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The Role of Digital Twin in 6G-Based URLLCs: Current Contributions, Research Challenges, and Next Directions

ANTONINO MASARACCHIA[1] (Senior Member, IEEE), DANG VAN HUYNH[2] (Member, IEEE), TRUNG Q. DUONG[2] (Fellow, IEEE), OCTAVIA A. DOBRE[2] (Fellow, IEEE), ARUMUGAM NALLANATHAN[1] (Fellow, IEEE), AND BERK CANBERK[3] (Senior Member, IEEE)

[1]School of Electronic Engineering and Computer Science, Queen Mary University of London, E1 4NS London, U.K.
[2]Electrical and Computer Engineering, Memorial University, St. John's, NL A1B 3X5, Canada
[3]School of Computing Engineering and the Built Environment, Edinburgh Napier University, EH10 5DT Edingburgh, U.K.

CORRESPONDING AUTHOR: A. MASARACCHIA (e-mail: a.masaracchia@qmul.ac.uk)

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ABSTRACT Substantial improvements in the area of ultra reliable and low-latency communication (URLLC) capabilities, as well as possibilities of meeting the rising demand for high-capacity and high-speed connectivity are expected to be achieved with the deployment of next generation 6G wireless communication networks. This thank to the adoption of key technologies such as unmanned aerial vehicles (UAVs), reflective intelligent surfaces (RIS), and mobile edge computing (MEC), which hold the potential to enhance coverage, signal quality, and computational efficiency. However, the integration of these technologies presents new optimization challenges, particularly for ensuring network reliability and maintaining stringent latency requirements. The Digital Twin (DT) paradigm, coupled with artificial intelligence (AI) and deep reinforcement learning (DRL), is emerging as a promising solution, enabling real-time optimization by digitally replicating network devices to support informed decision-making. This paper reviews recent advances in DT-enabled URLLC frameworks, highlights critical challenges, and suggests future research directions for realizing the full potential of 6G networks in supporting next-generation services under URLLCs requirements.

INDEX TERMS 6G, digital twin, URLLCs.

I. INTRODUCTION

THE CONCEPT of URLLC has been regarded as one of the most revolutionary use cases since researchers and industry began working toward the deployment of fifth-generation (5G) mobile communication systems. Since then, significant improvements have been made to meet the stringent requirements of near-zero latency and ultra-reliable transmission, meaning communication lags of less than 1 ms with a communication error probability of less than 10^{-5} [1], [2]. However, the progress made so far in the field of URLLC is insufficient to meet all the Key Performance Indicators (KPIs) required by diverse mission-critical applications envisioned to become a reality with the deployment of 6G mobile networks. As highlighted in Table 1, 6G-based URLLC introduces more stringent requirements compared to 5G, including sub-millisecond latency, 99.99999% of communication reliability, and data transmission rates higher than 100 Gb/s. These requirements are essential for emerging 6G services such as industrial automation, intelligent transportation, telemedicine, the Tactile Internet, Virtual/Augmented Reality (VR/AR), and the Metaverse, all of which hold the potential to significantly enhance our everyday lives [3].

In addition, 6G is expected to provide significantly greater communication capacity to handle the massive surge in data traffic. By 2030, the global mobile subscriber base is projected to reach approximately 17 billion, with data traffic

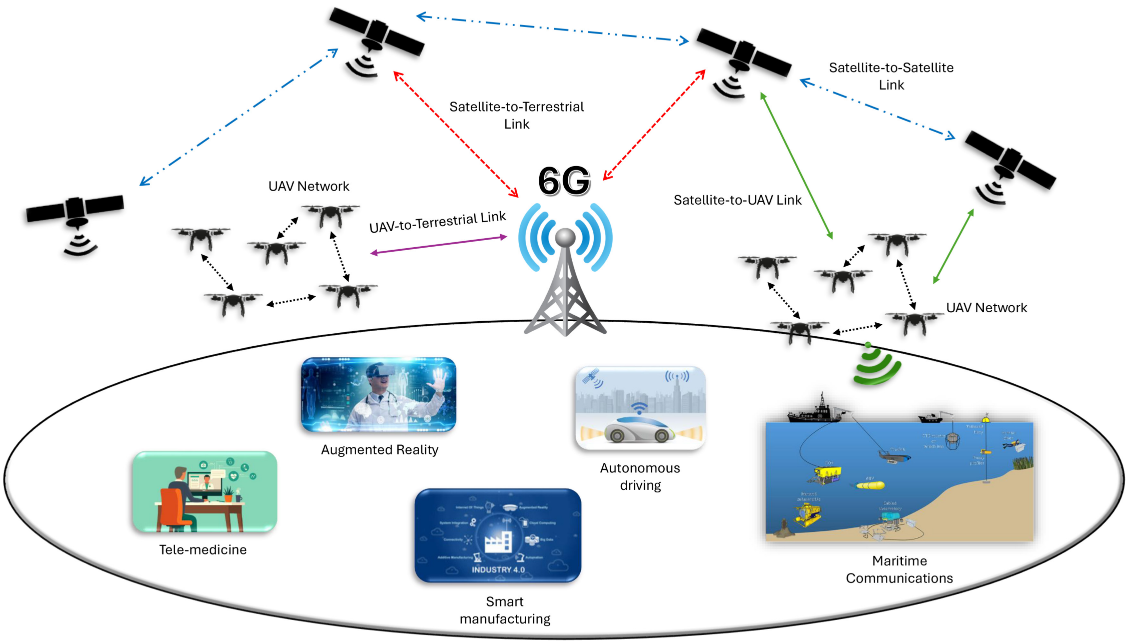

FIGURE 1. 6G ecosystem and related services.

TABLE 1. A comparison between 5G and 6G KPI metrics.

Key Performance Indicator	5G architecture	6G architecture
Peak Data Rate	20 Gbps	1 Tbps
User Experienced Data Rate	100 Mbps	1 Gbps
Area traffic capacity	10 Mbps/m^2	1 Gbps/m^2
Connection density	10^6 users/Km^2	10^7 users/Km^2
Latency	1- 10 ms	10 - 100 μs
Reliability	99.999 %	99.99999 %
Spectral Efficiency	30 bps/Hz	100 bps/Hz
Positioning accuracy	0.5 m	0.01 m

increasing to around 5 zettabytes per month. Moreover, exceptionally high levels of spectrum and energy efficiency, as well as connection ubiquity, will be essential to support the deployment of a massive number of Internet-of-Things (IoT) devices.

Meeting these requirements while adhering to URLLC constraints will necessitate enhancing various aspects of the underlying network, typically achieved by integrating innovative technologies into traditional cellular networks [4], [5]. As illustrated in Figure 1, incorporating satellites and UAVs in addition to conventional terrestrial terminals holds the potential for increased connection ubiquity and enhanced communication performance [6]. Indeed, when compared to traditional terrestrial base stations, UAVs, also known as drones, offer highly cost-effective and flexible solutions that extend coverage and enhance signal strength. These drones enable the establishment of line-of-sight (LoS) communication links, delivering superior link quality characterized by increased capacity and highly reliable data transmission [7], [8].

