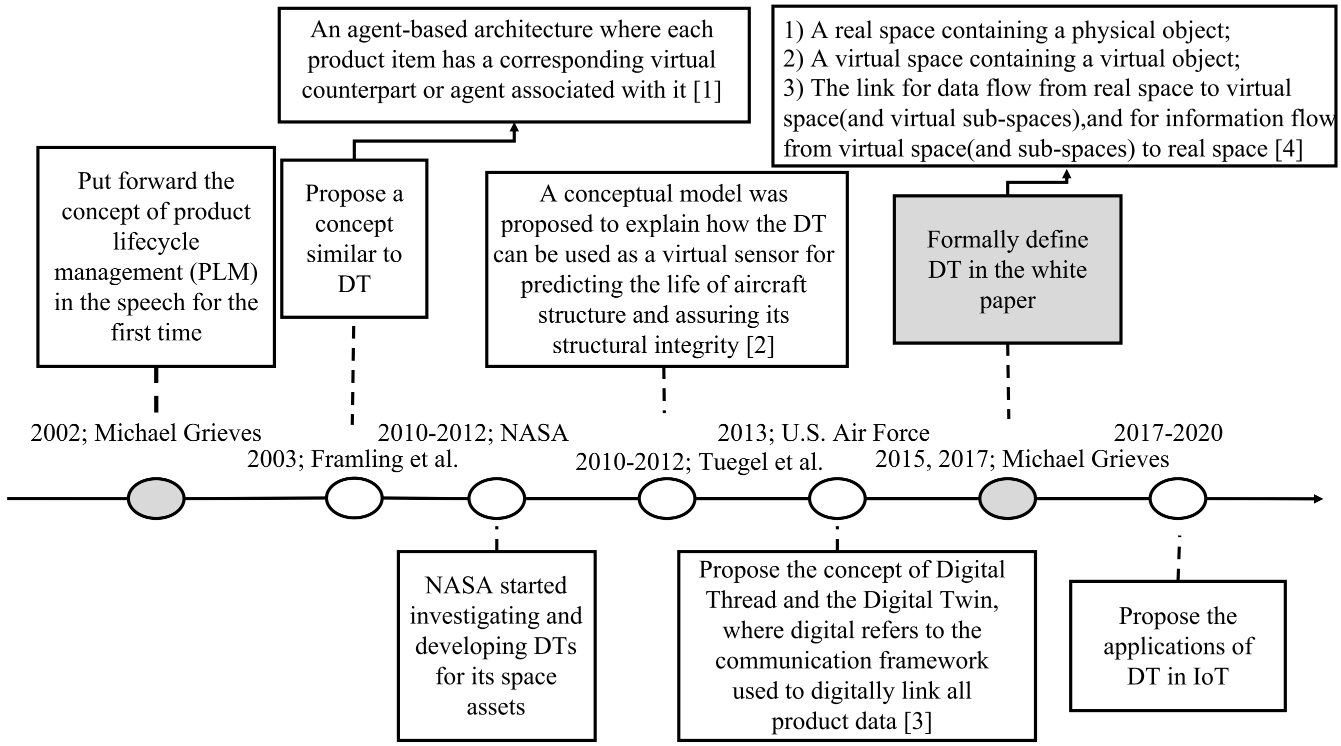

Fig. 1. Development timeline of DT.

TABLE I
DEFINITIONS OF DT

References	Definitions	Key points
[7]	DT is a digital representation of assets, processes or systems that are artificially constructed or in a natural environment.	Virtual model, Digital representation, Mirror, replica
[8]	DT is a virtual representation of a physical product or process, used to understand and predict the physical counterpart's performance characteristics.	
[9]	DT is a set of virtual information that fully describes a potential or actual physical production from the micro atomic level to the macro geometrical level.	
[10]	DT are software representations of assets and processes that are used to understand, predict, and optimize performance in order to achieve improved business outcomes.	Software, Simulation, Computerized model
[11]	That faster optimization algorithms, increased computer power and amount of available data, can leverage the area of simulation toward real-time control and optimization of products and production systems referred to as a DT.	
[12]	Integrated multi-physics, multi-scale, and probabilistic simulation composed of physical product, virtual product, data, services and connections between them.	Integrated system
[13]	DT is actually a living model of the physical asset or system, which continually adapts to operational changes based on the collected online data and information, and can forecast the future of the corresponding physical counterpart.	
[14]	Comprehensive physical and functional description of a component, product or system together with available operational data.	

II. DIGITAL TWIN NETWORK OVERVIEW

This section gives a brief overview of the definition of DT and presents the definition from the perspective of its characteristics and functions. Moreover, we show the difference between DT, DTN, and CPS.

A. Definition of Digital Twin Networks

Beyond the initiate definitions presented in Section I, new DT definitions have been made in recent studies. These definitions are divided into three categories, which are shown in Table I.

Three types of DT's definitions are given with different perspectives and different focuses. The first one mainly emphasizes the mirror model of a physical object. The mirror model or the so-called virtual representation indicates that there is no automatic data exchange between the physical object and the virtual model. Once the virtual model is created, the changes to the physical object will not cause the virtual model to change accordingly. This type of definition however neglects the co-evolution between the physical object and its virtual model. The second type of definition emphasizes DT as a computerized model, a simulation, or a software. The physical object simulation using the computer is conducive to understand, predict, and optimize the physical object,

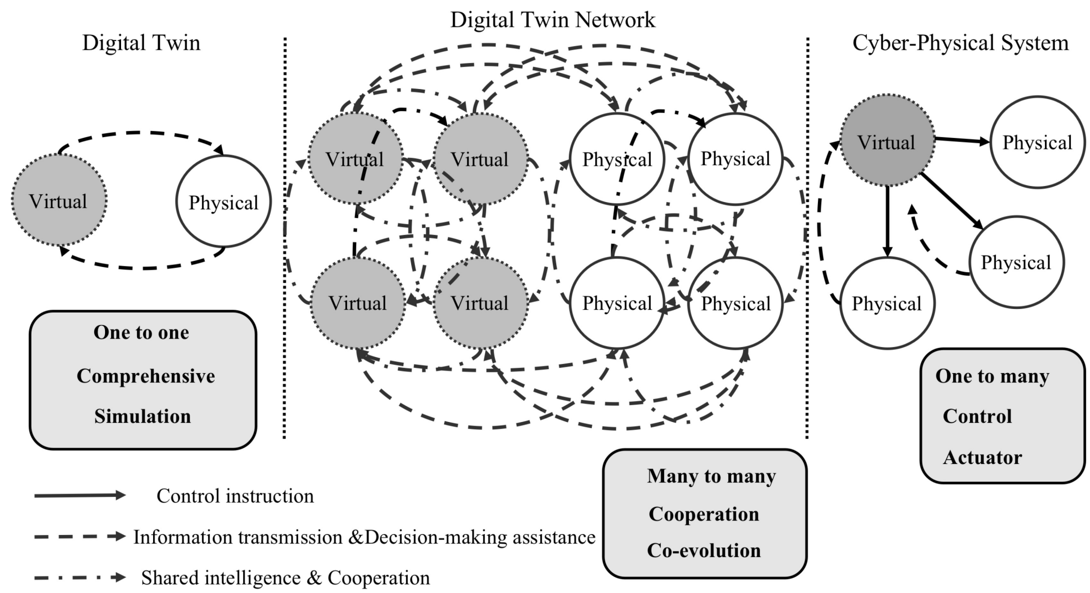

Fig. 2. Definition and difference of DT, DTN, and cyber–physical system.

which can enhance the performance of the physical object. This definition takes the data flow between the physical object and its digital model as an unidirectional way. The change of the physical object will affect the virtual model, but not the other way around. The third type defines DT as an integrated system. Here, DT is composed of a physical object, its virtual twin, data, services and connections between them. The virtual twin continually adapts to operational changes based on the collected online data and information and predicts the state of the corresponding physical object.

Based on the aforementioned definitions, we understand that DT is an intelligent and constantly evolving system, which monitors, controls, and optimizes the physical object through its life cycle. The physical object may have many forms, such as a machine, a human, or a human-related thing, a smart city. It should be noted that the data flow between a physical object and its virtual twin is bidirectional. In other words, the physical object outputs data to the twin, and the twin can also feed back information to the physical object. The virtual twin can be developed together with the physical object through data engineering.

