Digital Twin for 6G: Taxonomy, Research Challenges, and the Road Ahead

Antonino Masaracchia* (Member IEEE), Vishal Sharma* (Senior Member IEEE), Berk Canberk† (Senior Member IEEE), Octavia A. Dobre‡ (Fellow IEEE), and Trung Q. Duong* (Fellow IEEE)

[1]Queen's University Belfast, UK
[2]Istanbul Technical University, Turkey, and Edinburgh Napier University, UK
[3]Memorial University, Canada (email: odobre@mun.ca)

(Invited Paper)

CORRESPONDING AUTHOR: Trung Q. Duong (e-mail: trung.q.duong@qub.ac.uk).

ABSTRACT The concept of digital twin (DT) is constantly revealing as a key enabling technology for the deployment of mobile communication services envisaged for the sixth-generation (6G) Internet-of-Things (IoT). This paper aims at providing a comprehensive review of the current state-of-the-art DT-enabled 6G oriented network services. The main characteristics of this new key enabling technology and its critical aspects are highlighted. An overview of the 6G network requirements for the deployment of its innovative envisioned services is firstly provided, emphasizing how the DT concept represents a complementary key enabling technology for them. This is followed by a brief introduction of the DT technology. Subsequently, a comprehensive classification and analysis of the research advancements on DT-enabled 6G services currently available in literature is provided. This paper is concluded by highlighting the most representative challenges and future directions necessary for the deployment of this promising and innovative technology.

INDEX TERMS Beyond fifth-generation (5G) network, Digital Twin (DT), Internet of Things (IoT), Internet of Vehicles (IoV), sixth-generation (6G) network.

I. INTRODUCTION

THE notable improvements observed during the last two decades on wireless sensor networks, Internet-of-Things (IoT), Internet-of-Vehicles (IoV), as well as on cloud/edge based computing, artificial intelligence and machine learning (AI/ML), are continuously contributing to further increase the huge proliferation of smartphones, tablets and new wearable electronic devices, which will inevitably bring to a traffic overload of the current 5G networks. Indeed, according to the forecast provided by the International Telecommunication Union Radiocommunication Sector (ITU-R) [1] it is foreseen that 5G will not be able to accommodate the huge volume of mobile traffic and subscribers in 2030 and beyond, which will reach 5016 exabyte per month. This will be mainly caused through the deployment of new use cases and services like extended reality (ER), tactile internet, intelligent transportation systems, global ubiquitous connectivity and pervasive intelligence [2].

However, the support of these disruptive use cases and applications envisioned for 2030 and beyond, require additional features and increased network performances compared to 5G networks. These are then envisioned to be introduced through the deployment of 6G mobile communication systems [3], [4]. In particular, 6G will be expected to provide:

- Up to 1 Tbps data rate through the advancements on THz communications;
- Up to 1 Gbps user experienced data rate in downlink;
- A communication latency of 10 μs;
- Support of mobile vehicles with speed up to 1000 km/h;
- Connection density to support massive machine type communications (mMTC), i.e., up to 10^7 users per km^2;
- Spectral efficiency up to 90 bps/Hz in downlink and 45 bps/Hz in uplink;
- Up to 1 Gbps/m^2 in some deployment scenarios such as indoor hot spots;
- 99.99999 % communication reliability;
- 1 GHz operational bandwidth for operation in higher frequency bands like THz communications or optical wireless communications;
- A position accuracy of cm thanks to the employment of THz;
- Improved data timeliness in terms of age-of-synchronization (AoS) age-of-information (AoI), and age-of-task (AoT).

All these key performance indicators (KPIs) will definitively support the delivery of 6G-oriented services which will shape our daily life and will also pave the way for environmental digitalization, in which the concept of digital twin (DT) will play a key role. Indeed, DT is defined as a virtual replica of a physical product/system in the real world that, based on the usage of artificial intelligence (AI) techniques and big data analytics, is able to simulate its behaviour and use in real time. This will allow then to test the product/system in different environments and understand the best action to take in order to optimize the product/system itself [5]–[8]. In other words, DT is used to create comprehensive digital models of physical environments. This can be possible thanks to the two-way data communication exchange between the physical object and the digital model that permits to take real-time decisions in order to rapidly improving the development, sustainability and efficiency of the product/system.

During the last two decades, DT is continuously becoming a top strategic technology mainly investigated in industrial sectors including manufacturing, energy, industrial assets and structures in order to perform real-time monitoring aimed at improving the production throughput and the safety of the work environment [9], [10]. For example, big tech leaders like Microsoft, General Electric and Siemens are currently adopting the concept of DT in order to optimise their products life cycle. This way will open up new opportunities for more advanced engineering applications [11], [12].

Based on the previous discussion, it is evident that DT represents not only a 6G related service, but the DT concept and the 6G networks represent two interdependent concepts. Indeed, DT can be labeled as a valid candidate toward the development of 6G architecture by deploying digital representations of different physical objects, ranging from aerospace and autonomous systems to healthcare and Indus-

try 4.0 services, which can be optimized through AI based mechanisms integrated into the DT itself. Indeed, the usage of DT entities for 5G and beyond 5G networks has recently gained significant interest from leading telecommunication companies like Ericsson [13] and Huawei [14]. On the other hand the achievement of 6G KPIs requirements, will further contribute to the development of more powerful DT entities for which their implementation involves massive multi-source data flow for data collection, analysis and visualisation in real-time [15]. In the following we introduce the more relevant areas in which the introduction of DT will be beneficial. The potential use cases of DT for 6G IoT are summarised as Fig. 1.
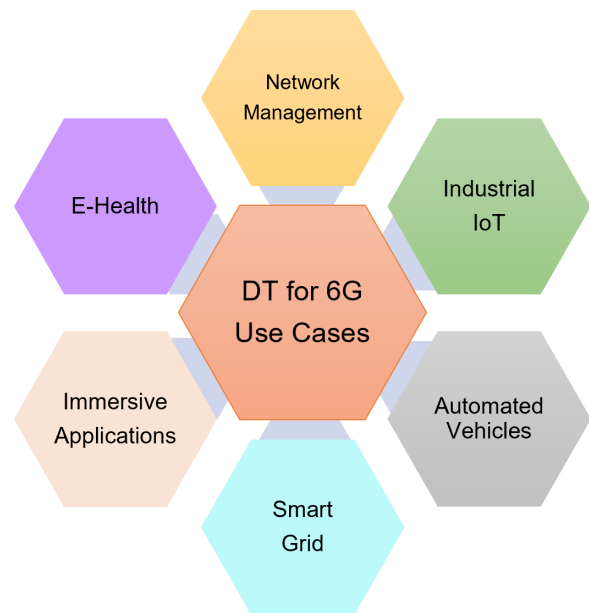

FIGURE 1. Use cases of DT for 6G Internet of Things

A. Network Management

To date, the main applications where the DT technology has been adopted can be found in sectors like manufacturing, healthcare, and aviation. Recently telecommunication companies have also started developing DT of network components for being fully integrated in 6G networks. In this fashion, as in the industrial sector, having a digital replica of a telecommunication network will be beneficial to significantly improve all the phases of a network life-cycle, from the design to the deployment and expansion phases of a network. Indeed, thanks to the modularity of DTs, network designers and engineers will be able to create a hybrid-simulation environment which will support the network design process by exploiting the existing knowledge provided by DTs networks' components. However, in contrast to the still currently used network planning tools and simulations, the DT-based systems are connected to real deployed physical subsystems. This approach — since DT is enabled to run AI modules generating knowledge

from real-time data — allows the whole system to evolve as the deployment proceeds, by optimising the operational parameters of the networks. In other words, by checking all the possible scenarios in different contexts, AI entities will select the best network configuration that provide the highest quality-of-service (QoS). In addition, the adoption of AI-based mechanisms also provides network resilience against potential device disruption by performing prediction and strategic planning. This also results in reducing costs for telecommunication companies that currently need device redundancy within the network, which obviously represents an extra cost. An AI-enabled DT can predict potential disruptions that can be managed before happening, guaranteeing resiliency by avoiding the deployment of costly redundant copies for each component. Finally, thanks to the concept of transfer learning, based on the experience gained at the AI modules, the adoption of DT into communication network will also be beneficial for designing new network architecture and testing new services, by allowing network operators to be leaders for the delivery of a particular new service or to monetise their experience and knowledge created from data analysis [7].

B. Industrial Internet-of-Things

During the last few years, the rapid global upsurge of IoT devices has contributed and still continue to contribute to completely revolutionizing the industrial sector in a way that will allow industrial manufactures to provide automated and intelligent product and services. The industrial IoT (IIoT) strongly relies on the availability of short distance wireless communications technologies which should guarantee ultra-reliable and low latency communications (URLLCs) [16], [17]. This means that IoT has stringent QoS requirements like communication latency of less than 0.5 ms and transmission reliability of 99.999% at least, as well as low jitter levels and high transmission efficiency. Although 5G networks provide substantial improvement in terms of URLLC, these does not result sufficient to satisfy IIoT applications. From this perspective, the DT technology has been further promoted as a possible solution to address the above issues. Indeed, the possibility to have digital replicas of each industrial device and to constantly collect high amount of real-time data from them will permit to simulate, analyze and forecast the behaviour of each industrial device, which will be useful to control and increase the efficiency of the entire production process. This way, the information technology will be integrated into the manufacturing sector increasing production efficiency as well as reducing the design costs [18].