In addition, deploying RIS on building facades creates opportunities for smart propagation environments. These environments can effectively mitigate path loss and channel sparsity. This because, by leveraging external signals, RIS technology reflects incident wireless waves in desired directions, optimizing connection links between base stations and users, paving then the way towards more robust and efficient communication networks [9]. Last but not least, combining the capabilities of RIS technology with UAVs gives rise to the concept of RIS-equipped drones. These advanced drones further enhance the communication performance of next-generation wireless networks, offering unprecedented improvements in coverage, capacity, and reliability [10].

In addition to integrating UAVs and RIS as part of advanced physical layer technologies, the upper layers of the 6G network architecture are poised for significant upgrades. One notable innovation is MEC, which has emerged as a powerful solution to address the stringent latency requirements of 6G-based mobile services [11], [12], [13]. By leveraging MEC, mobile devices can offload computationally intensive tasks — either partially or entirely — to MEC servers strategically located at the network edge. This enables devices with limited computational power, such as IoT devices, to meet the latency requirements of their specific applications while conserving energy [14].

While the integration of these innovative technologies promises to revolutionize URLLC in next-generation wireless networks, it also presents additional challenges in meeting the requirements of the underlying network. This is primarily due to the introduction of new optimization constraints in resource allocation. For instance, in UAV-assisted communications, the limited battery life of drones necessitates critical optimization of their positions or flight paths to maximize network coverage and extend operational time. These challenges become even more complex when multiple UAVs are deployed in a single area. Similarly, the deployment of RIS requires precise tuning of reflective coefficients to achieve the desired network performance. Furthermore, MEC systems demand efficient resource allocation strategies, including optimal distribution of computational resources for each user and the development of effective user-association policies. Although various optimization frameworks have been proposed in literature to address each of these challenges either singularly or within a combined communication infrastructure [15], [16], [17], [18], [19], [20], [21], [22], [23], the majority of them need to search optimal solutions for resource management according to dynamic wireless channel and traffic loads. This, due to the complexity and size of 6G communication scenarios, will bring to high computing delay, which cannot achieve the requirements of URLLC. Furthermore, they are optimal only for specific layers of the network — primarily the physical and medium access control (MAC) layers — whereas it is also essential to consider the stochastic nature of delays and reliability issues in the upper layers of the network. Last but not least, the theoretical models adopted for network performance analysis are mainly based on simplified models and assumptions, which often are not exactly the same as real-world networks, leading then to suboptimal URLLC management policies. Then, one can easily notice how to overcome these URLLC related challenges, innovative methodologies and solutions are urgently required for 6G systems [24].

These may include sophisticated cross-layer optimization technologies capable of identifying performance limits and providing solutions to achieve the desired levels of end-to-end (E2E) latency and communication reliability. Furthermore, the adoption of model-free machine learning methods has demonstrated significant potential. Under these perspective, DT-based approaches, which leverage AI and DRL mechanisms, have been identified as a keystone technology for solving optimization challenges in complex future wireless network scenarios, facilitating the delivery of 6G-oriented services [25], [26], [27], [28]. A DT-based approach involves continuously collecting data from every physical device in the network, enabling the device to be digitally replicated (or 'twinned') on a server. This allows for real-time updates of the device's status and the overall network environment, offering a significant advantage over analytical models, which, as mentioned earlier, may result in suboptimal management policies. Simultaneously, DTs are equipped with machine learning capabilities that leverage the network status to identify optimal cross-layer decision policies for network resource allocation — including drone deployment, coverage control, mobility management, optimal configuration of RIS coefficients, and MEC resource allocation — with reduced computing delay and better awareness of the underlying system [29]. This makes it possible to potentially meet URLLC requirements. Essentially, the DT-based approach represents a shared intelligence concept across all devices, paving the way for the successful deployment of increased communication capacity with near-zero latency and ultra-reliability requirements critical for next-generation 6G services.

A. MOTIVATION AND CONTRIBUTIONS

Building on the previous discussion, it becomes evident that existing solutions in the literature fall short of fully addressing the stringent requirements of URLLC in 6G networks. This presents an urgent need for innovative, efficient, and scalable approaches to overcome these challenges, which could otherwise impede the widespread adoption of 6G related services. In this context, the DT paradigm has emerged as a transformative enabler for meeting the demanding URLLC constraints in 6G services. Despite its potential, there is a noticeable gap in the literature — no comprehensive tutorials or review papers currently articulate a clear and actionable vision of how DTs can deliver near-zero latency and ultra-reliable communication. To address this critical gap, this paper offers an in-depth review of the most significant and current research on DT-enabled 6G URLLC, providing a valuable resource for advancing 6G communication infrastructures. More specifically, this paper provide the following contributions:

- A brief but exhaustive overview about URLLCs requirements for 6G-oriented services;
- An illustration how, thanks to its features, DT paradigm represents a promising solution in terms of real-time optimization;
- A review of the most promising DT-based architectures enabling URLLCs currently available in literature;
- A discussion about the remaining challenges and future directions in this research area.

The rest of the paper is organized as follow. Section II provides a brief but exhaustive discussion about the main requirements for the full roll-out of time-sensitive and mission critical 6G-based URLLC services. An introduction about the principles and potentialities of using a DT paradigm are provided in Section III. The paper continues in Section IV, which contains a review about recent works on DT-enabled solutions for guaranteeing 6G based URLLC requirements. Furthermore a use case scenario showing how effectively the usage of DT can contribute in reducing the network latency is provided in Section V. Current challenges and future research directions are discussed in Section VI. Finally, the paper is concluded in Section VII.

II. PRINCIPLES AND ASPECTS FOR 6G-BASED URLLC

As previously mentioned, the advent of 6G wireless communication networks will bring the widespread adoption of new technologies and use cases poised to revolutionize everyday life. However, enabling these innovative services requires addressing significant challenges related to network latency and reliability. This section briefly discusses the key requirements necessary to support the full deployment of 6G-based services constrained by URLLC.