According to the viewpoints presented above, we describe a comprehensive definition of DT and generate the definition of DTN. DT encompasses three parts: 1) a physical object; 2) its virtual twin; and 3) a mapping between the physical object and its virtual twin that enables the co-evolution of both physical and virtual sides. DT is the accurate digital replica of a real-world object across multiple granularity levels, and this real-world object could be a device, machine, a robot, or an industrial process or a complex physical system. Next, we move to DTN. Here, we define DTN as a many-to-many mapping network constructed by multiple one-to-one DTs. In other words, DTN uses advanced communication technologies to realize real-time information interaction between the physical object and its virtual twin, the virtual twin and other virtual twins, and the physical object and other physical objects. DTN realizes the dynamic interaction and synchronized evolution of the multiple physical objects and virtual twins, by using accurate DT modeling, communications, computing and physical data processing technologies. In DTN, physical objects and virtual twins can communicate, collaborate, share information, complete tasks with each other, and form an information sharing network by connecting multiple DT nodes.

B. Comparisons of Digital Twin, Digital Twin Network, and Cyber-Physical System

Considering the similarity between the concepts of DT, DTN, and CPS, here we clarify these concepts. CPS is physical and engineered system whose operations are monitored, coordinated, controlled, and integrated by a computing and communication core [15]. Both CPS and DT integrate computational algorithms and physical components. Fig. 2 shows the concepts of DT, DTN, and CPS and the differences of them.

First, from the perspective of application scenarios, these three concepts are quite different. CPS is a system that mainly consists of sensors and actuators, and it is originally designed to fit for embedded systems. Unlike CPS, DT and DTN are mainly produced in industrial practices, such as aviation and smart factories. To meet the demands of industrial applications, DT and DTN are Model-Based Systems Engineering empowered and is built with data and models as the main elements. Furthermore, DT is suitable for reflecting a single independent object, while DTN applies to model a group of objects with complex internal interactions. For example, modeling a building in the virtual space through the DT approach helps optimizing the entire life cycle of the building in terms of design, maintenance, and so on, which only depends on the analysis and decision making according to the building's own state data. In contrast, when building a virtual model of an industrial automation production line, DTN should be taken to model and reflect the collaborative relationship between multiple industrial components involved in the production process.

Second, from the perspective of technical principles, CPS integrates computation, communication, and control technologies to add new functions to the physical system. Through these technologies, real-time sensing, dynamic control, and information services for complex systems are realized. Unlike CPS, DT intends to create the virtual twin for a physical object, so as to simulate and reflect its states and behaviors through modeling and simulation analysis. Furthermore, DT uses data engineering to predict and control the physical object's states and behaviors through feedback. Therefore, the main principles of DT are the model and the data fed back by a model. DT focuses on modeling an individual physical object in the virtual space, and a DT model always gathers and processes the object's state information in an independent mode without interacting with other models. Constrained by the information collection and processing capabilities of an individual DT model, the constructed object model may be not accurate, and both time and energy consumption of this construction process may be high. In contrast to DT, DTN takes the collaboration between multiple DTs to model a group of objects. The information of the physical object, the processing capability of the DT model, and some intermediate processing results can be shared among the collaborative DTs. This cooperation approach greatly saves the processing time delay and energy consumption and helps to improve the modeling efficiency.

Finally, from the perspective of physical virtual mapping relations, CPS may affect multiple physical objects. It may contain multiple physical components. To map these components to the virtual space, there is a many-to-one relation in the implementation. DT provides comprehensive physical and functional descriptions of components, products, or systems. The main goal of DT is to create high-fidelity virtual models to truly reproduce the geometric shapes, physical properties, behaviors, and rules of the physical world. Enabled by DT, virtual models and physical objects may keep similar appearances (like twin brothers) and the same behavior pattern (like mirror images). In addition, the model in the digital space can guide the operation of physical system, and adjust physical process through feedback. With the help of two-way dynamic mapping, both the physical object and the virtual model evolve together. Considering the mirroring effect of each physical and logical entity pair, we classify the mapping relationship between physical and virtual space in the DT system as a one-to-one method. The mapping relationship of DTN is characterized by many-to-many.

In summary, all the three concepts promote smart manufacturing through a closed loop of state sensing, real-time analysis, efficient decision making, and precise execution, while they have their own characteristics, respectively, as follows.

1) CPS is an early method of controlling physical space through virtual feedback that focuses on system control. Due to the many-to-one relation between physical entities and virtual models, CPS is not easy to expand to a large scale.
2) DT is an intelligent and constantly evolving system that emphasizes the high-fidelity virtual model of the physical object. The mapping relationship between physical and virtual spaces in the DT system is a one-to-one method, which is more scalable.
3) DTN is extended by multiple DTs. By applying communications between DTs, one-to-one mapping relationship can be easily expanded to DTN. The mapping relationship is also more conducive to network management. Combined with the advanced data processing, computing, and communications technologies, DTN can easily facilitate information sharing and achieve more accurate state sensing, real-time analysis, efficient decision making, and precise execution on physical objects. The use of the network form to build a complex large-scale system has the stronger reliability and higher efficiency.

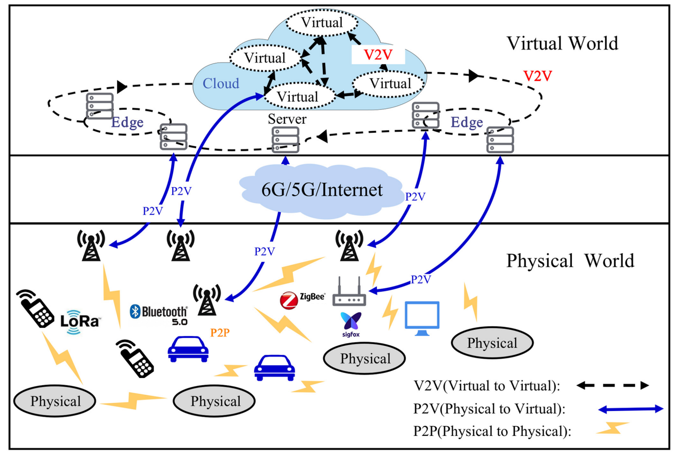

Fig. 3. P2P, P2V, and V2V communications in DTNs.

III. Key Technologies in DTN

In this section, we present the key technologies in DTN, including communications, physical data processing, DT modeling, cloud computing, and edge computing.

A. Communications

Communications are fundamental to realize DT and DTN. The communications support the information exchange of the entire DTN. Fig. 3 compares physical-to-physical (P2P), physical-to-virtual (P2V), and virtual-to-virtual (V2V) communications in DTN.

1) Physical to Virtual Communications: The P2V communications mean that a physical object realizes information transmission with a virtual twin through wireless communication technologies and shares the data of the physical object in real time and accepts feedback from the virtual twin. The communication technology here mainly uses wide-area network wireless communication technology, such as LoRa and 5G/6G cellular communications. In this scenario, the physical object is a wireless terminal, connected to the wireless access network through a wireless communication base station

(BS), and finally connected to the virtual twin on the Internet. The communication infrastructure must be robust enough to support real-time interactions between physical and virtual. In order to realize practical P2V communications, it is necessary to satisfy four main requirements for accurate mapping and real-time feedback.

requirements for Network Digital twin

physical to virtual communication

1) The communication latency needs to be low. The communications are characterized by the fact that most of interactions must take place in real time. In the scenarios that have strict real-time requirements, the P2V communication latency is required. For instance, the communications between a physical body and its virtual body in health emergency detection, remote surgery, and medication control require ultralow latency. The communications between intelligence transportation systems and virtual systems in highway warning systems also require low latency. The requirement in latency depends on the time sensitivity of both the physical objects and the feedback data. If the evolution of the physical objects in the scene heavily relies on the real-time feedback of the virtual twins, then reducing the latency of P2V is very important.
2) The transmission reliability needs to be high. The most important part of realizing DT is accurate modeling. Only when the reliability of communications is guaranteed, can accurate data be transmitted in real time to achieve dynamic high-fidelity modeling. In many scenarios, such as medical treatment, some data errors may cause serious medical accidents. Other applications may require medium transmission reliability, such as ship or workshop maintenance. Different considerations can be made for the priority of diverse applications to meet the reliable requirements of scenarios. In general, DT relies on models for prediction and optimization, and there will be at least medium requirements for communication reliability.
3) The privacy and security of data transmission between physical and virtual need to be high. For example, personal identification information and health data need to be encrypted during transmission.
4) The network bandwidth and capacity must increase faster than the demand of these interconnected objects in the network. As more and more interconnected physical objects and virtual twins are added to the DTN, the communications infrastructure should be able to transmit unprecedented messages simultaneously without severe effect on latency.