C. Connected Automated Vehicles

In addition to revolutionize the manufacturing and industry sector, the rapid and continuous development and deployment of large numbers IoT devices is also fostering the creation of the so called connected automated vehicles (CAV) sector. This represents another complex landscape with several challenges, ranging from traffic management to onboard diagnostic and awareness of the surrounding environment, that need to be addressed. Then it becomes natural to consider how the availability of real-time data from vehicles can strongly contribute in addressing these challenges. Then, the DT paradigm has been recognized as a valid and potential tool to facilitate the deployment of CAV services. Data collected from vehicles will be firstly used to obtain a virtual representation of all the vehicles of interest. Subsequently these virtual models can be used to simulate different scenarios with the aim of obtaining essential insights for the deployment of CAV — related services like safety critical services, traffic management, digital maps with real-time status updates of lanes, as well as autonomous driving models, onboard diagnostic and logistics for the deployment of intelligent transportation systems envisaged for the future smart cities [19].

D. Motivation and Contribution

From the previous subsections, one can notice how the DT technology will be an essential enabler for the deployment of future 6G network services. As a result, the investigation on how the adoption of the DT paradigm as a potential key enabler for the deployment of future 6G services is a very attractive research topic. To the best of our knowledge, neither tutorials nor review papers aimed at providing a view about current state-of-the-art of DT application to different areas, as well as related challenges and future research directions for each of them, are currently provided in literature. This paper provides a comprehensive discussion about the most relevant and current research activities in the field of DT-aided 6G networks, aiming then at filling in this gap in the current literature. In particular this article provides the following contributions:

- It presents a brief overview about DT and its development process within the years.
- The most promising DT-enabled frameworks and architecture for 6G related services are classified and reviewed.
- Finally, challenges and future directions in this groundbreaking research area are discussed.

The rest of the paper is organized as follow. A brief overview of the DT systems is provided in Section II, while the review of the most relevant DT-enabled 6G services and future challenges are presented in Section III and Section IV, respectively. The paper is finally concluded in Section V.

II. Overview of DT systems

As mentioned before, the advent of IoT in the last two decades has strongly contributed to the massive diffusion of sensor embedded devices continuously exchanging huge amount of data, i.e., big data, through the Internet. At the same time, we have also witnessed scientific advances

in data fusion techniques, big data analytics and cloud computing, which represent very powerful tools for storing and elaborating big data and obtaining important knowledge aimed at improving physical systems' performances. This approach of big data analytics, as well as the integration of AI models for processing IoT data represent the motivating factor in the development of the DT technology, which is constantly gaining interest in different application fields like manufacturing, aerospace, healthcare and medicine.
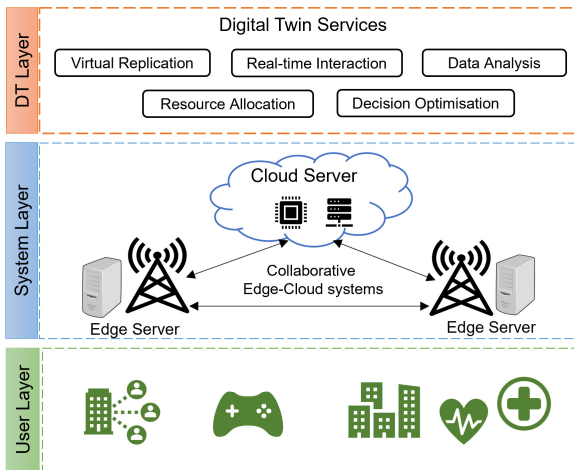

FIGURE 2. A general framework of DT-aided 6G IoT systems

As mentioned earlier, the apparition of the DT concept can be traced back to 1970 when NASA created a mirrored systems during the Apollo 13 mission [20]. This was beneficial as thanks to simulations it was possible to both manage the accident of the exploded oxygen tank that happened two day after the launch, and to find the best way for getting Apollo 13 crew back to earth alive. After this first example, several informal definitions about DT have been introduced. The first informal definition occurred in 2002, during a presentation that Michael Grieves gave about the ideal concept of product life management (PLM). In this definition, lately formalized in [21], the DT was represented as a three dimensional (3D) structure composed by *i)* a physical device for the real space, *ii)* a corresponding virtual representation, and *iii)* a communication link for data exchange between the real space and the virtual space. Just one year after, the definition about an *agent-based architecture where each product item has a corresponding virtual counterpart or agent associated with it* has been proposed by Framling [22]. This definition highlighted how important is for a PLM system access to an accurate and precise view of its physical counterpart: from the time when it is designed/deployed and throughout all its time of use. The proper definition of DT appeared only 10 years after Grieves attempt. In particular, it was proposed by NASA [23], which defined DT as *an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin*. After this definition several

other definitions have been provided by Tuegel *et al.* [24]–[26] and the US air force [27].

Trying to provide a more uniform and simple definition for DT, as summarized in Fig. 2 for 6G IoT systems use case, a DT can be represented as *a set of physical machine/objects connected to computer-based models that constantly simulate/emulate the life of that physical entities*. [28], [29]. In this way, thanks to the continuous interaction between the DT, its physical counterpart and the external surrounding environment, the DT will be always aware of what is happening in the physical world. Moreover, it will be able to follow the life cycle of its physical twin as well as to optimize its processes and functions through a closed loop optimization. Furthermore, trough simulations of novel configurations and usage of AI and Big data analytics tools, DT is able to predicts future statuses like, system defects, damages, and failures, which will provide the possibility to preventively apply maintenance operations or activate self-healing mechanisms.

Based on the definition and illustration provided above about DT and its potentialities, it is clear how the availability of some resources is necessary for the realization of one or more DT entities. First of all, *networking devices* are necessary in order to enable the data exchange between both physical and virtual twin, as well as between different DTs in located in the surrounding environment. Furthermore, cloud-based connections are necessary for the communication between the DT and domain experts. This enable the DT to continuously receive dynamic data that guarantee it to have a faithful status description about the real system how it is evolving. As result, each DT will be able to send back to eah of the forementioned parts, i.e., physical twin, other DTs in the environment, domain experts, useful insights and prescriptions for system maintenance and optimization. Once the communication framework is enstablished, DTs also need access to a *data storage systems*. This will be firstly useful to store historical data that reflect the physical twin memory and describe important characteristics of it that must not change over time [30]. In addition to this static data, the DT also needs to store dynamic data received from the physical twin and eventually from others DTs located in the surrounded environment. However, these data also require to be categorized and analyzed in order to, as mentioned earlier, obtain consistent and accurate understanding aimed at deriving useful predictions and insights for system maintenance and optimizations. This will be possible through the usage of efficient high-dimensional data analysis techniques and data fusion algorithms, which must be embedded within the DT. In this context AI based algorithms like feature selection and feature extraction tasks represent important tools to enable and provide a proper closed-loop optimization process aimed at optimising the physical system [31]. In particular, the usage of tools like pattern recognition, unsupervised/supervised learning, and statistical applications, will enable a DT to completely characterizes and understand

input data from the real physical twin and/or the surrounding environment [32], resulting then into a very powerful 6G-oriented paradigm which will find application in different sectors such as manufacturing, aviation, autonomous systems and healthcare.

III. Recent works on DT for 6G oriented services

As already discussed in previous sections, even if DT can be viewed as a 6G oriented service, DT concept and 6G architecture represent two strictly complementary concepts. In light of that, a systematic review of the most recent and scientific relevant works on DT enabled 6G oriented services will be provided in this section. Furthermore, based on the more relevant areas in which potentialities of DT have been investigated, a classification of these works is also provided with a respective subsection. This classification is illustrated in Fig. II and works are reviewed in the respective subsections.
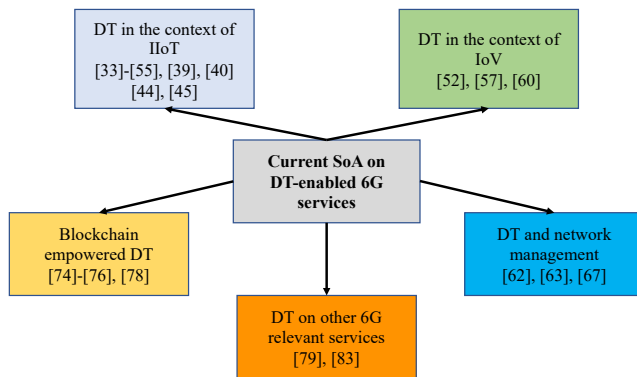

FIGURE 3. Classification of Current SoA on DT-enabled 6G services.