A. RELIABILITY REQUIREMENTS

The term reliability indicate the capacity of the communication link of transmitting a specific amount of data within a predefined temporal window ad with an extremely low error probability [30]. In the context of 5G communication technology, the level of reliability has been defined as the capacity of maintaining a communication error probability of 10^{-5} while transmitting 32 byte of a communication frame within 1 ms temporal window [31]. Although this represents a very strict and challenging requirement to achieve, the reliability requirements are expected to be pushed towards lower levels of error probabilities with the advent of 6G communication technology. More specifically, for 6G-oriented services such as telesurgery, intelligent transportation, AV/VR, and smart manufacturing, it is expected to achieve around 10^{-5} and 10^{-9} of communication reliability [32]. This requires the investigation and design of physical layer technologies with more optimal and efficient capabilities than the ones adopted in the 4G/5G communication networks. These ranges from the design of new channel coding schemes to the definition of new channel estimation techniques. As regards the realm of channel coding techniques, so far the most promising approach, already proposed in the context of 5G networks, seems to be the usage of low-density parity check (LDPC) codes for data transmission and polar codes for transmissions within the control channels [33], [34]. However, 6G-oriented services will be based on the usage of energy constrained IoT devices and applications with a wide variety of rate requirements, meaning that also a focus on energy efficiency during encoding, as well as flexibility in both length and rate will be required. In other words, it will result necessary to develop new coding techniques possessing characteristics that allow higher levels of flexibility for decoders meeting various KPI trade-offs. For instance, specific decoders may excel in low-latency scenarios while others prioritize higher throughput, despite offering similar reliability for a given length and rate. This is recently put the lights on the concept of unified coding as a possible enabler for competitive 6G channel coding [35]. On the other hand, techniques such as random matrix theory, high-dimensional covariance estimation schemes, as well as the usage of AI/ML, are gaining a lot of attention as channel estimation techniques for 6G networks [36].

B. LATENCY REQUIREMENTS

In the context of communication systems, latency refers to the time it takes for a data packet to complete a round-trip over-the-air transmission between the communication ends. This encompasses various phases, as a packet traveling from the transmitter (Tx) to the receiver (Rx) can encounter different types of latency, such as control plane latency, user plane latency, and E2E latency. Among these, the E2E latency represents the most complicated since it involves different phases of the communication protocol stack like data processing, queuing, scheduling, and possible re-transmission.

In the context of 5G and beyond 5G (B5G) communication technologies, it is expected that for certain types of delay-sensitive services the maximum packet transmission time interval (TTI) should not be exceed 1 ms [37]. To accomplish this, the concept of short time slots that span only a fraction of a millisecond — typically consisting of 2, 4, or 7 symbols, instead of the traditional long TTI of 14 symbols — has been introduced. These shorter slots are well-suited for short-packet communications typically representing the traffic originated from sensors involved in machine-type communications [7]. However this implies the usage of a different approach compared to the one adopted in 4G/5G networks. For instance, the authors in [38] demonstrated that an extremely short preamble, consisting of just one orthogonal frequency division multiplexing (OFDM) symbol, can meet the latency requirements of B5G factory automation systems while still ensuring accurate packet detection and channel estimation. However, in order to meet the latency requirements of other types of 6G-oriented services, in addition to investigate new types of modulation schemes, it will result necessary to investigate new techniques, ranging from the optimization of network slicing procedures to the usage of federated learning and edge computing [39].

C. NETWORK AVAILABILITY

Network availability is a critical requirement for deploying classical URLLC services such as tele-surgery, autonomous vehicles, and remote robotic control. It is defined as the coverage probability with high throughput and specific Quality of Service (QoS) constraints. High levels of network availability are essential for ensuring the quality and stability of remote operation controls, particularly in scenarios involving tele-operated and autonomous driving activities. For example, in the case of autonomous driving, continuous and seamless flow of operational data facilitated by high network availability enhances road safety by enabling the sharing of critical information such as potential accidents and adverse climate conditions. Current network infrastructure are able to guarantee 95% of network availability and only for small-scale networks, while 6G-based URLLC services will require a guarantee of 99% of networks availability [40]. [40], [41], [42]. For this reason, the primary challenges lay in significantly enhancing network availability and developing effective methods to analyze and enhance it in large-scale networks. Additionally, security considerations are crucial for URLLC-related services to prevent potential risks such as unauthorized control of devices through spoofed signals or intentional dissemination of malicious messages within the networks under consideration.

III. DIGITAL TWIN: PRINCIPLE AND POTENTIALITIES

This section will provide a brief overview about the concept of DT. More specifically, a high level representation that summarize all the main involved entities is firstly provided. Subsequently the potentialities that this paradigm holds as

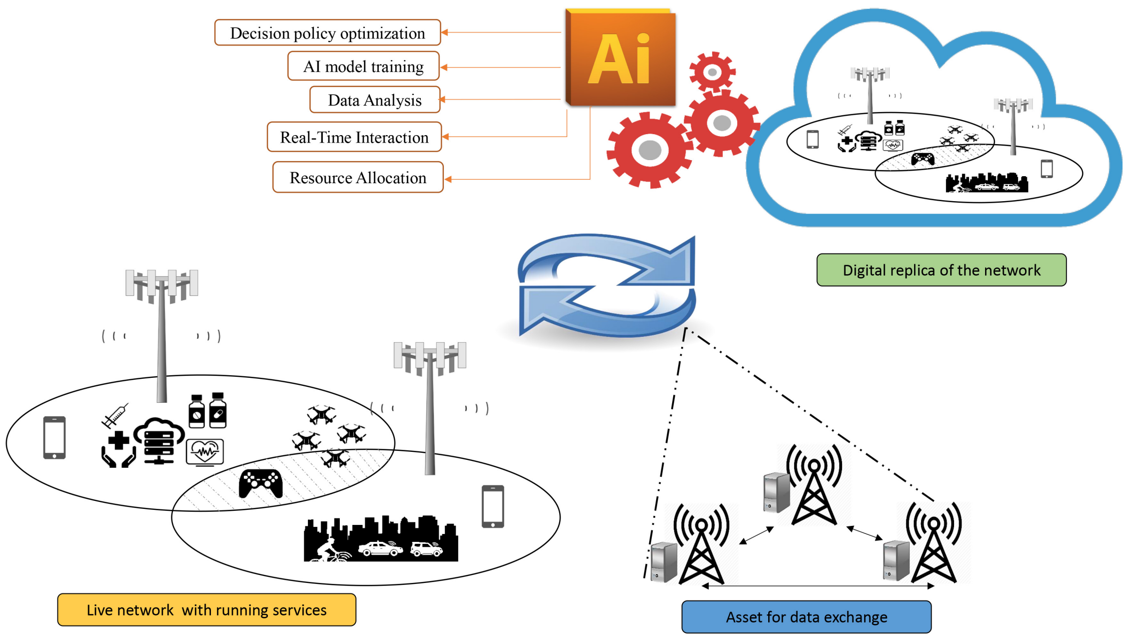

FIGURE 2. **A representation of digital twin architecture.**

key enabler technology for next generation networks are also illustrated.