2) Physical-to-Physical Communications: P2P communications ensure information interaction and information sharing between physical objects. Various wireless/wired devices, such as sensors, RFIDs, actuators, controllers, and other tags can connect with IoT gateways, Wi-Fi access points (APs), and BSs supporting the communications between P2P. Besides, the network connection is enabled by a diverse of communication protocols, such as the wireless personal area network (WPAN), ZigBee etc., and low-power wide-area networks (LPWANs) technologies, including LoRa and narrowband IoT (NB-IoT).

is this required?

3) Virtual-to-Virtual Communications: V2V communications, which logically take in the virtual space, mirror the communication behavior that occurs in the real physical world. More specifically in the IoV case, V2V communications refer to data transmission between the DT model entities of the vehicles. Unlike the communications between physical vehicles that consume wireless spectrum resources and radio power, this virtual mode mainly depends on DT servers' computing capability to model the data transmission behavior.

TABLE II
COMPARISONS OF P2V, P2P, AND V2V IN CURRENT COMMUNICATIONS ENVIRONMENT

Communications / Metrics	P2V	P2P	V2V
Reliability	Low	Low	High
Latency	High	High	Low
Capacity	Low	Low	High
Connectivity	Low	Low	High

The main benefit brought by V2V communications is the data transmission modeling, which breaks through the time constraint in the physical world. We note that the communications between real vehicles consume a certain amount of time. However, in the virtual space, the same communications behavior can be completed in a very short time. Thus, we can reflect or simulate a long period of communication behavior with low time cost. Furthermore, for given communication behavior, it can occur earlier in the logical space than in the physical space. The effect of logical communications can be used to guide the scheduling of real IoV resources.

Edge intelligence, which consists of AI-empowered edge computing servers, is a key enabling technology for achieving V2V communications. These servers provide the necessary computing capability for the channel model construction and data transmission, while AI learns the characteristics of the IoV network and adjusts the communication modeling approach.

B. Comparisons of Physical-to-Virtual, Physical-to-Physical, and Virtual-to-Virtual Communications

Due to different communications environments, P2V, P2P, and V2V have different requirements in terms of reliability, latency, capacity and connectivity. Table II compares P2V, P2P, and V2V communications in DTN.

First, P2V and P2P both require high communication reliability. However, for V2V, the shared information and models between different twins are not the main data of modeling and feedback, the reliability of transmission can be relatively low. For latency, the requirements in P2V and P2P transmission are very high, especially in time-sensitive scenarios. For V2V, virtual twins can share information based on a long communications period. That means, V2V communications have low real-time requirements. As for communication capacity, since all the three types of communications need to transmit a large amount of real-time and continuously updating data, the data volume is very large, which is also a challenge of communications capacity.

As for network connectivity requirements, P2V has the high connectivity requirement, followed by P2P and V2V, since P2V needs to update the model quickly and make predictions and feedback in real-time. While P2P and V2V mainly transmit collaborative information, although the amount of information is large, the network connectivity requirements are relatively low.

C. Physical Data Processing

As large amount of physical data is transmitted to the server, it is necessary to use data effectively through data processing methods. The raw data generated by physical objects have the characteristics of multisource, multiscale, and high noise. Meanwhile, as the scale of DTN expands, the amount of data collected by physical object sensors will also increase, and we envision that the amount of data collected by sensors may exceed the order of 100 Gbit/s. If data of this magnitude is directly transmitted through the communications system, it will cause congestion. Accordingly, data needs to be cleaned to deal with data missing, data redundancy, data conflicts and data errors in DTN. Attributed to the characteristics of raw data in DTN, it is necessary to fuse the data to improve the robustness and reliability of the twin data and expand the modeling dimension of virtual twins. Tao *et al.* [16] have studied the data fusion for DT of a shop floor and suggested enabling technologies for the data fusion, including data generation, modeling, cleaning, clustering, mining, and evolution.

1) Data Fusion for Dimensionality Reduction: Sensor data can be fused and reduced in dimensionality, such as converting pictures or video data into specific information (such as state parameters) of the desired target through the recognition algorithm. This can reduce redundant information and retain only the necessary messages, which significantly reduces the dimension of sensor data volume and achieves more accurate modeling. Ricks *et al.* [17] proposed an order-reduction technique for DT, which has been applied in the high-fidelity generalized method of cells to enhance the efficiency of data processing.

2) Data Fusion for Matching: The fused data can provide a basis for data matching. Usually, in DTN, there are many similar physical objects, and most of their state parameters and empirical data can be used for reference. Matching physical object data with high similarity through the recognition algorithm can help the data of the physical object clustering, processing, and analyzing better, thereby improving the utilization of data and realizing the efficient integration of data of multiple physical objects.

3) Data Fusion for Expansion: The fusion of multiple sensor data can expand the effective information volume. For example, in the DTN of a traffic system, a camera can obtain target information in a larger range, including the target type and approximate location and integrate the experience of other physical objects, which will effectively solve the problem of radar detection blind spots. The extended data will be analyzed in the twin to support better security and planning development of the transportation system.

D. Digital Twin Modeling

DT modeling is the foundation to build the entire DTN. Fig. 4 shows the DT modeling in a software-defined way. In order to reduce the complexity and unmaintainability of

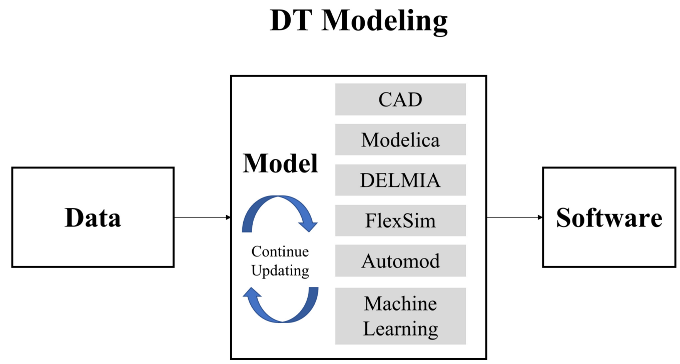

Fig. 4. DT modeling.

modeling, we first need to clarify the modeling framework. Several studies have designed a common framework based on the analysis of the needs of researchers and the industry. Tao *et al.* [18] proposed a DT 5-D model encompasses physical part, virtual part, data, connection, and service modeling. Schroeder *et al.* [19] introduced a DT modeling architecture, including the device layer, user interface layer, Web service layer, query layer, and data repository layer. Liu *et al.* [20] presented a DT four-layer model, including the data assurance layer, modeling calculation layer, DT function layer, and immersive experience layer. Among the aforementioned studies, Tao *et al.* [18] mainly emphasized the driving of physical objects, virtual twins, and services by twin data composed of physical data, virtual data, service data, and historical experience. This kind of modeling framework has been widely recognized. The frameworks in [19] and [20] are mainly considered from the function perspective. However, none of the above modeling frameworks takes into account the cooperative characteristics of P2P and V2V. This kind of modeling framework is not conducive to the collaborative evolution of large-scale DTN.

A further step based on the modeling framework is to model a specific physical object. The DT model should be developed in a way that facilitates its adaptation to different scenarios. For instance, some systems focus on high-fidelity simulation while the other systems concerned about parameter prediction or state estimation. To enhance the intelligence of modeling and simulation, large-scale sensor networks with complex topological structures and large amounts of real-time data are deployed in a physical network. By investigating the DT modeling methods, the literature mainly focuses on three aspects: 1) specific models with restricted application areas generated in a modeling approach; 2) multidimensional model with diverse functions; 3) generic model generated by standard methods.