A. DT in the context of IoT

As mentioned earlier, nowadays the Internet of Things (IoT) vision is continuously extending into a lot of different sectors including also the industrial environment, bringing then to the development of complex scenarios like IoT. Indeed, this type of scenario will have multiple and heterogeneous devices working in the same area but adopting different protocols and data formats. Then guaranteeing a good level of coordination between them to support industrial operations, i.e., manufacturing and assembly, with stringent QoS and safety critical requirements can result into a very difficult task to achieve. In this context, layering and separating functionalities within the industrial environment will play the a key role to dynamically control the communications between different industrial devices according to applications and context requirements. However, there is still the problem of network heterogeneity since currently industrial environments are composed of several IP sub-nets, each of them containing a small set of strictly related equipment collaborating to complete a specific task. These sub-nets

are connected through network gateways that are usually manually configured, which represents a time-consuming and prone to error operation that discourages the dynamic reconfiguration of industrial networks. With the aim of address this issues, authors in [33] presented an Application-driven digital twin networking (ADTN) middleware that supports the interaction simplification with heterogeneous distributed industrial devices, as well as the maximization of QoS in industrial environments by dynamically managing network resources. To reach these objectives, they proposed a layered architecture consisting of a physical layer containing physical devices, an edge layer containing a DT and an Edge Network manager, and a control room having a clear picture of both physical and virtual environment. The main purpose of the proposed ADTN, is to support the dynamic aggregation and configuration of heterogeneous industrial devices, i.e., sensors, actuators, and simple devices, as well as their orchestration through an optimized Software Defined Network (SDN) framework based on a cross-layer approach which takes into consideration application-specific QoS requirements and network configuration capabilities. Through computer simulation it has been highlighted how the proposed ADTN is able to significantly lower the management complexity of the industrial environments, as well as to maximize the efficient dispatching of data packets.

Authors in [34] proposed an intelligent edge-based DT for robotics application, where the set of intelligence capabilities, aimed at facilitate and enhanced automation and control operations, like task learning, prediction and optimization, are mainly offloaded to an intelligent computing, i.e., DT, placed at the edge of the network. More in details, they proposed a DT consisted in a computation stack model containing the operational states of the robot, its control flexibility and behaviour,and an analytic stack module aimed at monitoring, simulating and predicting the behavior of the physical robot through the adoption AI/ML modules. An End-to-End (E2E) scenario has been considered to implement and validate the proposed solution through set of experiments. Furthermore, it has been highlighted the importance of having a 5G/6G architecture in order to fulfill the networking requirements for offloading the robot's modules to the edge. Last but not least, it has been also showcased how the intelligence module can play a key role to ease automation and optimization, i.e. re-configuring the robot's parameters, by guaranteeing the best performance of the task process.

The concept of DT in the context of hazardous gas detection and tracking during factory production processes has been presented in [35]. Indeed, during factory production processes there is always the possibility that flammable and toxic gases are released, which can accumulate in local areas after a period of time with the risk of reaching high concentrations that can either burn or explode when exposed to fire or to a change of pressure. For this reason, monitoring harmful industrial gases represents an important industrial

automation task that can both prevent heavy disasters and casualties. Then, in this view authors analyzed an IoT scenario where several sensors are deployed within the industrial area to be monitored in terms of gas concentration. Those sensors, referred as perception layer, are organized in clusters. For each cluster there is a cluster head that collects gas concentration data from each node within its respective cluster and sends it to the network edge layer, which keep DT representation of each sensing node. Finally, there is the control layer composed of multiple cloud servers, which connect the base stations of the edge layer to the cloud which is in charge of allocating resources for the sensing data collection task. Based on this three-layer structure, a two-stage industrial hazardous gas tracking algorithm referred as ST-COM has been proposed. This algorithm, which is based on a state transition model has been proven to obtain good levels of gas diffusion boundary for early warning, as well as to reduce communication delay time between layers and maximise the energy efficiency of perception layer, i.e., energy consumption for data reporting. Extensive simulation results highlighted how, compared with other gas detection algorithms presented in literature [36], [37], the proposed gas detection algorithm achieve better performances in terms of average communication delay, reduced energy consummation, and lower error detection.

In order to support the development of of smart and autonomous processes envisaged in the context of Industry 4.0 the enhancement of DT with AI concept represents a very strong candidate. Indeed, thanks to the possibility of having AI/ML enabled mechanism monitoring industrial processes allows to improve agility, cost efficiency, and user experience [38]. Due to it s importance, a discussion about the role of AI in addressing some of the most relevant challenges in Industry 4.0, mainly related to the DT has been provided in [39]. They firstly introduced the concept of DT based on cloud, edge and fog computing, integrating also emerging networking technologies such as 5G and WiFi 6E. Subsequently, they carried out an experimental validation in order to highlight how AI agent result beneficial in order to predict the next movement(s) of a robotic arm by using real data as input for the DT.

Another work related to the application of the DT concept in the context of IoT has been presented in [40]. Even in this work it has been highlighted how, in order to increase processing efficiency and prolong battery lifetime, IoT networks needs to offload tasks at the edge of the network. However, in contrast with other works considering a similar scenario, in this case it has been highlighted the importance of considering the randomness of tasks arrival at the edge servers which is a more reasonable assumption [41], [42]. In this view, they proposed a computation offloading mechanisms for DT Networks (DTN) aimed at minimising the network efficiency, which is the ratio between long-term total energy consumption and the corresponding long-term aggregate time required to accomplish the computation tasks.

The algorithm is based on deep reinforcement Learning (DRL) Empowered Stochastic computation which jointly optimize the transmission power, the required bandwidth, and resource allocation for computation offloading. It has been validated through numerical simulations carried out by varying the number of devices, the number of the edge servers, as well as parameters of the DRL algorithm. In particular they used an asynchronous actor-critic (AAC) based algorithm which outperforms in terms of lower system cost respect to a deep-Q network (DQN).

In the context of manufacturing, depending on the type of operations required to complete a specific process through closed-loop feedback mechanisms, the DT can be classified as *i)* a monitor which provides information about operational states of the respective physical objects, *ii)* a simulation/emulation entity, containing machine learning models aimed at predicting and describing the behaviour of the physical, and *iii)* an operational entity recommending actions manufacturing worker aimed at enhancing the industrial process. In this way, will be then possible the realization of platform independent services where a set of machinery and humans collaborate by establishing an efficient, agile and smart manufacturing environment [43]. In this is part of the 5G and Beyond 5G vision results then of paramount importance to understand how 5G/6G capabilities like smart orchestration, computation offloading and dynamic scaling are able to provide the required KPIs like low communication latency with high reliability, as well as required bandwidth and efficient scalability of the system. In this view, authors in [44] implemented and evaluated an Edge Robotics DT emboding the concept of DT operational as service. Through this study the provided evidence on how 5G/6G networks and more in particular Edge computing represent very essential technologies to support the most demanding DT use cases. In particular, compared to WiFi, 5G/6G RAN technology is able to provide better performances in terms of lower susceptibility to interference as well as in enabling remote control of 20 ms latency, which are essential for industrial and critical environments. On the other hand, offloading part of the software tasks at the edge of the network provides potential savings of 16% and 34% in terms of CPU and memory usage, respectively.

A Digital twin empowered URLLC-based edge network architecture for industrial automation has been proposed in [45]–[47]. More in details, they considered a scenario where a set of IoT devices needs to offload part of their task to edge servers, which should be offloaded and completed with the minimum latency in order to respect the URLLC constraints. In this case, an optimization problem aimed at minimizing the worst-case of the total DT latency by jointly optimizing user association, offloading policies, transmit power, and estimated processing rates of IoTs and Edge Servers, is firstly formulated. Subsequently, they proposed an iterative algorithm based on alternating optimization approach executed at the DT level. Through simulations they shown how the joint

optimization of communication and computation variables permits to further decrease the overall latency compared with other benchmarks like, fixed power, fixed frequency and fixed user association. This study has been further extended in [48] highlighting the importance of having optimal edge association policy and optimal offloading policy in order to reduce the overall end-to-end latency.

B. DT for Internet of Vehicles

The high proliferation of different types of sensors and their successful application into vehicles have contributed to the development of the so called IoV [49]–[51]. Within this concept we will assist to the constant development an deployment of DT for traffic data management. In particular, the possibility to analyse and perform minim with massive IoV data through DT will allow to make scientifically rational decisions in terms traffic resource management and optimization aimed at alleviating traffic jams. However, these mechanisms of traffic data analysis and pattern recognition must be able to deal with weather related exceptions, as well as change of the environment or battery issues at sensors, that cannot guarantee the 100% data availability of IoV sensors. This in turn will cause incomplete and sparse data collection from some sensors, raising then big challenges in terms of traffic condition predictions and traffic resource scheduling [52], [53]. In order to address this highly relevant issue, a time-efficient neighboring data search technique, named Locality-Sensitive Hashing strategy, have been proposed in [54]. The effectiveness of the proposed solution has been proven by conducting experiments by using real traffic data set collected from the traffic administration agency of Nanjing city of China. Based on the collected data set, it has been shown how respect the proposed method achieved better performances in terms of Mean Absolute Percentage Error, Mean Absolute Error and Root Mean Square Error, as well as in terms of less required computational time in providing a short-term traffic flow and velocity prediction, compared to Naive K-NN , Enhanced K-NN [55] and GRU [56].