A. BRIEF OVERVIEW

Although the concept of DT is becoming very popular within the last few year, its origin are rooted in the second half of 20th century. More precisely in 1970 during the launch of Apollo 13 shuttle to the moon. On that occasion, the lunar landing was aborted after an oxygen tank explosion in the service module two days after the mission, disabling electrical and life-support system within the shuttle. Then in order to find the best way for getting Apollo 13 crew back to earth alive, NASA created a computer-based version of the shuttle allowing to run several simulations that permitted to find the best landing strategy [26]. However, the first formal definition of DT started to arrive later within the start of 21th century, with the definition of a product life management (PLM) provided by Grieves and Vickers [43], and subsequently improved by Framling, where the DT was defined as an agent-based architecture in which each product item has a corresponding virtual counterpart/agent associated with it [44]. However, the more official definition is the one provided by NASA in 2010, where the DT can be seen as a set of computer-based models that constantly collect data from their physical twin (PT) counterpart in order to run simulations/emulations representing the life-cycle of the PT as well as its possible evolution in the future based on particular circumstances [45], [46]. Indeed, according to this definition and the illustrative high-level representation provided in Figure 2, DTs have continuous interaction with their physical counterparts and the external environment. Within the DT paradigm it will be possible to create a digital replica of a live network which will be constantly updated with data collected from the real-world deployments through dedicated asset for data exchange. This means that DTs will be able to track the life cycle of their PTs and enhance their inner processes and functions through closed-loop optimization. Additionally, by simulating new configurations and employing AI and Big Data analytics tools, a DT can forecast future conditions such as system defects, damages, and failures. This foresight empowers proactive maintenance operations or the activation of self-healing mechanisms.

B. BENEFITS OF DT-BASED SOLUTIONS

As evident from our previous discussion, the concept of DT represents a powerful approach for proactive management of real physical devices. The possibility of continuously collecting data from these devices, in conjunction with the most recent and advanced AI/ML-based big data analytic techniques that empower DT, enables the acquisition of valuable knowledge aimed at improving the performance of physical systems. For these reasons, the usage of DT has been highlighted as a keystone technology for achieving optimal resource allocation in 6G-based networks, enabling then the possibilities to meet the KPIs of specific URLLC services, especially those based on IoT and autonomous driving, which involve real-time resource optimization of various network resources [26].

For example, most IoT-based sensor applications are envisioned to rely on the usage of MEC servers, which allow those sensors to offload either partly or entirely computationally intensive tasks at the server side, permitting them to save energy and fulfill time constraints of a specific application. Such approach requires an optimal resource allocation policy in terms of users association with a specific

TABLE 2. Summary of current state of the art works on DT-assisted URLLCs in 6G: Part-1.

Work reference	Investigated Scenario/Objective	Results and Insights
[55]	An optimization problem aimed at determining the optimal allocation of Resource Blocks (RBs) to ensure eMBB and URLLC requirements, as well as fairness among users sharing the same bandwidth	The work demonstrates how a DRL-based approach, capable of running offline within the DT, enables the exploration of optimal allocation policies for various conditions. The DRL algorithm exhibits strong convergence performance and effectively meets the strict latency requirements of URLLC while ensuring the reliability of eMBB.
[56]	A digital twin-based approach for optimizing user association, resource allocation, and offloading probabilities in a MEC system, while ensuring compliance with URLLC requirements.	The resulting framework was able to minimize energy consumption by 87% compared to other baselines, while meeting both URLLC and delay-tolerant service requirements
[57], [58]	A DT-based approach as a potential solution to minimize communication latency in an Industrial IoT communication scenario, while adhering to URLLC constraints.	It has been demonstrated that, through an efficient optimization algorithm based on the AO approach and IA, the DT-aided method intelligently utilizes available resources to minimize worst-case communication latency.
[59]	An investigation into how the lack of synchronization between physical entities and their DT representations impacts the entire system. In this case, the deviation between the digital representation and the real system's parameters is modeled as a normal distribution.	The design of a DT-assisted robust task offloading scheme based on machine learning, which, compared to other benchmark schemes, significantly reduces task offloading latency and energy consumption, while also accounting for potential uncertainties and deviations.
[60], [61]	An investigation into the feasibility of implementing a DT-based solution using a distributed approach, with the main objective of solving a fairness-aware latency minimization problem for the underlying network, subject to URLLC constraints.	The study showed how the proposed distributed approach was able to reach the same performances of a centralised one, but with reduced execution time.

server as well as the computational resource associated to each user-specific task. In this regard, the application of DT based solution has been proven to be an effective solutions to find the optimal policy that permits to increase processing efficiency and prolong battery lifetime of sensors, as well as network and efficiency and service specific delays [47], [48], [49].

On the other hand, within the context of autonomous driving, commonly referred to as the Internet of Vehicles (IoV), a continuous evolution and implementation of DT for managing traffic data is envisioned for the near future. Indeed, leveraging DT to analyze vast IoV data enables the possibility of informed decisions aimed at mitigating/minimizing traffic congestion. Furthermore, it allows for addressing specific challenges such as limited data availability due to severe weather-related exceptions or battery issues in vehicle sensors, which cannot guarantee 100% data availability [50]. Additionally, it promotes the adoption of social-aware principles, a very recent data-collection paradigm which have proven to be effective for task-specific data collection and analysis [51], [52].

Last but not least, the DT principle has been highlighted as a powerful enabler for Industrial IoT. More specifically in the context of smart manufacturing. Indeed, within this area the usage of DT can be exploited in multiple ways, ranging from the monitoring and prediction about the behavior of the corresponding factory entity, to the recommendation of optimal actions for both workers and machines in order to enhance the entire industrial process. This approach enables then the creation of platform-independent services, facilitating collaboration between machinery and humans to establish an efficient, agile, and intelligent manufacturing environment [53], [54].

IV. RECENT WORKS ON DT FOR 6G ORIENTED URLLC

This section offers a structured review of recent, significant research on DT-enabled URLLC systems tailored for 6G-oriented applications. The works are categorized according to the primary areas where DT potential has been extensively explored. A dedicated subsection for each category is provided. Tables 2 and 3 present concise summaries of each study.

A. DT FOR HETEROGENEOUS RESOURCE ALLOCATION

As already anticipated, with the advent of next generation wireless communication technology three main groups of services are envisioned to be delivered, which can be broadly categorized into enhanced mobile broad band (eMBB), massive machine-type communications (mMTC), and URLLC, each of them with specific requirements. Indeed eMBB based services are expected to provide improved data rate, mMTC aim at serving IoT devices, while URLLC are necessary for services that requires latency not greater than 1 millisecond and connection reliability higher than 99.999%. However, all these types of services are expected to be delivered within the same bandwidth, meaning that appropriate scheduling mechanisms able to guarantee for example both eMBB and URLLC requirements will be necessary. This is primarily

TABLE 3. Summary of current state of the art works on DT-assisted URLLCs in 6G: Part-2.