1) Specific Model: Specific model is consisting of one modeling approach which fits in its particular application areas. Due to the appointed requirements of given scenarios, virtual twins are usually designed with different special models. For instance, in [21], a DT of a power converter is defined as a real-time, probabilistic simulation model with stochastic variables, developed using generalized polynomial chaos expansion. Their model has a significantly low computational cost in comparison to other methods. This kind of digital modeling has been widely used in conventional DT. We observe that special models can be well adapted to the particular needs of different environments. However, in most scenarios, it is difficult to establish mathematical models that exactly fit for a given complex physical system. Specific virtual models may undermine the efficiency of DT in a large scale DTN. Incorporating data technologies into DT modeling is a promising approach to address such problems.

2) Multidimensional Model: A multidimensional model with diverse functions consists of several specific submodels, which meets multiple needs. In [22], the 3-D printed DT model is constructed by a mechanistic model, a sensing and control model, a statistical model, and an intelligent technology, such as big data and machine learning. Although this multidimensional model can match various requirements of complex environments, it is difficult to collaborate between models and has poor scalability, which is not conducive to large-scale DTN deployment. A general modeling method suitable for most environments is needed.

3) General Model: General models are always formed by applying standard tools. General modeling is an appealing approach, which can act as an standard modeling to build a large-scale DT ecosystem in different scenarios. There are several studies on manufacturing simulation for the production design and operation analysis, such as Modelica [23], DELMIA [24], FlexSim [25], Automod [26], etc. These tools provide many production-related libraries and smart visualizers using 3-D factory. For instance, Schluse *et al.* proposed a new approach to simulation technology called "virtual test beds." Virtual testbeds provide comprehensive simulations of interacting DT in their operational environment in various application scenarios [27]. Moreover, virtual testbeds introduce new structures and processes to consistently use simulations throughout the life-cycle. Bao *et al.* proposed a model-based definition (MBD) technology providing the product DT with a digital manufacturing information carrier in the design phase, the manufacturing phase, and the Maintenance, Repair & Operations phase. After adopting MBD technology, the 3-D model serves as the single data source. Processing design, tooling design, part processing, and part inspection are implemented based on MBD data, which can achieve parallelization and collaboration of product design, manufacturing, and service. In [28], to meet the requirements of model adaptability and distribution, the physics-based models of vertical transportation systems have been proposed. Their model consists of a reference model, a library of model components, or a set of predefined models and constructed by the object-oriented modeling tools Modelica. However, the current general models focus on modeling on the surface, while ignoring the deeper meanings of models and relationship between the models.

E. Cloud Computing

Cloud computing is a large-scale computing approach that utilizes the Internet to realize the sharing of computing, storage, and other resources anytime, anywhere and on demand. DTN that focuses on computational speed and centralized processing can be deployed on cloud servers. Through cloud servers, a large amount of data can be processed in a short time (a few seconds), so as to provide a powerful DTN service. In addition, the cloud architecture facilitates the organization and management of a large number of connected physical objects and virtual twins, as well as the combination and integration of real-time data and historical experience. In the cloud architecture, various types of storage devices can work together through application softwares to jointly provide data storage and business access for enterprises. Due to the diversification of requirements, DTN in different scenarios has different requirements for computing speed and latency. For example, in a large-scale Internet of Vehicles, there are many connected vehicles, many types of services are provided, the speed of vehicles is fast, and the road condition information is complex. If the large amount of data cannot be processed and utilized in a timely and effective manner, the old useful message may be quickly covered by newly generated information. Meanwhile, if a large amount of burst data needs to be processed urgently, the computing resources with fast processing speed can meet the computing requirements. On the other hand, in an industrial manufacturing twin network, there is very little immediate and sudden data to be processed. It is more about the long-term maintenance data processing of industrial equipments, and the long-term prediction of a product life cycle, the requirements of latency, and calculation speed are relatively low.

F. Edge Computing

Edge computing refers to a new computing model that analyzes and processes a portion of data using the computing, storage, and network resources distributed on the paths between data sources and the cloud computing center. User privacy, power consumption, latency, cost, and the availability of wireless links are all important issues in DTN applications. For example, in the medical scenario, private information leakages and network security issues can not be ignored. Edge computing has been recognized as a promising solution to protect privacy, reduce latency, save power and cost, and increase reliability. Therefore, edge computing is particularly suitable for DTN scenarios with low delay, high bandwidth, high reliability, and high privacy requirements.

1) Cooperative Edge Computing: In DTN, physical data processing and analyzing require lots of computing resources. Collaborative edge computing between edge nodes can improve the quality of service. When an edge node has many computing tasks with a long task queue, it will easily causes high latency. If other nodes have free computing resources, they should share the computing tasks with the overloaded nodes. It is very important for multiple edge nodes to keep workload balance and provide low-latency computing services, in particular, when DTN provides services for time-sensitive scenarios, such as intelligence transportation systems and medical scenarios.

2) Cooperative Cloud-Edge-End Computing: To meet the large-scale computation and AI for real-time modeling and simulation in DTN, cooperative end-edge-cloud computing is necessary. Edge servers process the data that need to be responded in real time. The cloud sever provides strong

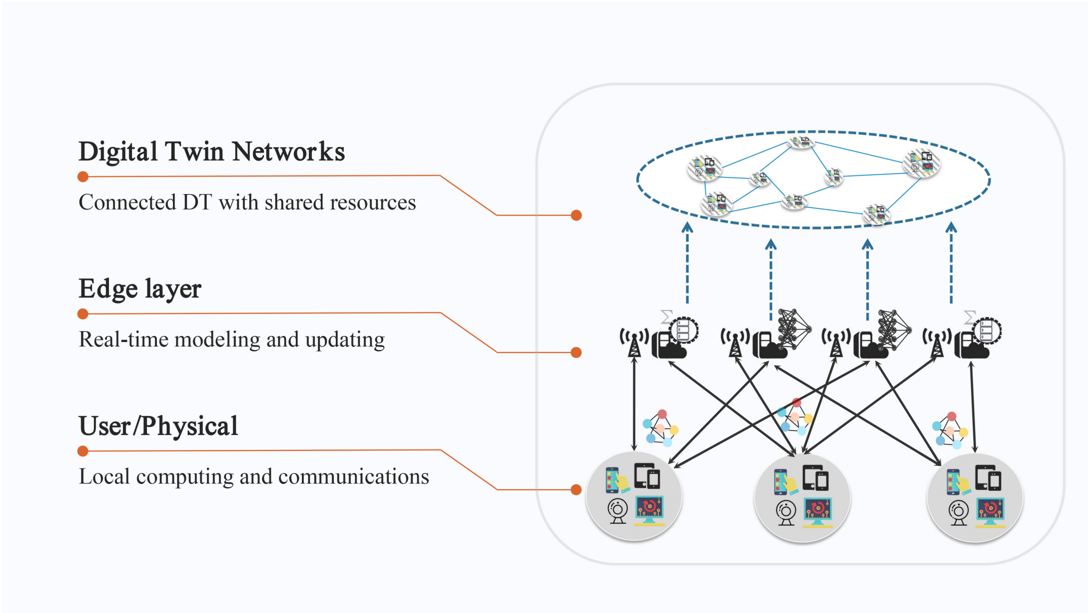

Fig. 5. DITENs.

LOOK AT DITEN

computing power and integration various information. The interaction between edge nodes and cloud in real time can solve the problem of data heterogeneity for the cloud. Cooperative end-edge-cloud computing can provide low-latency computation, communications, and model continuous updating for DTN. In addition, when the storage resources of the edge nodes are insufficient, the cloud can store part of the data and transmit the data to the client through the network when needed, which saves storage resources on the edge.