The concept of vehicular edge computing represents another important paradigm that will contribute to the deployment of intelligent transportation system services. Indeed, even if compared with portable devices the processing power of smart vehicles can result powerful, intelligent transportation services often require the execution of computationally extensive tasks, which can be either partially or completely offloaded to another more processing powerful vehicle or road side units (RSU) with adequate computing power, respectively. However, since these scenario have to deal with the time-varying topology of vehicular networks, the resource competition between different offloading node pairs for task scheduling offloading can result to be a very complex optimization problem. Since the adoption of a centralized AI/ML manager scheduling all the resources for task offloading would represent beneficial in solving such optimization

problems [57], [58], it would result impractical due to massive connected smart vehicles, highly dynamic topology and limited wireless spectrum. In order to cope with this challenge, a new vehicular edge computing network based on DT and multi-agent learning has been proposed in [59]. Based on the potential matching relations between supply and demand of computing resources, the proposed framework resulted able to efficiently aggregates vehicles by greatly reducing the complexity of task offloading scheduling. In this case, each node of the network, i.e., vehicle, is represented in the DT as a logical entity with its own tasks, competing capability set, resource prices and available transmission rate sets. Through this representation vehicles are aggregated using a gravity based model [60] that measure the association between two nodes. Subsequently, based on this aggregation, a Coordination Graph based Multi-agent Deep Deterministic Policy Gradient (CG-based MADDPG) learning scheme is adopted to optimize edge resource allocation. The effectiveness of this model in reducing offloading cost compared with other benchmark schemes like, MADDPG without aggregation and independent learning, has been proven through numerical simulations carried out by using historical mobility traces of taxi cabs in San Francisco Bay area.

From what mentioned before, in the context of smart-vehicles network there is the requirement of disseminating and sharing huge amount and high diversity contents with stringent delays among vehicles. Nowadays, the usage of mobile edge caching paradigm has been labelled as a promising paradigm to alleviate this issue since it allows to reduce the content delivery time by bringing contents closer to end users. In addition, the possibility to cache contents locally at vehicles and subsequently shared through D2D communication represent an additional possible solution. Recently, the concept of social aware vehicular networks has obtained great attention in improving the content dispatch efficiency by using social characteristic of drivers [61]. Although these resulted to be very promising approaches for reducing the content delivery, they open several very unique challenges to be be addressed, like efficient management of both local and edge resources, and road traffic distribution according with channel quality and content popularity. Under this perspective, authors in [62] proposed a social-aware empowered vehicular edge networks DT caching architecture. In this case, the concept of DT has been exploited to gather data from the physical network to comprehensively capture vehicular social features by exploiting an internal long-short term Memory network. Furthermore, has been also empowered with a deep deterministic policy gradient learning approach aimed at maximizing the system utility providing an optimal vehicular caching cloud/edge caching in diverse traffic environments. The performance of the proposed schemes in terms of delay reduction, utility maximization and local caching probabilities has been validated through numerical simulations based on a real road map.

C. DT for network management

It is now fully clear and understood that one of the most critical aspect of 6G networks will be the presence of hundreds of billions of connected end devices that will generate a huge amount of data traffic. In this context, the DT paradigm has emerged as a promising technology that permits to optimize network resources at network edge in order to accomplish with users' requirements and what edge servers can provide [63]. However, 6G networks will result into a very heterogeneous scenario with dynamic network states. This means that there will be a plenty of dynamic network states creating the need to find solutions to resource optimization problems with increasing complexity. As result, the mapping relations between edge servers, that represents DTs with adequate computation resources, and respective end devices should be carefully designed. Recently, Mobile Edge Computing (MEC) paradigm has been highlighted to be a promising solution in addressing limitation issues faced to apply DT concept in 6G networks. In this regards, a DT empowered edge network model enriched with MEC paradigm has been proposed in [64]. They firstly designed a DT model for 6G wireless networks. Subsequently, they formulated an edge association problem where DT placement and DT migration have been considered in conjunction with dynamic network states and mobile end users. The main goal of this optimization problem was to place and mitigate DTs of users in the edge servers in order to reduce the average system latency and to improve user utility. An optimal solution for this highly complex problem has been derived with the of DRL and transfer learning. Through numerical simulation has been illustrated the effectiveness of the proposed solution in reducing the average system latency while improving the convergence rate respect to other benchmark approaches.

A DT assisted task offloading based for the support of mobile edge computing in 6G networks has been proposed in [65]. In that works, authors considered a scenario with a set of mobile users that, due to their computation constraint, need to offload some of their tasks to one or more edge servers in order to complete them within a certain amount of time constraint. This scenario poses then a double challenge in the selection of the best set of edge servers. In particular, in line with users requirements, edge servers should be selected with *i)* enough computation rate, and *ii)* the best channel condition. Indeed, both these requirements result essential in reducing the task completion. Furthermore also the security aspect is considered. Indeed, in order to avoid data leakage and tampering, all the transactions are supposed to be monitored through a blockchain structure, which owns the characteristics of data immutability and traceability. However, accomplish task offloading considering all these aspects can result to be time consuming. Then authors proposed to use a DT which hold a digital replicas of all the devices status, and run a DT based traffic offloading policy based on a Markow Decision Problem (MDP) formulation.

Simulation results shows how their proposed approach, obtained as decomposition of the original problem into two sub-optimization models, i.e., power reduction solved by Decision Tree Algorithm (DTA) and time overhead reduction solved Double Deep-Q-Learning (DDQN), outperform in terms of achieving lower latency and lower power consumption of the whole network, respect to other approaches proposed in literature [66], [67].

Beside the concept of federated learning, recently the Google AI team proposed the concept of federated analytics [68], which follows the same principle of federated learning but for different scope. In particular, federated analytics is intended for deriving analytical insights like model evaluation, data quality measurement and heavy hitter discovering from distributed data sets but without exposing the raw data. Then, this type of approach would result very useful in the context of IoT and IoV networks, were understanding data distribution would result beneficial for operational and behavioural purposes while preserving user privacy. Under this perspective, a DT for Federated Analytics Using a Bayesian based Approach has been proposed in [69]. In particular, they considered a scenario with a set of users were each user performs on-device private data analysis locally and upload it to the local edge server, which will provide a global data distribution estimation. In particular, this is performed through a federated Markov chain Monte Carlo with delayed rejection that, through numerical simulations, resulted able to achieve both 50% and 95% higher values of accuracy and convergence compared with Metropolis-Hastings algorithm and random walk Markov Chain Monte Carlo method.

D. Block Chain embedded Digital Twin

Due to their nature and definition, DT represents a digital copy of physical counterpart operating in the real physical world [70], which thanks to the sensory data collected from the real device will permit to build predictive models that are essential to optimize industrial operations as well as to monitor physical assets for their maintenance [71]. Then, according to this concept, DTs can be viewed as a dynamic entity always updated with real-time data from real objects that is processed in order to capture live performances. In order to achieve this objective of creating DTs that result flexible, scalable and resilient to operational changes, collaborations and interactions between different entities and developing teams represent a primary requirement. Furthermore, these interactions must be documented in order to ensure privacy, security, traceability and transparent history monitoring. [72]. However, the adoption of traditional methods with centralized managing authorities [70] does not represent the most efficient approach. On contrary, the adoption of a decentralized and distributed ledger has been recently labeled a more powerful and efficient solution to address this issue [73]–[75]. Under this perspective, authors in [76] conducted a study related to the design and implementation of a

decentralized blockchain-based solution aimed at guaranteeing secure and trusted traceability, as well as accessibility, immutability of transactions, logs, and data provenance in all the phases of DT development, i.e., from the design phase to the delivery phase. The entire creation process is based on the usage of Ethereum Smart Contract. In particular, this type of smart contract are intended to facilitate all DT's development phases in terms of logistics tracking as well as in managing all the history of transactions Information details of DTs are stored and shared using an InterPlanetary File System (IPFS) which ensures reliability, accessibility, and integrity of stored data. As result, in addition to be decentralized, the proposed blockchain-based solution result to be secure, immutable, tamper-proof, immutable, which represent essential needs of any industry. Security and cost analysis, as well as a public available smart-contract code, has been provided within the study.