Work reference	Investigated Scenario/Objective	Results and Insights
[62]	Development and evaluation of a MEC-based URLLC DT architecture designed to deliver a robust computing infrastructure by simultaneously optimizing task offloading and caching strategies on nearby edge servers, while ensuring stringent reliability and low-latency requirements essential for future Metaverse services.	The proposed DT model employs an alternating optimization-based solution to determine the optimal configuration that meets network requirements. Additionally, this study demonstrates how leveraging caching techniques can mitigate the impact of synchronization discrepancies between the DT and the physical environment.
[63]	A blockchain-supported hierarchical digital twin framework designed to learn optimal computation and communication allocation policy for IoT networks under URLLCs constraints.	This study illustrates how using a distributed blockchain environment allows the DT to balance system delay and energy consumption while improving system reliability/security and learning accuracy.
[64]	Authors propose a DT-based approach for RIS-aided MEC system under URLLCs constraints. A DDPPG-based policy is implemented at the DT level to find the optimal solution which minimise the total E2E latency by jointly optimising beamforming vector at RIS, transmit power of users, bandwidth allocation, processing rates, and task offloading parameters.	When compared to the scheme without a RIS, the proposed method achieves up to 60% lower transmission delay and 20% lower energy consumption.
[65], [66]	Idea of a DT agent aimed at minimising the overall communication latency of the underlying UAV-assisted and MEC-enabled network infrastructure under URLLCs requirements.	The DT agent is able to find the optimal solution which jointly optimise the transmit power, offloading factors, and the processing rate of IoT devices and ES in order to minimise the overall communication latency.
[67]	Spatial-Information DTN defined as a dynamic satellite network used to observe, simulate, and forecast real-world situations and behaviors through designated protocols, algorithms, and tools.	Thi DT-based approach has been validated, showing an effective capability in improving the URLLC performances of Space-Air-Ground Integrated Networks.

driven by the fact that, compared with eMBB, URLLC traffic is unpredictable and scattered in practice, necessitating the dynamic and intelligent allocation of resources through real-time interaction with the environment. To tackle this pressing issue, which could impede future service deployment, and inspired by the capability DRL to derive optimal policies in non-stationary settings, a DT-enabled DRL framework was proposed for the joint scheduling of URLLC and eMBB in [55]. With this approach, the scheduling problem is formulated as an optimization task aimed at identifying the ideal Resource Block (RB) allocation for eMBB users and an optimal subset for URLLC users, while ensuring fairness among all users. Given the complexity of this optimization problem, a DRL-based solution running offline within the DT was proposed to explore the optimal allocation policy for a range of conditions. This strategy demonstrated how the DT-based approach mitigates the risk of failing to guarantee URLLC services in real-world networks. The effectiveness of this method has been validated through numerical simulations, showing that the DRL algorithm not only converges well but also meets the stringent latency requirements of URLLC while maintaining eMBB reliability.

B. DT FOR MEC-BASED SERVICES

A digital twin approach for optimizing user association, resource allocation, and offloading probabilities in a MEC system, subject to URLLC constraints, has been proposed in [56]. In this case, authors considered a MEC scenario where a set of M access points (AP) have to serve a set of $K = K^u + K^b$ users that can have either URLLC requirements (K^u) or have access to delay tolerant services (K^b). For such scenario, a DT-replica of the underlying network is created in a central server where an offline trained deep-learning based algorithm is trained in order to provide the best user association policy. In addition they also designed a low-complexity optimization algorithm aimed at optimizing the resource allocation policy and offloading probabilities at each AP. The proposed framework resulted able to minimize the energy consumption by 87% when compared with other baselines, while guaranteeing both URLLC and delay-tolerant service requirements.

Authors in [57], [58] considered a DT-based approach as potential solution to minimize the communication latency of an Industrial IoT communication scenario subject to URLLC constraints. More specifically, they considered a communication scenario where a set of K Industrial IoT devices need to offload some tasks to a particular edge server embedded within a multi-antenna AP. Leveraging the digital replica of the network, the DT can identify the optimal solution for minimizing worst-case communication latency. This is achieved by jointly optimizing the transmit power of IoT devices, their association with APs, the partitioning of tasks for offloading, and the processing rates of both users and edge servers. Such solution was made possible by designing an efficient optimization algorithm that combines an alternating optimization (AO) approach with inner approximation (IA) techniques. The effectiveness of this approach was demonstrated through numerical results, showing how intelligently the DT-aided approach uses the available resources to minimize the worst-case communication latency.

More recently, authors in [59] considered the effects caused by the lack of synchronization between physical entities and the respective DT representations, evaluating how this would impact the entire real-world system. In their study, they addressed the challenge of optimizing task offloading, resource allocation, and power management for mobile devices in a DT-assisted URLLC-enabled mobile edge network, while accounting for deviations between actual values and those estimated by the DT. Deviations in the digital representation were modeled as a normal distribution. Based on this setup, they formulated an optimization problem to minimize latency and energy consumption under uncertainty by optimizing task offloading, resource allocation, and power management. To solve this problem, they developed a DT-assisted robust task offloading scheme using machine learning, which, compared to benchmark schemes, achieved a substantial reduction in task offloading latency and energy consumption, even considering the deviations from real-world parameters.

The approaches discussed so far have been based on the assumption of a centralised DT solution. However this approach will not result efficient as the size of the network increases as well as in cases when the edge serves (ES) are deployed within widely distributed areas. Motivated by this, authors in [60], [61] investigated the possibility of a DT-based solution with distributed approach. The investigation about the possibility of using a distributed approach was twofold. From one side it was investigated as possible suitable solutions for large scale scenarios. Alternatively, this approach was employed as an effective solution for addressing complex, non-convex resource allocation problems in next-generation wireless networks. The primary goal was to achieve fairness-aware latency minimization within the network, while meeting the key URLLC constraints. This was accomplished by jointly optimizing various communication and computation parameters, including communication bandwidth, transmission power, task offloading portions, and the processing rates of UEs and ESs. Through numerical simulations it has been outlined how the proposed distributed approach was able to reach the same performances of a centralised one in terms of guaranteeing the URLLC requirements but with reduced computational time. It is also worth mentioning that this work also highlighted how to a divergence in the DT representation respect to the real world corresponds a deprecation of the system performances.

All the DT-enabled solutions for MEC service provisioning previously introduced may result not fully suitable to metaverse applications like AR/VR. Indeed these type of services may require storage of data at the edge of the network, i.e., edge data caching [68], while the previously illustrated work only optimized edge computing and task offloading. With respect to this, an innovative DT scheme for the support of metaverse oriented services support was proposed in [62]. In particular authors designed a MEC-based URLLC DT architecture able to provide powerful computing infrastructure for jointly optimizing task offloading, and task caching techniques in nearby edge servers, while guaranteeing stringent requirements of reliability and low latency envisaged to be mandatory for the future networked systems. In doing so, using the digital representation of the underlying network, the DT uses an alternating optimization (AO)-based solution to find the optimal solution able to meet the network requirements. Also in this case authors illustrated the effects of the deviation between the estimated parameters at the DT and the real parameters in the network, showing that caching represents an effective possible solutions to alleviate this.