Recently, Lu *et al.* proposed a new paradigm that integrates DT with edge networks, called the DT edge networks (DITENs), to fill the gap between physical edge networks and digital systems. DITEN provides real-time and reliable techniques in support of novel heavy-computation services, including AR/VR and autonomous driving, Fig. 5 shows DITEN in a layer perspective. To strengthen communication security and data privacy protection in DITEN, they propose a blockchain empowered federated learning scheme. To further improve efficiency of the integrated scheme, they propose an asynchronous aggregation scheme and use DT empowered reinforcement learning to schedule relaying users and allocate bandwidth resources. Approach can considerably enhance both communications efficiency and data security for IoT applications [29] and [30]. Moreover, Lu *et al.* [31] introduced DT wireless networks (DTWNs) to migrate real-time data processing and computation to the edge plane. Based on DTWN, they propose a blockchain empowered federated learning framework for collaborative computing. An optimization problem is formulated for edge association by jointly considering DT association, training data batch size, and bandwidth allocation to balance the learning accuracy and time cost of the proposed scheme. This scheme yields improved efficiency and reduced cost compared to benchmark learning methods. Sun *et al.* [32] proposed a mobile offloading scheme in DITEN to minimize the offloading latency under the constraints of accumulated consumed service migration cost during user mobility. The proposed scheme effectively reduces the offloading latency, the offloading failure rate, and the service migration rate in the 6G network, as compared to benchmark schemes with DT assistance. Dai *et al.* [33] proposed virtual models of IIoT entities created by monitoring real-time states of devices and BSs. Then, the authors formulate the stochastic computation offloading and resource allocation problem to minimize the long-term energy efficiency. All these studies bring a brand new paradigm taking advantage of edge computing and DTN, but it is still in the infancy stage.

IV. Technical Challenges

Despite the benefits and promising paradigms of DTN, there are significant challenges remaining to be addressed.

A. P2P and P2V Communications

The virtual twins in DTN perform continuous sensing and information gathering from their physical objects and other virtual twins. Model updating, intelligence sharing, and predicting are based on live-streaming data. The communication network between P2P and P2V has heterogeneous characteristics. Challenges related to latency and connectivity will arise, under the large-scale data-intensive communications requirements.

1) Network Structure: The realization of the DTN requires high fault tolerance and high reliability by harnessing modern communications and information technologies to enable the communication infrastructure that provides network coordinated monitoring and control capabilities. P2P and P2V communications are both based on a very complex heterogeneous network, which establishes connections between various types of networks through various communication technologies. Meanwhile, a large amount of data transmission across networks can also cause delays and information congestion in the network. It is difficult to develop network technologies and standards that can effectively transmit data within the network. High fault tolerance and high reliability are the key goals of the DTN network structure. Instructions for virtual twins require flexible mechanisms. When the virtual space issues deviate instructions, the behavior and state of the entire network and the physical space should not be disturbed. Predicting the instructions of the virtual twin through machine learning and judging it by comparing with the instructions generated by the actual data may reduce the impact of the information deviation on the physical object.

2) Low Latency: In P2P and P2V, low latency is required. This latency is a combination of sensor latency, data processing latency, network latency, and feedback latency. For time-sensitive application scenarios, ultralow-latency requirements is necessary in remote surgery and medication control. Therefore, ultralow data processing time and low network latency are required to ensure the real-time update between a virtual twin and a physical object. The following solutions can alleviate this problem. The first is edge computing, which can reduce latency and allow higher computational complexity within limited resources. It can meet high computing power and low-latency requirements in DTN. Next, latency is significantly reduced by the 5G beyond and 6G mobile and wireless communication technologies. Distributed machine learning is a potential solution, which can allocate computing tasks to several nodes for simultaneous computing to significantly improve the efficiency and flexibility of data processing.

3) Hyper Connectivity: The connections between P2V and P2P play an important role in DTN. Challenges with attributes, such as power outages, software, or ongoing deployment errors are impacting the connectivity inside DTN. The requirements for network connectivity are different in divergent scenarios. For example, in the construction and operation of offshore drilling platforms and floating production platforms, DTN can realize real-time data analysis, improve asset integrity assessment, increase operating efficiency, and reduce the probability of downtime. In such a static scenario, it is easy to keep high connectivity in the network, while the demand for connectivity is relatively low, mainly for long-term maintenance. For example, in intelligent transportation systems, the connectivity of the network will be low because of the high mobility. In this environment, timely feedback and high connectivity are needed to deal with unexpected situations that may occur in the transportation system.

B. V2V Communications

V2V communications have the characteristics of high speed, high reliability, customization, and predictability. It is the communications between virtual twins for information sharing. However, these characteristics also bring new challenges.

1) Reliable Information: V2V communications enable information sharing between virtual twins. However, when sharing a large amount of information, the information needs to be integrated. For example, a certain area that occurs sudden dense communications and critical information may be lost or ignored. If the information is not integrated, it may consume too much resources to run the system. In static scenarios, such as in life-cycle maintenance of a production, the data are more predictable and regular. In this case, there are few emergencies. However, in dynamic scenarios, especially those with strict time and low fault tolerance, the data reliability requirements are higher.

2) High Fault Tolerance: In V2V communications, fault tolerance is required. If incorrect information is shared among multiple similar virtual twins, the virtual twin may not establish accurate model and feedback wrong information to the physical object. For all applications of DTN, fault tolerance is very important. A micro-error of the model may have a huge impact on the entire simulation operation, in particular, in dynamic scenes, the time is strict and the information accuracy requirements are higher.

C. Physical Data Processing

Data processing enable physical data to reduce dimensionality, match, and expand to achieve accurate modeling in DTN. Physical data are the foundation of data processing, while the data uncertainty and data visualization may bring plenty of significant challenges.

1) Data Uncertainty: In DTN, due to the different environments and types of physical objects, the distribution of physical data is different, which does not satisfy the assumption of independent and identical distribution. Affected by the number and type of physical objects and the network environment, the data reception rate, and the transmission rate have time-varying characteristics. In addition, due to objective factors, such as missing data or measuring instrument accuracy, as well as supervisory factors such as privacy protection, the quality of the physical data may be different, which has a great impact on data processing and modeling .

2) Data Visualization: Data visualization is an important part in data processing in DTN, particularly in dealing with large-scale network where data are generated enormously. The data in DTN are characterized by large size, high dimension, and heterogeneous. Therefore, an efficient data visualization solution is a challenge task to be addressed.

D. Digital Twin Modeling

The modeling and simulation in DTN are based on diverse tools that can achieve high-fidelity virtual visions of physical objects. However, specific modeling designed for scenarios cannot be adaptively applied to multiple applications. This may severely hinder the adoption of the DTN technology. Moreover, both high-precision modeling problem and error model problem will bring challenges to the reliability of DTN.

1) Standardization Framework: DTN contains a variety of subsystems, and each subsystem with different functions and different forms has different models including geometric models, simulation models, business models, data models, etc. Although modeling frameworks have been developed in previous studies, there is no framework that can meet different virtual modeling demands and accurately formulate an entire DTN. To achieve a wider range of DTN, different domain models must be standardized to construct a more comprehensive and complex DTN. The framework needs to flexibly support the combined models to realize the effective application of different stages and scenarios. In addition, the problem of interoperability of multiple models can also be addressed by establishing the DTN standard framework.

2) High-Precision Modeling: Traditional DT modeling is based on general programming language, simulation language, or special simulation software to write the corresponding model. It only has a reference role in the actual system operation process which cannot supplement virtual models with data in real time to achieve high-confidence prediction of physical objects. At present, the discussion of multilevel and multidimensional advanced modeling technology is still limited. Traditional modeling is too simple to achieve the comprehensiveness and accuracy required by DTN, and most modeling methods have disadvantages, such as poor flexibility, complicated configuration, and error prone. Further development is needed in modeling and simulation technology to construct a reliability DTN.

3) Model Continues Updating: The goal of DT modeling is to achieve a comprehensive and accurate modeling of physical objects. The virtual model can be updated synchronously based on physical data, represent, diagnose, predict, and make decisions on physical space. However, the principles of most physical objects are not clear, and high-fidelity models of physical objects cannot be obtained. Therefore, the continuous updating of models based on principles and data, the diagnose and prediction based on incomplete information and unclear principles are very challenging. The continuous update of the model requires accurate data and enough computing power to support, which is also a challenge for DT modeling.

E. Computing

Edge and cloud computing enable DT data to be processed in real time and facilitate AI to be implemented in DTN. Despite the benefits of integrating DTN with cloud and edge computing, there are significant challenges remaining to be addressed.