According to what has been explained until now, the concept of DT in mainly characterized by a continuous online data collection from physical devices, which is then used to map these Cyber Physical Systems into living digital models that through the usage of data analytics will result helpful in performing precise decision making actions for resource allocation. A classical example can be represented by central cloud-based server collecting data about the environment and running states of IoT network devices in order to develop behavioural models based different possible states of the considered environment. However, this traditional computing architecture can incur into high communication load that would inevitably bring to network performance degradation, as well as data security issues. Under this perspective a Communication-Efficient model DT Edge Networks by exploiting the Federated Learning concept has been proposed in [77], which has been subsequently extend in [78] by incorporating Permissioned Blockchain to address data security issues. In particular, learning models based on local data from IoT devices are firstly constructed locally, i.e., at user plane level. Exploiting then the concept of Federated learning [79], local models are subsequently aggregated to construct DT models of IoT devices. Such aggregation model process to build a global model is performed at base stations (BS), which are equipped with the necessary computing and caching resources for executing the consensus process necessary for guaranteeing consistency in the global model through the permissioned blockchain. Since IoT devices have limited computing and communication resources, a deep neural network (DNN) for parameters transmission from IoT to BS has been also developed. Through extensive numerical simulations has been illustrated how, compared to other benchmark approach, i.e., traditional asynchronous model update and aggregation, the integrated blockchain and federated learning scheme resulted able to provide comparable accuracy but with considerably higher efficiency.

In the context of DT environment, data integrity and protection deserves also attention. Indeed, if data stored into the DT is lost or tampered, analysis results will deviate greatly. Then, at DT level there is the need of performing integrity check before feeding the simulation data. Under this perspective, an analysis on the importance of data integrity checking and time state verification for DT security has been conducted in [80]. Furthermore they also proposed a synchronized provable data possession (PDP) scheme based on the blockchain technology, which represented the first blockchain synchronization service able to enable all entities to access the same clock. It has been designed in order to guarantee anonymity, unforgeability and high detectable probability. Furthermore, it is provably secure since it is based on RSA. Through implementation and efficiency analysis it has also been illustrated how the proposed synchronization service results to be practical in the DT based environments, as well as how its communication latency is reasonable with most of the DT use case requirements.

E. Other DT use cases

Due to the potentialities provided by the DT technology, authors in [81] proposed a novel DT- based intelligent framework aimed at facilitating the implementation of resource-intensive algorithms in UAV swarm. In particular, it has been considered a scenario where a UAV swarm is employed to carry out tasks supervised by an intelligent controller equipped with high computation and data processing units for both building virtual high-fidelity representation of the physical and performing complicated calculations aimed at providing intelligent cooperation decisions. More specifically, the considered controller contains artificial intelligence and data analytics mechanisms aimed at exploring global optimal strategies. Furthermore it is also able to control the physical entity through a virtual-physical interface. The overall structure is considered in the context of a time-varying environment where UAV swarm missions are classified depending on their requirements on bandwidth, latency, throughput, and packet loss. Then, the controller train a DNN that, based on data analysis and mission requirements, select the optimal medium access control mode among CSMA/CA [82], DTDMA [83], ESTDMA protocol which is used for multi-hop communication with slight modification of STDMA [84]. Simulation results illustrated how the controller is able to provide efficient decisions and to release them to the physical entity in a very timely way.

Recently, a new vision for DT, referred as Spiral DT framework, has been presented in [85]. Basically, in addition to the classical 3-D vision of DT containing a physical product (PP), a virtual product (VP) and optimization utility for improving the performances of the product through the collected data, this 6-D representation also contains performance data generated by the PP, a spiral ring, where each ring is intended to represent an improved version of PP, and a dynamicity part referring to the fact that every improved version of the PP generates an improved version of the VP itself. With such DT structure, it is envisaged

that a better optimization, efficiency, and management of production process can be provided. Furthermore, it is envisaged the integration of quantum-resilient blockchain within this structure, which will replace "ECDSA" with quantum-safe hash-based signatures, providing then an immediate confirmation of time critical transactions.

IV. Challenges and Future Directions

From what described and illustrated above, it is clear how DT technology represents a very important key enabling technology for the deployment of 6G oriented services. However, this research field is still at its infancy stage and with some important issues and challenges that, at the time of writing, still need to be further studied and addressed.

A. Infrastructure and connectivity

One of the first challenges that need to be faced for the deployment of DT based services is related to infrastructure and connectivity. Indeed, by definition DT will require high-performance information technology infrastructures able to operate, manage and execute intensive and computation hungry machine and deep learning algorithms. To achieve this purpose it will results necessary the usage of high-performance graphics processing unit (GPUs), which can currently have a cost up to $10.000 each depending on the specific technical needs. This can represent a huge CAPEX to face depending on the size of the DT features needed. In order to overcome this challenge the concept of GPU's as a service will play an important role. In this way, big leading companies like Google, Amazon and Microsoft are envisioned to provide unique on-demand services similar to traditional cloud-based applications, breaking the barrier of high costs.

On the other hand, providing connectivity between a DT and its physical twin (PT) system represents another important challenge, especially when a large number of sensors needs to be connected simultaneously and with real-time controlling requirement. Indeed, since sensors and more in general IoT devices represent source of feeding data to AI algorithms, missing IoT data from one or more devices due to connectivity failure, could affect the accuracy of data mining and then the performance of the running system. Then a good level of connectivity and robust solutions to prevent power outages at sensors and software errors need to be developed.

B. Data Accuracy and Consistency

As mentioned earlier, one of the most important requirements for the implementation of a DT is the availability of consistent data from the PT counterpart in real-time. This will permit to have an high fidelity representation of all the processes running into the physical entity, enabling then the possibility to take action aimed at optimizing the entire process flow of the considered system, as well as to predict particular configuration scenarios that need particular

attention. For example, in the case of industrial IoT processes, the availability of high fidelity data of all the involved machinery can result useful to increase the efficiency of the entire production line. Another case can be related to the vehicular scenarios where an high fidelity representation of vehicles in a city can result useful in preventing either traffic jams or collision through the proper management of the traffic light system. Similar to the vehicular scenario, a high-fidelity representation of a communication network infrastructure and related users can permit to predict traffic overload of the network and then design an optimal network configuration for its management. Although rate of synchronization and virtual representation's fidelity are specific to the DT's use-cases, missing data from one of multiple entities in the context may cause degradation of the entire system performances. This means that data exchanged between DT and PT must be constant, uninterrupted and noise-free. If the data is poor and inconsistent, it runs the risk of the DT underperforming as it is acting on poor and missing data.

C. Mobile users management

Mobility is another important challenge that needs to be addressed especially in the context of IoV oriented applications. Indeed, continuous and seamless connectivity must be guaranteed to smart vehicles in order to avoid that a mobile device associated with DT system might incur into service interruption due to moving outside the coverage area of the access point or base station associated with the twin. A possible solution might be consider the handover to another DT object based on user mobility prediction. Then, the development of very accurate mobility prediction model as well as efficient solutions for both model and learning transfer from a DT to another before that the PT will connect to the new DT must be developed.

D. Massive Access of IoT devices

Beside user mobility, the management of massive number of IoT envisioned in 6G network represents another crucial challenge to deal with [86]. Indeed, the grant-based random access protocols commonly adopted into current networks may lead to long scheduling delays or, even worse, will result impossible to some devices to have access to the network. This because, in order for accessing the wireless network, grant-based random access protocols require each user to choose a preamble from a pool of orthogonal sequences. These sequences are chosen from a finite set and then the probability that two or more devices would choose the same random access sequence is high. This cause the lost of synchronization between DT and PT since the last one is required to periodically through a random access procedure in order to establish a connection with its respective DT replica. Currently, the most common approach in order to address this issue is represented by the design of appropriate multiple access techniques. However, the realization of new

multiple access techniques is not trivial. This because there is a lack of information theoretic concepts since short packets are usually employed in massive access while conventional multiple access theory is based on long message transmission. Another possible open direction can be represented by starting to use DTs of the network in order to perform an appropriate resource allocation aimed at guaranteeing network access to all the devices located in the area of interest, and scale-up the procedure when a massive number of devices will be introduced. Then, new scalable approaches need to be designed and proposed.

E. Data Security and Privacy

One of the key component for the realization of a DT is the communication medium between the DT and its physical counterpart. Since there will be a continuous data flow exchange between DT and PT, it is clear how guaranteeing data protection and privacy represents an essential requirement, especially in the context of IoT and autonomous driving systems. Indeed, there is the risk of a vast amount of sensitive data that can be breached. In this way, the implementation of DT must follow the current practices and updates in security and privacy regulations. Furthermore, increased attention to preserving data integrity is also required since the risk of losing important information is high when data flows to, and from, the real twin, or in-between the servers hosting the DT itself. Last but not least, another important point to be addressed is related to the trust issues with DT. In particular, in addition to tackle with mechanisms for data security it will result necessary to put in place mechanisms which can permit to understand if a DT is trustful or not. Then, it is clear how the communication links between DTs and their PTs represents a potential area of weakness in terms of data corruption and breach that can create disturbances for businesses. Currently, approaches to deal with these issues include the usage blockchain technologies to ensure data privacy and integrity as well as trust and transparency in various use cases. However, the DT security related literature is still at its infancy stage.

V. Conclusion

This paper contains a systematic review ont the current SoA in the field of DT-based 6G oriented services and applications. A brief overview about the most relevant KPI and challenges for the implementation of 6G networks has been firstly provided. Subsequently, it has been highlighted how the concept of DT paradigm can results complementary to the delivery of 6G IoT oriented services, and then a classification and systematic review and of the recent research activities currently found in literature has been provided. The paper is finally concluded by illustrating the main challenges currently faced for the deployment of DT technology as well as future direction in this area.