Although DT has been recognized as powerful solution to guarantee sustainable computing at the edge of the network by fulfilling the URLLC requirements, data privacy and protection for data exchange between IoT devices and ES, as well as security and trust when a distributed approach is performed like in [61], represent aspect of paramount importance to take into account during the design of a DT system. In this regards, authors in [63] proposed a blockchain-supported hierarchical digital twin for IoT networks to achieve secure and reliable computation while guaranteeing the possibility of real-time interaction with underlying URLLC constraints. More specifically, they proposed a DRL method based on proximal policy optimization (PPO) to learn optimal computation and communication allocation policy within a distributed blockchain digital environment, which balance system delay and energy consumption while improving system reliability based on ensuring the learning accuracy of IoT devices.

C. DT FOR RIS, UAV AND SATELLITE ASSISTED URLLCS

RIS have recently emerged as a crucial technology for enabling smart propagation environments. This technology is based on passive reflective elements, or metasurfaces, which are linked to a control unit that adjusts the reflective properties of each element. By doing so, the RIS can direct incoming radio signals toward a specified target, enhancing signal control and optimizing the propagation environment. This result ultimately beneficial in improving the propagation characteristics, i.e., increased signal-to-noise ratio at the receiver, in context with poor channel and with energy-constrained devices [69]. In this regards, the possibility of including RIS technology into DT-based infrastructure is gaining attention [28]. Under this perspective, a DT-based and RIS-assisted MEC system operating under specific URLLC constraints was examined in [64]. The DT replica incorporates a DRL mechanism, specifically a Deep Deterministic Policy Gradient (DDPG) algorithm, designed in order to identify the optimal solution for minimizing the system's total end-to-end latency. This is achieved by jointly optimizing the beamforming vector at the RIS, user transmit power, bandwidth allocation, processing rates, and task offloading parameters. The authors demonstrated that their approach reduced transmission delay by up to 60% and energy consumption by 20% compared to a setup without RIS. Furthermore, the DDPG approach outperformed other deep learning methods, such as Proximal Policy Optimization (PPO), as well as conventional alternating optimization techniques.

The possibility of using the benefits UAV-assisted communications in order to create MEC services able to support mission critical services with URLLCs requirements has received attention from the research community [70], [71]. Based on this, authors in [65], [66] proposed a DT-assisted UAV-based edge networks. In this context they exploited the idea of a DT agent aimed at jointly optimizing the transmit power, offloading factors, and the processing rate of IoT devices and ES in order to minimise the overall communication latency of the underlying communication infrastructure, required to meet URLLC requirements. Simulation results illustrated the sensibility of the system in performing the optimal resource allocations in order to meet the requirements and reduce the communication latency.

Within all its vision, as illustrated in Figure 1, the deployment of 6G networks is envisaged to provide a unified network infrastructure where terrestrial communications, satellite systems, and aerial networks are all interconnected to provide seamless connectivity trough the ubiquitous Internet. This vision is referred as Space-Air-Ground Integrated Networks (SAGIN) [72]. Then, in contrast to single network systems and UAV-assisted communication, from one side the SAGIN architecture will provide more extended coverage, higher flexibility and efficiency. But on the other hand it faces new challenges such as time variability, management of heterogenous devices and self-organization networks, which can drastically penalise its capabilities of guaranteeing URLLC requirements. One potential solution to overcome these challenges is through the creation of a digital representation of the SAGIN architecture, enabling simulations and predictions of the future state of physical entities to prevent potential network failures. This approach was explored by the authors in [67], who introduced the concept of a Spatial-Information Digital Twins Network (DTN). With such approach it is indeed possible to monitor, simulate, and forecast real-world conditions and behaviors using specialized protocols, algorithms, and tools for such dynamic satellite system. The insights gained from this analysis can then be fed back into the physical network to assist with resource allocation and equipment maintenance, ultimately optimizing the entire network. Building on this idea, the authors demonstrated its effectiveness in enhancing URLLC performance in SAGIN networks by developing an Intelligent Coordinated Scheduling Algorithm (ICSA). This algorithm schedules various heterogeneous tasks while taking into account crucial information about the physical network. They showed how the ICSA can be implemented on the DTN to determine the optimal policy, maximizing total priority and completion rates while meeting URLLC requirements.

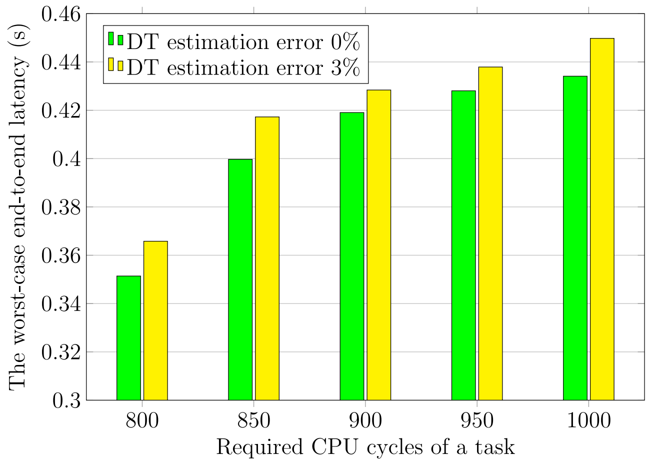

FIGURE 3. Impacts of digital twin estimation error on the end-to-end latency of task processing.

V. A DT-ENABLED URLLC USE CASE

In this section, we illustrate the performances of a DT technology in 6G-based URLLC for industrial automation. Specifically, DT is used to replicate the computing capacity of Industrial Internet of Things (IIoT) devices and edge servers.

For our simulations, we consider a small-scale autonomous factory scenario, where a multi-antenna base station serves multiple single-antenna IIoT devices. The computational tasks from these IIoT devices can be partially offloaded to the edge server associated with the base station for execution. The computing capacities are set to 3 GHz for the IIoT devices and 15 GHz for the edge server. Additionally, the energy budget for each IIoT device is 1000 J. The reliability requirement for URLLC transmissions is 10^{-9} [58].

To demonstrate how DT estimation error affects the E2E latency of IIoT devices, we ran simulations with varying settings for the required CPU cycles to process a task. Figure 3 shows the worst-case E2E latency among IIoT devices over a range of required CPU cycles with different levels of DT estimation error. Specifically, as the required CPU cycles for a task increase, the worst-case E2E latency gradually rises. Additionally, Figure 3 highlights the impact of DT estimation error on the latency obtained. The more accurately the DT estimates the processing rate of the physical system, the better the performance achieved. This finding reflects the practical application of DT technology in real-world scenarios.

VI. CHALLENGES AND RESEARCH DIRECTIONS

Within the last two subsections, it has been illustrated how the adoption of DT-based solutions holds a very valuable potential toward the realization of URLLC for 6G-related services. However, as one can easily notice from Section IV, this represents an early stage research field where only few studies have been conducted so far. This means that there are still some challenges and issues that need to be addressed in order to make the usage of DT for URLLC-based 6G networks service a reality. The most relevant and critical are discussed within this section.