1) Architecture: The implementation of DTN requires intensive computing and caching resources. Although cloud and edge computing could meet these demands, there is also a lack of a standard architecture supporting edge empowered DTN operation. The architecture needs to consider DTN's connectivity, information characteristics, resource constraints, management efficiency and the orchestration of resources, applications, and services.

2) Resource Limitation: Storage resources and computing resources of edge nodes are limited. The data from the virtual model need to be analyzed by applying intelligent algorithm. Applying intelligent algorithms requires the supporting of storage resources. How to store different models for data analyzing at the edge nodes to satisfy the demand of different physical objects needs to be discussed. It's important to improve the efficiency of data analyzing which can ensure the accurate feedback to physical. At the same time, huge computing resources will be consumed in the data analyzing, while the computing resources of edge nodes are limited. A migration task strategy may decline the stressful on edge nodes which will greatly improve the data quality feedback to physical objects.

3) Environmental Dynamics: The dynamic challenges of an environment mainly include the dynamics of DTN connections and that of task requirements. With edge computing, physical objects are mainly connected to edge nodes through wireless networks. The anti-interference ability of wireless channels is weak and signals are easily interrupted, especially in a high-speed moving environment, such as an intelligent transportation system. The movement of physical objects will break the original communication resource allocation state, resulting in instability of the communication system. For the dynamics of task requirements in DTN, there are many types of physical objects, the corresponding computing task requirements will also be quite different. The data generated by highly similar physical objects may also be different, and the required resources are also different. It is very important to optimize the allocation of limited resources at the edge to support the dynamic computing task requirements of DTN.

V. Applications

In this section, several DTN application scenarios, including manufacturing, aviation, healthcare, 6G network, intelligent transportation system, and urban intelligence are presented. Fig. 6 shows the applications of DTN.

A. Manufacturing

Various new national advanced manufacturing strategies, such as Industry 4.0 and Industrial Internet are issued to achieve smart manufacturing. Traditional manufacturing has problems, such as limited production efficiency and product life cycles too long. The current digital factories have problems, such as nonreal-time interaction and low data utilization during production. Based on DTN, it can effectively improve the transparency and optimization of the product production process, and improves the production intelligence level. The deployment of DT and DTN, especially combined with intelligent analysis and communications technologies, greatly benefits the connection from physical objects to virtual counterparts.

DTN can be applied to different aspects of manufacturing. When designing parts, the full-life cycle of the parts can be simulated through the virtual model, and design defects can be found in advance to realize accurate parts design. In the production line of the factory, through the virtual model of the entire production line, the production process can be simulated in advance, and problems in the process can be found in order to achieve more efficient production line management and process optimization. As for the entire factory, the virtual twin of the factory can be fully optimized, including factory construction, product production, life prediction and maintenance of all industrial equipments, etc., to achieve efficient digital management and low cost in manufacturing. Moreover, DT can be used in physical and pricing

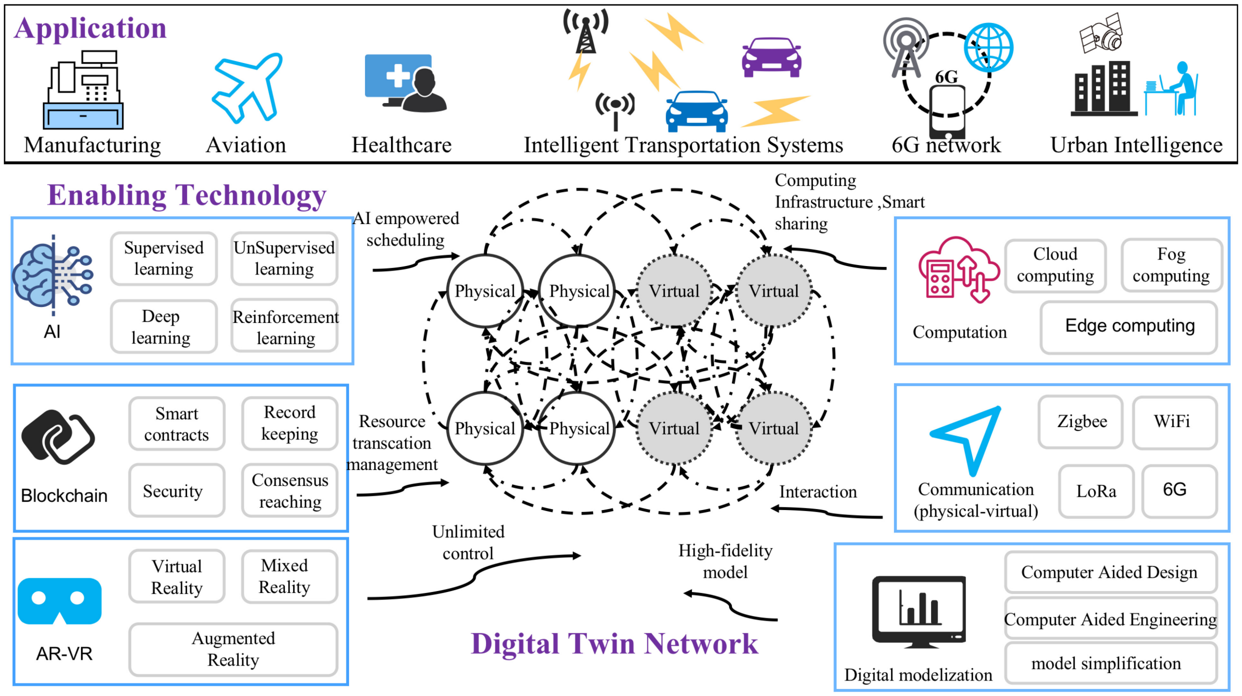

Fig. 6. Applications of DTNs.

objects driven by predictive performance data. A typical manufacturing scenario is the shop-floor paradigm toward smart manufacturing, which can be applied to aid the interaction and convergence between physical and virtual spaces [16]. Based on DT, the DT shop floor reflects the shop floor in dual visions, the physical and the virtual, which makes these two parts keep in consistency and to be optimized by each other. Data from both physical and virtual sides, as well as the fused data, are provided to simulate and optimize the manufacturing process and promote the production efficiency. Additionally, DT can flexibly simulate the production process by collecting the data of the entire production process, the state, and the production capacity of the system, to manage and optimize the whole manufacturing process from the input of raw material to the output of the finished products [34]. In summary, high efficiency production and precision manufacturing in shop-floor paradigm can be realized by DT.

Although industrial applications benefit a lot from DTN, there are still some challenges in applying this technology for manufacturing. First, in industrial scenarios, the information sharing between physical and virtual spaces is often undermined by the co-channel interference from other equipments, which leads to data missing and errors. How to build accurate DT models of the manufacturing facilities based on the incorrect data is a critical challenge. Second, in modern automatic production lines, a large number of industrial facilities work cooperatively under the management of DTN. There are complex and variable relationships between these facilities in production scheduling and product quality assurance. It is difficult for the DTN to build a matching twin model and obtain an optimal manage strategy under this complex scenario. Third, in industrial manufacturing, information privacy protection in DT formation is also a challenge. Building DTN and continuously updating DTN require core data, such as production parameters and user's personal information. In the information delivery process, especially through wireless communications, privacy may be leaked to malicious attackers. Thus, how to protect privacy in the DTN operation is also a key issue to be addressed.

B. Aviation

Aviation is also a part of the manufacturing. In the field of aviation, DT is mainly used for aircraft maintenance, risk prediction, aircraft structuring, and starting self-repair mechanism, where the data processing and problem diagnose capability are greatly enhanced. However, as the DT concept still in its infancy stage, most of the proposed researches cite the concept of DT but do not explicitly mention DT. For example, Yang *et al.* [35] built a virtual twin of the aircraft and used the automatic image tracking method to predict the crack tip deformation and crack growth of aluminum alloy and steel. Bielefeldt *et al.* [36] proposed a method for detecting fatigue cracks by constructing a metamodel of the aircraft wing.