REFERENCES

[1] ITU-R, "IMT Traffic Estimates for the Years 2020 to 2030," July 2015.
[2] W. Jiang, B. Han, M. A. Habibi, and H. D. Schotten, "The road towards 6g: A comprehensive survey," *IEEE Open Journal of the Communications Society*, vol. 2, pp. 334–366, Feb. 2021.
[3] H. Viswanathan and P. E. Mogensen, "Communications in the 6g era," *IEEE Access*, vol. 8, pp. 57 063–57 074, Mar. 2020.
[4] W. Saad, M. Bennis, and M. Chen, "A vision of 6g wireless systems: Applications, trends, technologies, and open research problems," *IEEE Network*, vol. 34, no. 3, pp. 134–142, Jun. 2020.
[5] R. Saracco, "Digital twins: Bridging physical space and cyberspace," *Computer*, vol. 52, no. 12, pp. 58–64, Dec. 2019.
[6] M. Raza, P. M. Kumar, D. V. Hung, W. Davis, H. Nguyen, and R. Trestian, "A digital twin framework for industry 4.0 enabling next-gen manufacturing," in *Proc. 9th International Conference on Industrial Technology and Management (ICITM)*, 11-13 Feb 2020, pp. 73–77.
[7] C. Altun, B. Tavli, and H. Yanikomeroglu, "Liberalization of digital twins of iot-enabled home appliances via blockchains and absolute ownership rights," *IEEE Communications Magazine*, vol. 57, no. 12, pp. 65–71, Dec. 2019.
[8] G. Szabó, S. Rácz, N. Reider, H. A. Munz, and J. Pető, "Digital twin: Network provisioning of mission critical communication in cyber physical production systems," in *Proc. IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT)*, 01-03 Jul 2019, pp. 37–43.
[9] Y. Xu, Y. Sun, X. Liu, and Y. Zheng, "A digital-twin-assisted fault diagnosis using deep transfer learning," *IEEE Access*, vol. 7, pp. 19 990–19 999, Jan. 2019.
[10] R. Revetria, F. Tonelli, L. Damiani, M. Demartini, F. Bisio, and N. Peruzzo, "A real-time mechanical structures monitoring system based on digital twin, iot and augmented reality," in *Proc. Spring Simulation Conference (SpringSim)*, 29 April - 02 May 2019, pp. 1–10.
[11] Y. Lu, C. Liu, K. I.-K. Wang, H. Huang, and X. Xu, "Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues," *Robotics and Computer-Integrated Manufacturing*, vol. 61, p. 101837, Feb 2020.
[12] H. X. Nguyen, R. Trestian, D. To, and M. Tatipamula, "Digital twin for 5g and beyond," *IEEE Communications Magazine*, vol. 59, no. 2, pp. 10–15, Feb. 2021.
[13] F. Foo, "Digital Twins Catalyst Reflections from Digital Transformation World, https://www.ericsson.com/en/blog/2019/6/digital-twins-catalyst-booth-reflections-from-digital-transformation-world," Jun 2019.
[14] Huawei, "Huawei Launches Industry's First Site Digital Twins Based 5G Digital Engineering Solution, https://www.huawei.com/en/news/2020/2/site-digital-twins-based-5g-digital-engineering-solution," Feb 2020.
[15] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2405–2415, Apr. 2019.
[16] S. Mumtaz, A. Alsohaily, Z. Pang, A. Rayes, K. F. Tsang, and J. Rodriguez, "Massive internet of things for industrial applications: Addressing wireless IIoT connectivity challenges and ecosystem fragmentation," *IEEE Industrial Electronics Magazine*, vol. 11, no. 1, pp. 28–33, Mar. 2017.
[17] C. Perera, C. H. Liu, and S. Jayawardena, "The emerging internet of things marketplace from an industrial perspective: A survey," *IEEE Transactions on Emerging Topics in Computing*, vol. 3, no. 4, pp. 585–598, Dec. 2015.
[18] J. Tan, X. Sha, B. Dai, and T. Lu, "Wireless Technology and Protocol for IIoT and Digital Twins," in *Proc ITU Kaleidoscope: Industry-Driven Digital Transformation (ITU K)*, 7-11 Dec 2020, pp. 1–8.
[19] C. Schwarz and Z. Wang, "The role of digital twins in connected and automated vehicles," *IEEE Intelligent Transportation Systems Magazine*, pp. 2–11, Jan. 2022.
[20] NASA, "The Ill-Fated Space Odyssey of Apollo 13, https://nssdc.gsfc.nasa.gov/planetary/lunar/apollo13.pdf," 2002.
[21] M. Grieves and J. Vickers, "Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems," *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches*, pp. 85–113, Aug 2017.

This article has been accepted for publication in IEEE Open Journal of the Communications Society. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/OJCOMS.2022.3219015

A. Masaracchia *et al.*: Preparation of Papers for IEEE OPEN JOURNALS

[22] K. Främling, J. Holmström, T. Ala-Risku, and M. Kärkkäinen, "Product agents for handling information about physical objects," in *Processing Science Report code: TKO-B 153/03*, Nov 2003.

[23] NASA, "Draft Modeling, Simulation, Information Technology & Processing Roa, https://ai.googleblog.com/2020/05/federated-analyticscollaborative-data.html," Nov 2010.

[24] E. J. Tuegel, A. R. Ingraffea, T. G. Eason, and S. M. Spottswood, "Reengineering aircraft structural life prediction using a digital twin," *International Journal of Aerospace Engineering*, vol. 2011, Oct 2011.

[25] E. Tuegel, "The airframe digital twin: Some challenges to realization," in *Prc. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*, Apr 2012.

[26] B. Gockel, A. Tudor, M. Brandyberry, R. Penmetsa, and E. Tuegel, "Challenges with structural life forecasting using realistic mission profiles," in *Proc. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*, Apr 2012.

[27] U. A. Force, "Global Horizons Final Report: United States Air Force Global Science and Technology Vision, https://www.hsdl.org/?view&did=741377," October 2019.

[28] K. Hribernik, T. Wuest, and K.-D. Thoben, "Towards product avatars representing middle-of-life information for improving design, development and manufacturing processes," in *Digital Product and Process Development Systems*, Oct 2013, pp. 85–96.

[29] B. R. Barricelli, E. Casiraghi, and D. Fogli, "A survey on digital twin: Definitions, characteristics, applications, and design implications," *IEEE Access*, vol. 7, pp. 167 653–167 671, Nov. 2019.

[30] D. Kiritsis, "Closed-loop plm for intelligent products in the era of the internet of things," *Computer-Aided Design*, vol. 43, no. 5, pp. 479–501, May 2011.

[31] Q. Qi and F. Tao, "Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison," *IEEE Access*, vol. 6, pp. 3585–3593, Jan. 2018.

[32] K. Warmefjord, R. Sderberg, L. Lindkvist, B. Lindau, and J. S. Carlson, "Inspection Data to Support a Digital Twin for Geometry Assurance," in *Proc. ASME International Mechanical Engineering Congress and Exposition*, Nov 2017.

[33] P. Bellavista, C. Giannelli, M. Mamei, M. Mendula, and M. Picone, "Application-driven network-aware digital twin management in industrial edge environments," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 11, pp. 7791–7801, Nov. 2021.

[34] L. Girletti, M. Groshev, C. Guimarães, C. J. Bernardos, and A. de la Oliva, "An intelligent edge-based digital twin for robotics," in *Proc. IEEE Globecom Workshops*, 07-11 December 2020, pp. 1–6.

[35] Z. Lv, J. Wu, Y. Li, and H. Song, "Cross-layer optimization for industrial internet of things in real scene digital twins," *IEEE Internet of Things Journal*, vol. 9, no. 17, pp. 15 618 – 15 629, Sep 2022.

[36] W. Xia, M. Sun, and Q. Wang, "Direct target tracking by distributed gaussian particle filtering for heterogeneous networks," *IEEE Transactions on Signal Processing*, vol. 68, pp. 1361–1373, Feb 2020.

[37] J. Yan, J. Dai, W. Pu, S. Zhou, H. Liu, and Z. Bao, "Quality of service constrained-resource allocation scheme for multiple target tracking in radar sensor network," *IEEE Systems Journal*, vol. 15, no. 1, pp. 771–779, Mar. 2021.

[38] K. Xia, C. Sacco, M. Kirkpatrick, C. Saidy, L. Nguyen, A. Kircaliali, and R. Harik, "A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence," *Journal of Manufacturing Systems*, vol. 58, pp. 210–230, Jan. 2021.

[39] M. Groshev, C. Guimarães, J. Martín-Pérez, and A. de la Oliva, "Toward intelligent cyber-physical systems: Digital twin meets artificial intelligence," *IEEE Communications Magazine*, vol. 59, no. 8, pp. 14–20, Aug. 2021.