A. COMPUTATIONAL INFRASTRUCTURES

At the highest level of the DT architecture, one of the most critical challenges for ensuring the deployment and full utilization of DT potential lies in providing powerful computational infrastructures. These are essential for enabling DTs to execute and manage resource-intensive, computation-hungry AI/ML frameworks designed to identify optimal decision policies and extract meaningful insights from data collected by various physical devices. To achieve this, it will be necessary to deploy edge/cloud servers equipped with high-performance GPUs, which currently have an average cost of around $10,000, depending on specific requirements. This presents a significant capital expenditure (CAPEX) challenge for network service providers. One potential solution to address this challenge is the adoption of the GPU as a Service model. Leading AI/ML computing companies, such as Amazon, Microsoft, and Google, are expected to alleviate the high CAPEX barrier by offering on-demand GPU services similar to existing cloud-based applications.

In addition to CAPEX, another significant challenge related to computational infrastructure is the curse of dimensionality. The widespread adoption of IoT devices will inevitably result in highly complex optimization problems and tasks that must be solved within strict time constraints. To address this, Quantum-Based Computing (QBC) has emerged as a promising solution that is gaining substantial attention from both academia and industry. By leveraging the principles of quantum superposition, entanglement, and parallelism, QBC demonstrates significant potential for achieving rapid learning speeds when processing large-scale datasets in probabilistic environments [73], [74].

B. DATA CONSISTENCY AND SYNCHRONIZATION

In addition to provide high-performance computational resources, another important requirement for the deployment of DT technology that needs attention is the process of collecting data from the corresponding PT counterpart. The main challenges in this process can be broadly classified into two main categories: *i)* availability of real-time data and *ii)* managing missing data from sensors. In the first case, guaranteeing the data exchange between the DT and its corresponding PT results essential to have an high fidelity representation of all the processes running into the physical entity. This in turn permit to provide the optimal decision policy for the considered system. If real-time synchronization is not provided, this can cause sub-optimality configurations of the PT or even worse system performance deprecation. For example, the lack of real-time synchronization can cause parameter estimation errors, which, as illustrated in Section V, may result in suboptimal decision policies that fail to meet the URLLC requirements. Similarly, missing temporarily data from some sensors and/or other end-user devices would result in having incomplete and sparse data collection, raising then big challenge in terms of data analysis which can potentially lead the AI engine to take the wrong decision even if it has a real-time representation of all the network components. Then, it will result necessary to provide adequate strategies for guaranteeing synchronization between DT and corresponding PT, as well as consistency of data collected from end-users in order to provide the optimal configurations for the underlying network. Authors in [62] demonstrated that increasing the caching capacity of a MEC-based URLLC digital twin architecture can reduce communication latency in the presence of estimation errors. This indicates that utilizing MEC servers with appropriate caching capabilities can help address E2E issues arising from the lack of synchronization. However, research in this area is still in its infancy, and further contributions are needed to advance the field.

C. DATA ANNOTATION AND COMPLIANCE

To date, the process of labeling or tagging data with relevant information to make it understandable and usable for AI/ML algorithms, i.e., data annotation, is performed manually by human operators. In the context of DT-based application for 6G networks, this process may result to be very tedious and time consuming due to the vast amount of data that the DT will constantly receive, hindering its capability to fulfill the URLLC requirements. Then, the main challenge here will be to provide reliable and scalable frameworks for the autonomous provision of data annotation functionalities. Indeed, scalability represents the requirements in order to face the exponential increase of data to manage. On the other hand, reliability refers to the ability of providing correct annotation in order to guarantee accurate prediction as well as reliable visualization services of the data itself.

Another aspect that will require attention is related to the concept of data compliance. Indeed, the data used in the DT ecosystems must firstly be treated in line with local data protection regulations such as the General Data Protection Regulation (GDPR) in the European Union, the California Consumer Privacy Act (CCPA) in the United States. This in the vision of safeguarding the privacy and security of sensitive information collected and processed within digital twin systems. In addition, ensuring compliance with cross-border data transfer regulations and vendor/partner agreements is essential for maintaining compliance throughout the digital twin ecosystem and mitigating risks associated with data handling practices. These aspects are mainly necessary in order to ensure the deployment of trusted DT systems that analyze data by guaranteeing accountability, sustainability and safe operation of the underlying network.

D. DATA SECURITY AND PRIVACY

The implementation of DT systems holds immense potential to transform network management through the application of AI-driven logic. Nevertheless, the incorporation of AI introduces notable security and privacy considerations. A primary concern revolves around data privacy, as the deployment of DT-based networks requires the gathering of extensive user data for training AI/ML models, often without users being fully informed or having control over how their data is managed by external systems. This increases the vulnerability to unauthorized access or potential data breaches. Moreover, the transmission of user data to DTs is susceptible to various attacks, including data poisoning attacks that manipulate ML models, thereby compromising system performance and integrity. Additionally, AI-based systems may be targeted to exploit vulnerabilities in network nodes, exacerbating security risks. To confront these challenges, promising approaches such as federated learning, homomorphic encryption, differential privacy, and adversarial ML techniques offer avenues to enhance security and privacy safeguards in DT systems. However, further research is essential to comprehensively explore and refine these solutions, ensuring effective mitigation of security and privacy risks in DT deployments.

E. DT SCALABILITY

Another significant challenge that must be addressed is the efficient scalability of DT solutions to adapt to the massive proliferation of IoT devices while ensuring optimal decision policies that meet URLLC requirements. This is a non-trivial issue. With the rapid growth of mobile IoT devices, the volume of data to be processed will increase drastically. Additionally, communication scenarios will become more complex. Together, these factors may lead to increased computational time required to determine optimal resource allocation policies, potentially failing to meet URLLC requirements.

Recently, the adoption of distributed approaches for building DT solutions has been identified as a promising method to address scalability challenges. As highlighted in [60], [61], distributed approaches can achieve similar performance to centralized systems while requiring less computational time. However, further investigation is needed to assess the feasibility of distributed DT solutions. Specifically, implementing distributed approaches requires optimal strategies for the underlying physical network, such as determining the best locations for edge or cloud servers.

In addition to distributed approaches and proper network planning, managing the vast amounts of data generated by physical devices is another critical aspect for ensuring the efficient scalability of DT-based systems. In this context, quantum-based computing is emerging as a promising solution. Leveraging principles of quantum superposition, entanglement, and parallelism, quantum-based computing has shown significant potential for achieving high processing speeds for large-scale datasets in probabilistic environments [73], [74]. Another promising technology to address the data management challenges in 6G networks is semantic communication (SC). Unlike traditional communication systems, SC focuses on extracting and transmitting only the essential meaning of a message, which is then interpreted at the destination. By reducing the volume of transmitted data, SC enables the efficient management and control of a vast number of devices [75], [76].