In aircraft, the structure is complex, the internal components are closely related, and complete safety performance needs to be guaranteed. Therefore, based on the DTN prediction of failure, real-time detection of sudden faults is the key to improving the safety performance of the aircraft. Meanwhile, building DT models of the aircraft can evaluate the overall status of the aircraft through real-time data analysis. The virtual twin can perform predictive maintenance and real-time repair. Moreover, the virtual space can provide the virtual vision of the air transportation system, which can help to optimize the flight routes.

The constructed DT models of the aircraft in the virtual space provide effective guidance for the flight state adjustment and flight route optimization in the real world. However, in the DT-empowered aviation, there are still some challenges to be addressed. Aircraft needs precise control, and wrong instructions and operations will cause a serious air disaster. Being an important reference for flight control, the aviation DT models should achieve high accuracy. However, the unreliable communication between the aircraft and the DT servers may bring some erroneous information for this model construction. How to eliminate the effects of the incorrect data and maintain the robustness of the DT model is a critical challenge. Moreover, in flight, the aircraft moves across several large areas and accesses to multiple DT servers. The way to coordinate these servers for building the DT model, which has comprehensive aircraft information of the whole flight, is still an unexplored problem.

C. Healthcare

DT in the health domain is an important research area for many researchers. With the development of the Internet of Things, it is possible to use a large number of human body intelligent monitoring equipments and environmental sensors to comprehensively detect a patient's health condition, and to establish a twin patient. The twin patient will collect the patient's physiological status and life style, medication input data and the data about patient emotional change over time. Thus, the twin patient can enable medical experts to provide patients with a full range of medical care and even accurately predict changes in the condition. This can prevent the condition from getting worse in advance. For example, psychologists have begun to use physical activity levels using actiraphys to predict the onset of different episodes of bipolar disorder [37]. For the trauma rehabilitation patients, the patient's physical fitness can be improved, and even early recovery by establishing a twin patient and tailoring a personalized recovery plan based on the user's real-time physical signs.

In addition to long-term detection of patient signs to control the condition, in remote surgery, the DTN also provides new possibilities. Experts can perform operations on the twin patient and perform all-round control of the surgery based on the data returned by the body. At the same time, they can also use the real-time physical data to predict the emergencies that may occur during the operation and get the optimal solution in advance. In this scenario, ultrafast and ultrareliable communication guarantees are required. In addition, DTN also makes it possible to develop twin organs with high accuracy and sensitivity. For medical devices, DTN can do the real-time monitoring, structural life prediction, and device management. Moreover, DT can be used in the health code services. Health code is a person's DT. The code is updated, dependent on the person's health, contacts, location, mobility. However, the combination of DTN and medical treatment also puts forward very strict requirements on the safety and privacy of digital patients. The implementation of DT in this industry should ensure a very high level of protection of personal data. Blockchain can be used for secure data sharing and private information protection.

D. 6G Networks

The 6G network aims to realize ultralarge capacity and ultrasmall distance communications, go beyond best effort and high-precision communications and converged multitype communications [38]. Thus, the 6G network may face challenges on security, spectral efficiency, intelligence, energy efficiency, and affordability. The appearance of DTN brings the opportunities in overcoming the above challenges. DTN can enable 6G to realize innovative services, e.g., AR/VR, automatic driving.

DTN provides a corresponding virtual network for 6G networks. The virtualized 6G network will collect traffic information on the entire network and use data analysis methods to discover network traffic patterns and detect abnormal traffic in advance. The 6G network uses the information fed back from the virtualized network to make preparations in advance to improve network security. In addition, by collecting and analyzing the communication data in the network, the rules of communication can be discovered to automate demand and provide services on demand. Since the communication demand can be predicted in advance, it can feed back to the 6G network to reserve resources, such as spectrum resources.

The appearance of DTN brings the opportunities in overcoming the security, spectral efficiency, intelligence, energy efficiency, and customization in the 6G network, while reshaping and accelerating the development of the 6G network. There have been studies combining DT and 6G network. For instance, in order to increase the higher capacity wireless communication links in the network, the authors propose DT for metasurface reflector management in 6G Terahertz communications [39]. DT is used to model, predict, and control the signal propagation characteristics of an indoor space to maximizes THz signal-to-noise ratio (SNR) in the system. Lu *et al.* introduced the DTWN by incorporating DTs into wireless networks, to migrate real-time data processing and computation to the edge plane. DTWN uses DT to mitigate the unreliable and long-distance communication between end users and edge servers in the 6G network. The integration of DT and 6G bridges the physical system with digital space and enables robust wireless connectivity. [31].

In addition to building a virtual model of the 6G network, DT can be used in the effective management of mobile cell towers, particularly for those in remote locations and hard to maintained [40]. Remote sensors can collect a range of data, on aspects, such as proximity, temperature, motion, and position with tower. According to these data a virtual tower can be set up, which can then be analyzed using data processing algorithms to management the tower.

E. Intelligent Transportation Systems

In recent years, urban transportation systems have faced the problems, such as traffic jams and traffic accidents. DTN can provide better services for drivers in urban lives by utilizing electronic sensor technologies, data transmission technologies, and intelligent control technologies.

First, DTN provides the virtual vision of the transportation system which can help to manage traffic and optimize public transportation service planning efficiency. Zhu *et al.* [41] presented a parallel transportation management and control systems that based on the artificial system, computational experiment, and parallel execution. The main idea of parallel transportation systems is very similar to that of DT. In parallel transportation systems, the data source includes the physical object data and social data, and the result shows that the congestion miles has been significantly reduced. Next, the traffic accident can be effectively predicted and avoided by processing the massive amount of real time transportation information in virtual system in DTN. Dong *et al.* [42] introduced a basic framework of parallel control and management for emergency response of urban rail transportation systems. This framework develops effective emergency control and management strategies for rail transport systems by modeling urban rail stations as points, the microscopic characteristics of urban rail connections between designated stations as lines, and the macroscopic properties of all the urban rail connections as networks.

DTN can also offer new opportunities to maintain transportation facilities, such as pavement degradation. By simulating the usage of transportation facilities in DTN, facilities malfunction can be predicted in advance, which helps to make maintenance decision in an appropriate way. In addition to the state-of-the-art topics, there are innovative services in DTN for transport, such as traffic information reporting, vehicles secure access, and vehicles data sharing. With the potential of implementing computing-intensive applications, edge computing is combined with DT to enhance intelligent transportation capabilities.

Although much promising advantages could be brought by DTN to the transportation systems, complex and dynamic traffic environment poses critical challenges in the DTN operation process. In DTN-enabled autonomous driving control, the smart vehicles' running states and perceived environmental information needs to be transmitted to the DTN servers in real time to update the virtual twin model. However, it is difficult to guarantee strict data transmission delay in such vehicular networks with highly dynamic topology and serious co-frequency interference. Moreover, hackers may attack or tamper the communication between the vehicles and the DTN servers, thus impairing the DT model construction and misleading the vehicle driving control. How to secure DTN operation in vehicular networks is a challenge to be addressed.

F. Urban Intelligence

Given the increasing population within the urban areas, sufficient services and environmental needs cannot be met easily. DT cities is an opportunity to cope with limited spaces and resources across the physical world. DT cities uses DT technology to create a virtual city can simulate and analyze various urban construction planning and urban application solutions. By summarizing the intelligence of urban historical development and cultural formation from the virtual city, the operation and management of the smart city can be realized.

At present, many countries begin to deploy DT for realize more advanced urban intelligence cities [7], [43], [44]. For instance, in [44], Amaravati, the new capital of the Indian state of Andhra Pradesh, is thought to be the first DT city. The initial 3-D prototype of the city, built using Cityzenith's Smart World Pro software, and the city uses ubiquitous multinode IoT sensors to monitor real-time construction progress, environment and health monitoring, etc. In [43], Singapore has built a city operation simulation system CityScope to realize functions, such as city simulation optimization, planning, and decision making. The Dutch city of Rotterdam [45] is at the forefront of the DT movement too. The virtual Rotterdam is used to improve infrastructure maintenance, energy efficiency, road and water transportation, and help fire-fighters travel tasks in emergency situations.