[40] Y. Dai, K. Zhang, S. Maharjan, and Y. Zhang, "Deep reinforcement learning for stochastic computation offloading in digital twin networks," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 7, pp. 4968–4977, Jul. 2021.

[41] Y. Mao, J. Zhang, S. H. Song, and K. B. Letaief, "Stochastic joint radio and computational resource management for multi-user mobile-edge computing systems," *IEEE Transactions on Wireless Communications*, vol. 16, no. 9, pp. 5994–6009, 2017.

[42] S. Mao, S. Leng, S. Maharjan, and Y. Zhang, "Energy efficiency and delay tradeoff for wireless powered mobile-edge computing systems with multi-access schemes," *IEEE Transactions on Wireless Communications*, vol. 19, no. 3, pp. 1855–1867, Mar. 2020.

[43] F. Tao and Q. Qi, "New IT driven service-oriented smart manufacturing: Framework and characteristics," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 49, no. 1, pp. 81–91, Jan. 2019.

[44] M. Groshev, C. Guimarães, A. De La Oliva, and R. Gazda, "Dissecting the impact of information and communication technologies on digital twins as a service," *IEEE Access*, vol. 9, pp. 102 862–102 876, Jul. 2021.

[45] D. Huynh, V. Nguyen, V. Sharma, O. Dobre, and T. Duong, "Digital twin empowered ultra-reliable and low-latency communications-based edge networks in industrial IoT environment," in *Proc. IEEE International Conference on Communications (ICC'22)*, 16-20 May 2022.

[46] D. V. Huynh, S. R. Khosravirad, A. Masaracchia, O. A. Dobre, and T. Q. Duong, "Edge intelligence-based ultra-reliable and low-latency communications for digital twin-enabled metaverse," *IEEE Wireless Commun. Lett*, vol. 11, no. 8, pp. 1733–1737, Aug. 2022.

[47] D. V. Huynh, V.-D. Nguyen, S. R. Khosravirad, V. Sharma, O. A. Dobre, and T. Q. Duong, "URLLC edge networks with joint optimal user association, task offloading and resource allocation: A digital twin approach," *IEEE Trans. on Commun.*, pp. 1–1, Sep. 2022.

[48] T. Do-Duy, D. Van Huynh, O. A. Dobre, B. Canberk, and T. Q. Duong, "Digital twin-aided intelligent offloading with edge selection in mobile edge computing," *IEEE Wireless Communications Letters*, vol. 11, no. 4, pp. 806–810, Apr. 2022.

[49] V. Jirkovský, M. Obitko, and V. Mařík, "Understanding data heterogeneity in the context of cyber-physical systems integration," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 2, pp. 660–667, Jul. 2017.

[50] Y. Zhang, J. Pan, L. Qi, and Q. He, "Privacy-preserving quality prediction for edge-based iot services," *Future Generation Computer Systems*, vol. 114, pp. 336–348, Jan. 2021.

[51] X. Xu, Z. Fang, J. Zhang, Q. He, D. Yu, L. Qi, and W. Dou, "Edge content caching with deep spatiotemporal residual network for iov in smart city," *ACM Trans. Sen. Netw.*, vol. 17, no. 3, p. 1–33, Jun 2021.

[52] Y. Li, X. Jiang, H. Zhu, X. He, S. Peeta, T. Zheng, and Y. Li, "Multiple measures-based chaotic time series for traffic flow prediction based on bayesian theory," *Nonlinear Dynamics*, vol. 85, no. 1, pp. 179–194, Jul 2016.

[53] X. Wang, L. T. Yang, Y. Wang, L. Ren, and M. J. Deen, "ADTT: A highly efficient distributed tensor-train decomposition method for IIoT big data," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 3, pp. 1573–1582, Jan. 2021.

[54] C. Hu, W. Fan, E. Zeng, Z. Hang, F. Wang, L. Qi, and M. Z. A. Bhuiyan, "Digital twin-assisted real-time traffic data prediction method for 5g-enabled internet of vehicles," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 4, pp. 2811–2819, May 2022.

[55] F. G. Habtemichael and M. Cetin, "Short-term traffic flow rate forecasting based on identifying similar traffic patterns," *Transportation Research Part C: Emerging Technologies*, vol. 66, pp. 61–78, May 2016.

[56] S. Wang, J. Zhao, C. Shao, C. Dong, and C. Yin, "Truck traffic flow prediction based on lstm and gru methods with sampled gps data," *IEEE Access*, vol. 8, pp. 208 158–208 169, Nov. 2020.

[57] H. Fatemidokht, M. K. Rafsanjani, B. B. Gupta, and C.-H. Hsu, "Efficient and secure routing protocol based on artificial intelligence algorithms with uav-assisted for vehicular ad hoc networks in intelligent transportation systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 7, pp. 4757–4769, Jan. 2021.

[58] Y. Dai, K. Zhang, S. Maharjan, and Y. Zhang, "Deep reinforcement learning for stochastic computation offloading in digital twin networks," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 7, pp. 4968–4977, Jul. 2021.

[59] K. Zhang, J. Cao, and Y. Zhang, "Adaptive digital twin and multi-agent deep reinforcement learning for vehicular edge computing and networks," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 2, pp. 1405–1413, Jun. 2022.

[60] J. E. Anderson, "The gravity model," *Annual Review of Economics*, vol. 3, no. 1, pp. 133–160, Sep. 2011.

[61] X. Wang, Z. Ning, M. Zhou, X. Hu, L. Wang, Y. Zhang, F. R. Yu, and B. Hu, "Privacy-preserving content dissemination for vehicular social networks: Challenges and solutions," *IEEE Communications Surveys Tutorials*, vol. 21, no. 2, pp. 1314–1345, Nov. 2019.

[62] K. Zhang, J. Cao, S. Maharjan, and Y. Zhang, "Digital twin empowered content caching in social-aware vehicular edge networks," *IEEE*

Transactions on Computational Social Systems, vol. 9, no. 1, pp. 239–251, Feb. 2022.

[63] T. H.-J. Uhlemann, C. Lehmann, and R. Steinhilper, "The digital twin: Realizing the cyber-physical production system for industry 4.0," *Procedia CIRP*, vol. 61, pp. 335–340, Nov. 2017.

[64] Y. Lu, S. Maharjan, and Y. Zhang, "Adaptive edge association for wireless digital twin networks in 6g," *IEEE Internet of Things Journal*, vol. 8, no. 22, pp. 16 219–16 230, Jul. 2021.

[65] T. Liu, L. Tang, W. Wang, Q. Chen, and X. Zeng, "Digital-twin-assisted task offloading based on edge collaboration in the digital twin edge network," *IEEE Internet of Things Journal*, vol. 9, no. 2, pp. 1427–1444, Jan. 2022.

[66] U. Saleem, Y. Liu, S. Jangsher, X. Tao, and Y. Li, "Latency minimization for d2d-enabled partial computation offloading in mobile edge computing," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 4, pp. 4472–4486, Apr. 2020.

[67] P. Yang, Y. Zhang, and J. Lv, "Load optimization based on edge collaboration in software defined ultra-dense networks," *IEEE Access*, vol. 8, pp. 30 664–30 674, Feb. 2020.

[68] S. M. D. Ramage, "Federated analytics: Collaborative data science without data collection, https://ai.googleblog.com/2020/05/federated-analyticscollaborative-data.html," May 2020.

[69] D. Chen, D. Wang, Y. Zhu, and Z. Han, "Digital twin for federated analytics using a bayesian approach," *IEEE Internet of Things Journal*, vol. 8, no. 22, pp. 16 301–16 312, Nov. 2021.

[70] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, "Digital twin-driven product design, manufacturing and service with big data," *The International Journal of Advanced Manufacturing Technology*, vol. 94, pp. 3563–3576, Feb. 2018.

[71] B. Schleich, N. Anwer, L. Mathieu, and S. Wartzack, "Shaping the digital twin for design and production engineering," *CIRP Annals - Manufacturing Technology*, vol. 66, no. 1, Apr. 2017.

[72] C. Mandolla, A. Messeni Petruzzelli, G. Percoco, and A. Urbinati, "Building a digital twin for additive manufacturing through the exploitation of blockchain: a case analysis of the aircraft industry," *Computers in industry*, vol. 109, pp. 134 – 152, Aug. 2019.

[73] A. Dorri, S. S. Kanhere, R. Jurdak, and P. Gauravaram, "Blockchain for iot security and privacy: The case study of a smart home," in *Proc. IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, 13-17 March 2017, pp. 618–623.

[74] H. R. Hasan and K. Salah, "Combating deepfake videos using blockchain and smart contracts," *IEEE Access*, vol. 7, pp. 41 596–41 606, Mar. 2019.

[75] P. Ruan, G. Chen, T. T. A. Dinh, Q. Lin, B. C. Ooi, and M. Zhang, "Fine-grained, secure and efficient data provenance on blockchain systems," *Proc. VLDB Endow.*, vol. 12, no. 9, p. 975–988, May 2019.