Then, it is clear how the adoption of distributed approaches, quantum-based computing, and semantic communication represent promising strategies for tackling DT scalability challenges. However, further research is required to fully realize these approaches, particularly in implementing robust distributed systems and developing practical quantum-based and semantic communication solutions.

VII. CONCLUSION

The deployment of the 6G wireless networks represents an unprecedented opportunity to address the demands for URLLC, then fostering the deployment of innovative services, which are expected to change our everyday lives. Under these perspectives, this paper provided an in-depth review of current DT-enabled URLLC frameworks. This because DT paradigm, enhanced by AI and DRL stands out as a transformative approach capable of providing real-time decision-making and optimization capabilities necessary to meet ambitious near-zero latency and ultra-reliability standards within complex 6G communication environments. Alongside, a use case study aimed at illustrating the effectiveness of DT in reducing the latency for 6G communication scenarios is also provided. The paper concludes by discussing the critical challenges and future directions which need to be undertaken in order to fully exploit the potential of DT in delivering URLLCs services.

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ANTONINO MASARACCHIA (Senior Member, IEEE) is a Lecturer with the Queen Mary University of London. His research interests include 6G networks, digital twin, generative AI and applied machine learning techniques to wireless communications, reconfigurable intelligent surfaces, UAV-enabled networks, and ultra-reliable low-latency communications. He is an Editor of IEEE COMMUNICATIONS LETTERS.

DANG VAN HUYNH (Member, IEEE) received the B.Eng. (Hons.) degree in information technology and the M.Sc. degree in computer science from Vietnam National University Ho Chi Minh City, University of Information Technology in 2017 and 2019, respectively, and the Ph.D. degree from the School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, U.K., in December 2023. He is currently a Postdoctoral Fellow with Memorial University, Canada, working under the Canada Excellence Research Chair in Next Generation Communication Technology Program. His research interests include wireless networking, edge/cloud computing, resource allocation and optimization, and applied AI/ML.

TRUNG Q. DUONG (Fellow, IEEE) is a Canada Excellence Research Chair and a Full Professor with Memorial University, Canada. He is also an Adjunct Professor with Queen's University Belfast, U.K., a Visiting Professor with Kyung Hee University, South Korea, and an Adjunct Professor with Duy Tan University, Vietnam. His current research interests include wireless communications, quantum machine learning, and quantum optimization.

He has received two prestigious awards from the Royal Academy of Engineering (RAEng): RAEng Research Chair in 2020 and RAEng Research Fellow in 2015. He is the recipient of the prestigious Newton Prize 2017. He is an Editor-in-Chief of IEEE COMMUNICATIONS SURVEYS AND TUTORIALS. He is a Fellow of the Engineering Institute of Canada and Asia–Pacific Artificial Intelligence Association.

OCTAVIA A. DOBRE (Fellow, IEEE) is a Professor and the Tier-1 Canada Research Chair with Memorial University, Canada. She has co-authored over 500 refereed papers in these areas. She serves as the VP Publications of the IEEE Communications Society. Her research interests encompass wireless communication and networking technologies, as well as optical and underwater communications.

Dr. Dobre obtained eight IEEE Best Paper Awards including the 2024 Heinrich Hertz Award. She was a Fulbright Scholar, a Royal Society Scholar, and a Distinguished Lecturer of the IEEE Communications Society. She was an Inaugural Editor-in-Chief (EiC) of the IEEE Open Journal of the Communications Society and the EiC of the IEEE Communications Letters. She is an Elected Member of the European Academy of Sciences and Arts, a Fellow of the Engineering Institute of Canada, the Canadian Academy of Engineering, and the Royal Society of Canada.

ARUMUGAM NALLANATHAN (Fellow, IEEE) has been a Professor of Wireless Communications and the Head of the Communication Systems Research (CSR) Group, School of Electronic Engineering and Computer Science, Queen Mary University of London since September 2017. He was with the Department of Informatics, King's College London from December 2007 to August 2017, where he was Professor of Wireless Communications from April 2013 to August 2017 and a Visiting Professor from September 2017 to August 2020. He was an Assistant Professor with the Department of Electrical and Computer Engineering, National University of Singapore from August 2000 to December 2007. He published more than 700 technical papers in scientific journals and international conferences. His research interests include artificial intelligence for wireless systems, beyond 5G wireless networks, and Internet of Things.

He is a co-recipient of the Best Paper Awards presented at the IEEE International Conference on Communications in 2016, the IEEE Global Communications Conference in 2017, and the IEEE Vehicular Technology Conference in 2018. He is also a co-recipient of the IEEE Communications Society Leonard G. Abraham Prize in 2022. He received the IEEE Communications Society SPCE Outstanding Service Award in 2012 and the IEEE Communications Society RCC Outstanding Service Award in 2014. He has been selected as a Web of Science Highly Cited Researcher in 2016, and from 2022 to 2024. He was a Senior Editor of IEEE WIRELESS COMMUNICATIONS LETTERS, an Editor of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, the IEEE TRANSACTIONS ON COMMUNICATIONS, the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, and IEEE SIGNAL PROCESSING LETTERS. He is an IEEE Distinguished Lecturer. He served as the Chair for the Signal Processing and Communication Electronics Technical Committee of IEEE Communications Society and Technical Program Chair and member of Technical Program Committees in numerous IEEE conferences.

BERK CANBERK (Senior Member, IEEE) received the B.Sc. degree in electrical engineering from ITU in 2003, the M.Sc. degree in telecommunications engineering from the Chalmers University of Technology, Sweden, in 2005, and the Ph.D. degree in computer science from ITU, Turkey, in 2011, where he was an Associate Professor with the Department of Computer Engineering from 2016 to 2021 and a Full Professor from 2021 to 2022. He is a Professor with the School of Computing, Engineering and the Built Environment, Edinburgh Napier University, U.K., where he leads interdisciplinary research and initiatives in AI-enabled digital twins, IoT communication, and smart wireless networks. He is also an Innovation Director of BTS Group, the biggest network automation and cloud computing company in Turkey. He was a Postdoctoral Researcher with the Georgia Institute of Technology, USA, from 2011 to 2013. He has been involved with several industrial research activities with leading technology companies worldwide, including research scholarship program funding with Google Deepmind, TUBITAK, BTS Group Turkey, Turkcell, Turkish Telekom, and Uniper Energy Germany. He is a distinguished recipient of the U.K. Royal Academy of Engineering's Global Talent Endorsement. He serves as an Associate Editor for IEEE COMMUNICATIONS SURVEYS AND TUTORIALS and a Lead Editor for IEEE ComSoc Best Readings on Digital Twins and Metaverse. In addition, he was an Associate Editor of the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, *Elsevier Computer Networks Journal*, *Elsevier Communication Networks Journal*, and IEEE COMMUNICATIONS LETTERS from 2014 to 2024. He is actively involved in several conferences as a TPC Chair and an Organizing Committee Member.