DT city is the core of smart city construction, which can promote many aspects, such as municipal planning, ecological environment management, traffic control, energy use management, etc. Based on powerful technical capabilities, such as digital identification, automatic perception, network connection, intelligent control, and platform services, the DT city model can run in parallel with physical cities, making urban development full of infinite possibilities.

VI. New Trends Related to DTN

In this section, we will discuss new trends related to DTN, including federated learning for privacy concerns, blockchain, and edge intelligence for DTN.

A. Federated Learning for Privacy Concerns

Federated learning is a distributed machine learning approach, which is motivated by decentralized computation and privacy concerns in recent years. It was first proposed in 2016 to solve the problem of Android mobile terminal local update. The goal is to implement efficient machine learning between multiple participants or multiple computing nodes under the premise of information security, personal privacy protection, and legal compliance.

In general, federated learning training process includes the following three steps. First, the server decides the training task and specifies the hyperparameter of the global model and the training process. Then, the server broadcasts the initialized global model ω_G^0 and the task to selected participants. Second, based on global model ω_G^t, each participant, respectively, uses its local data and the device to update local model parameter ω_i^t. The goal of the participant is to find optimal parameter ω_G^t that minimizes loss function $F(\omega_i^t)$, which can be presented as

$$\omega_i^{t^*} = \arg\min F\left(\omega_i^t\right). \tag{1}$$

The updated local model parameter are subsequently sent to the server. Third, the server aggregates the local models and then sends the updated global model parameter back to the data owners. The server minimizes the global loss, which can be shown as

$$F(\omega_G^t) = \frac{1}{N}\sum_{i=1}^{N} F(\omega_i^t). \tag{2}$$

With federated learning, the private data of each nodes do not need to be transmitted to others. Thus, federated learning can be used in scenarios, where data privacy is required and low-cost machine learning models can be used. At present, many machine learning models, such as logistic regression and tree structure models have developed gradually to laid the foundation for federated learning. Federated learning can help DTN expand its application field and help all kinds of physical objects as well as virtual twins to alleviate their concerns about the privacy of raw data. Federated learning can serve as an enabling technology for machine learning model training at DTN. In DTN, virtual twins and physical objects can collaboratively train a shared model while keeping data generated by own counterpart physical object. This approach improves the reliability and security of the system and enhances data privacy. Lu *et al.* [30] proposed an asynchronous federated learning framework of the DT-empowered Industrial IoT to achieve privacy protection in DTN. Still, federated learning also has certain shortcomings. In synchronous federated learning, the efficiency of each training round is restricted by the slowest node, i.e., the federated learning system is susceptible to the straggler effect. As mentioned in [30], the frequency and timing of aggregation should be carefully designed in federated learning, as the gain of global aggregation is nonlinear and the network environment, e.g., the channel state, is time-varying during the federated learning process.

B. Blockchain for DTN

Blockchain is a chain structure of data blocks arranged in a chronological order, which is essentially a tamper-proof distributed database that uses cryptography to ensure the security of each link in a decentralized manner. A blockchain is composed of peer-to-peer networks, distributed storage, consensus mechanisms, cryptography, and smart contracts. Therefore, the blockchain has advantages of decentralization, tamper resistance, anonymity, public verifiability, and traceability. Integrating DTN and blockchain brings security guarantee, trusted traceability, accessibility, and immutability of transactions in DTN.

There are few studies on the combination of DTs and blockchain. For instance, Hasan *et al.* [46] proposed a blockchain-based creation process of DTs, which uses smart contracts to govern and track transactions initiated by participants involved in the creation of DTs. Altun *et al.* [47] proposed a reference model that grants the ownership of the fog-located DT of a home appliance to its owner and promotes human-centric services and applications on this twin by utilizing blockchains and enabled clouds. Yaqoob *et al.* [48] envisaged how blockchain can reshape and transform DTs to bring about secure manufacturing that guarantees traceability, compliance, authenticity, quality, and safety. Due to the high latency and resource consumption of traditional blockchain schemes, it is hard to maintain a traditional blockchain in edge networks. Lu *et al.* [29] proposed a light blockchain scheme for DITENs and improved the blockchain scheme for efficient integration with the federated learning process.

The aforementioned studies show that the convergence of blockchain and DTN may potentially overcome the current drawbacks of DTN. However, the integration of DTN and blockchain is still in its infancy. Both industry practitioners and researchers aim at realizing scalable and deployable blockchain-based DTN platforms while there are a number of challenges in DTN, such as distributed consensus algorithms and data analytics with privacy-preservation.

C. Edge Intelligence

Edge intelligence integrates edge computing with artificial intelligence. Edge intelligence provides DTN with low-latency and high-security computing services with the ability to quickly process data and help physical objects to make high-quality decisions. On the one hand, DTN supported by edge intelligence can cope with rapidly changing scenarios. For example, in intelligent transportation systems, the edge servers can perceive information, such as population distribution, traffic flow, humidity, temperature, pressure, and air quality in real time. Such information is all real-time changes, and the artificial intelligence deployed on the edge can quickly process the real-time data and feedback in a short time. This is essential for public transportation planning, traffic control, and driving alerts of time-sensitive intelligent transportation systems. In some scenarios with high privacy and high security requirements, DTN supported by edge intelligence can also provide better services such as in medical care. On the other hand, for edge-deployed machine learning models, the physical data can facilitate the training of the model and improve the accuracy and efficiency of the model.

There are still some challenges in the combination of edge intelligence with DTN. In the edge environment, limited by the physical size and energy supply, equipment resources are usually very limited. The data volume of physical objects in DTN is huge, and the deployment of artificial intelligence at the edge also requires computing resource services. Therefore, reducing redundant data and designing lightweight machine learning models are very important in the combination of DTN and edge intelligence.

VII. Open Research Issues

As a newly emerging technology, only few research has been studied on DTN. There are still many open issues in DTN that need to be addressed. This section discusses and identifies several open issues in the development of DTN.

A. Security Vulnerability

Security and privacy are the main concerns for secure DTN. DTN is a complex system that consists of various networks and it is difficult to protect privacy and security. For example, the information sharing inside the network may raise security issues. In DTN, a pair of twins has a two-way feedback relationship with each other. The physical object may not be easily threatened, however, the attacker can easily change the virtual model or the data fed back by the virtual model. This kind of attack is harmful to critical scenarios, such as intelligent transportation systems and medical treatment. Moreover, in DTN, the data analytic computational intensive tasks processed by edge or cloud servers also bring security issues.

B. Privacy Leakage

DTN requires accurate modeling through data, the privacy issues of data and models cannot be ignored. Virtual modeling of the human body requires collection of various biological information of the body, as well as monitoring and recording information about the patient's surroundings and daily activities. The collected sensitive data will be analyzed and processed by cloud-based service providers or edge servers. These providers usually keep these data permanently driven by profits, and even share this data with other advertising agencies without the user's consent, thereby increasing the risk of privacy leakage. Therefore, how to balance the data utilization and protection of sensitive information is a significant challenge facing in DTN.

C. Cost-Effective Solutions

The construction of an initial comprehensive DTN depends on the utilizing of big data, ML, and other technologies. The cost of data collection based on comprehensive sensor deployment needs to be considered. Besides, the consumption of hardware resources, communication resources, computing resources, storage resources, etc., also need to be taken seriously. Minimizing the over costs in constructing DTN is a problem that needs to be discussed.

D. Two-Way Real-Time Interaction

Virtual twins receive data and control physical objects by real-time and reliable two-way communications. Due to the dynamic network environment, it is difficult to transmit such large-scale data in real time. Since the communication is wireless, the stochastic associated with the wireless channel may result in a poor transmission link, correspondingly longer service delay. The bandwidth, computation, storage, and energy of DTN all affect real-time two-way communication. The continuous update of the model, as well as the prediction with AI, involves heavy computation tasks. Overall, any of these may influence the connectivity of the two-way interaction.

VIII. CONCLUSION

This article has presented a thorough survey on the recent research and technological development in the area of DT, and envisioned the DTN deployment in its application domains. In particular, we gave key features and definitions of DTN and overviewed the key technologies for DTN. Moreover, we elaborated the technical challenges in DTN implementation and investigated potential addressing approaches. Finally, we showed promising application paradigms, technology evolution trends, and open research issues related to DTN.

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