[76] H. R. Hasan, K. Salah, R. Jayaraman, M. Omar, I. Yaqoob, S. Pesic, T. Taylor, and D. Boscovic, "A blockchain-based approach for the creation of digital twins," *IEEE Access*, vol. 8, pp. 34 113–34 126, Feb 2020.

[77] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Communication-efficient federated learning for digital twin edge networks in industrial iot," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 8, pp. 5709–5718, Aug. 2021.

[78] ——, "Communication-efficient federated learning and permissioned blockchain for digital twin edge networks," *IEEE Internet of Things Journal*, vol. 8, no. 4, pp. 2276–2288, Feb. 2021.

[79] ——, "Blockchain and federated learning for 5g beyond," *IEEE Network*, vol. 35, no. 1, pp. 219–225, Feb. 2021.

[80] T. Li, H. Wang, D. He, and J. Yu, "Synchronized provable data possession based on blockchain for digital twin," *IEEE Transactions on Information Forensics and Security*, vol. 17, pp. 472–485, Jan. 2022.

[81] L. Lei, G. Shen, L. Zhang, and Z. Li, "Toward intelligent cooperation of uav swarms: When machine learning meets digital twin," *IEEE Network*, vol. 35, no. 1, pp. 386–392, Feb. 2021.

[82] G. Bianchi, "Performance analysis of the ieee 802.11 distributed coordination function," *IEEE Journal on Selected Areas in Communications*, vol. 18, no. 3, pp. 535–547, Mar. 2000.

[83] L. Lei, S. Cai, C. Luo, W. Cai, and J. Zhou, "A dynamic tdma-based mac protocol with qos guarantees for fully connected ad hoc networks," *Telecommunication Systems*, vol. 60, no. 1, p. 43–53, Sept 2015.

[84] S. Cui, H. Yousefi zadeh, and X. Gu, "An optimal power control algorithm for stdma mac protocols in multihop wireless networks," *IEEE Transactions on Wireless Communications*, vol. 15, no. 5, pp. 3131–3142, May 2016.

[85] A. Khan, F. Shahid, C. Maple, A. Ahmad, and G. Jeon, "Toward smart manufacturing using spiral digital twin framework and twinchain," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 2, pp. 1359–1366, Feb. 2022.

[86] X. Chen, D. W. K. Ng, W. Yu, E. G. Larsson, N. Al-Dhahir, and R. Schober, "Massive access for 5g and beyond," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 3, pp. 615–637, 2021.

Antonino MAsaracchia (Member, IEEE) received the Ph.D. degree in electronics and telecommunications engineering from the University of Palermo, Italy, in 2016. From 2017 to 2018, he was a Post-doctoral Researcher at the Sant' Anna School of Advanced Studies, the BioRobotics Institute. Since September 2018, he has been a Research Fellow with the Centre for Wireless Innovation, Queens University Belfast, U.K. His research interests include fifth generation (5G) and beyond 5G networks, convex optimization and applied machine learning techniques to wireless communications, reconfigurable intelligent surfaces (RIS), UAV-enabled networks, and ultra-reliable and low-latency communications (URLLC). He is currently serving as Associate Editor for a section on Artificial Intelligence of Things published within Frontiers in the Internet of Things. He also serves as a Guest Editor for EAI Endorsed Transactions on Industrial Networks and Intelligent Systems and a Special Issue on Radio Frequency Energy Harvesting and Wireless Power Transfer published by Electronics (MDPI) for which he serves also as a Topic Editor. He serves as a Guest Editor for a Special Issue on Controls, Communications and Networking for Ad-Hoc Mobile Sensor Networks published by ICSES Transactions on Computer Networks and Communications. He has served as a Guest Editor for a Special Issue on Reliable Communication for Emerging Wireless Networks published by Mobile Networks and Applications (ACM/Springer).

Vishal Sharma (Senior Member, IEEE) received the B.Tech. degree in computer science and engineering from Punjab Technical University, in 2012, and the Ph.D. degree in computer science and engineering from Thapar University, India, in 2016. From November 2016 to March 2019, he was with the Information Security Engineering Department, Soonchunhyang University, South Korea, in multiple positions (from November 2016 to December 2017, he was a Postdoctoral Researcher, and from January 2018 to March 2019, he was a Research Assistant Professor). He was also a joint Postdoctoral Researcher with Soongsil University, South Korea. Before this, he worked as a Lecturer with the Department of Computer Science and Engineering, Thapar Univ ersity. He is currently working as a Lecturer (Assistant Professor) with the School of Electronics, Electrical Engineering and Computer Science (EEECS), Queen's University Belfast (QUB), Belfast, U.K. At QUB, he is also a Racial Equity Network School Co-Champion, a BCS Accreditation Liaison, and a Mental Health Ambassador (MHFA). Before coming to QUB, he was a Research Fellow at the Information Systems Technology and Design (ISTD) Pillar, Singapore University of Technology and Design (SUTD), Singapore, where he worked on the future-proof blockchain systems. He has authored/coauthored more than 100 journals/conference articles and book chapters and co-edited two books with Springer. His research interests include autonomous systems, UAV communications, network behavior modeling, 5G and beyond, blockchain, and CPS security. He is a Professional Member of ACM and the Past Chair of ACM Student Chapter-TIET Patiala. He was a recipient of four best paper awards. He serves on the Editorial Board of IEEE Communications Magazine, CAAI Transactions on Intelligence Technology (IET), Wireless Communications and Mobile Computing, IET Networks, and ICT Express, and the Section E ditor-in-Chief of Drones journal. He is also the Interim Co-Chair of the IEEE U.K. and Ireland Diversity, Equity, and Inclusion Committee

Berk Canberk (Senior Member, IEEE) has been an Adjunct Professor with the Department of Electrical and Computer Engineering, Northeastern University, since 2016. He is currently a Professor at Edinburgh Napier University, UK and is also with the Department Artificial Intelligence and Data Engineering, Istanbul Technical University. His current research interests include AI driven network automation and management, software-defined networking, 5G, 6G, and intelligent aerial networks. He was a recipient of the IEEE Turkey Research Incentive Award in 2018, the IEEE INFOCOM Best Paper Award in 2018, the British Council (U.K.) Researcher Link Award in 2017, the IEEE CAMAD Best Paper Award in 2016, and the IEEE INFOCOM Best Poster Paper Award in 2015.

Octavia A. Dobre (Fellow, IEEE) received the Dipl.Ing. and Ph.D. degrees from the Polytechnic Institute of Bucharest, Bucharest, Romania, in 1991 and 2000, respectively. Between 2002 and 2005, she was with the New Jersey Institute of Technology, Newark, NJ, USA. In 2005, she joined Memorial University, St. John's, NL, Canada, where she is currently a Professor and Research Chair. She was a Visiting Professor with the Massachusetts Institute of Technology, Cambridge, MA, USA, and Universit de Bretagne Occidentale, Brest, France.,She has authored coauthored more than 400 refereed papers in his research areas, which include wireless communication and networking technologies, and optical and underwater communications.,Dr. Dobre is the Director of Journals and Editor-in-Chief of IEEE Open Journal of the Communications Society. She was the Editor-in-Chief of IEEE Communications Letters, Senior Editor, Editor, and Guest Editor of various prestigious journals and magazines. She was also the General Chair, Technical Program Co-Chair, Tutorial Co-Chair, and Technical Co-Chair of symposia at numerous conferences. Dr. Dobre was a Fulbright Scholar, Royal Society Scholar, and Distinguished Lecturer of the IEEE Communications Society. She was the recipient of the best paper awards at various conferences, including IEEE ICC, IEEE Globecom, IEEE WCNC, and IEEE PIMRC. Dr. Dobre is an Elected Member of the European Academy of Sciences and Arts, a Fellow of the Engineering Institute of Canada, and a Fellow of the Canadian Academy of Engineering.

Trung Q. Duong (Fellow, IEEE) received the Ph.D. degree in telecommunications systems from Blekinge Institute of Technology, Sweden in 2012. In 2013, he joined Queen's University Belfast (U.K.) as an academic staff, where he is now a Chair Professor in Telecommunications. He also holds a prestigious Research Chair of Royal Academy of Engineering. His current research interests include quantum communications, wireless communications, signal processing, machine learning, realtime optimisation, and data analytic. Dr. Duong has served as an Editor/Guest Editor for the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, IEEE TRANSACTIONS ON COMMUNICATIONS, IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE COMMUNICATIONS LETTERS, IEEE WIRELESS COMMUNICATIONS LETTERS, IEEE WIRELESS COMMUNICATIONS, IEEE COMMUNICATIONS MAGAZINES, and IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS. Currently, he is serving as an Executive Editor for IEEE COMMUNICATIONS LETTERS. He received the Best Paper Award at the IEEE VTC-Spring 2013, IEEE ICC 2014, IEEE GLOBECOM 2016, 2019, IEEE DSP 2017, and IWCMC 2019. He is the recipient of prestigious Royal Academy of Engineering Research Fellowship (2015-2020) and has won a prestigious Newton Prize 2017..