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Digital Twin-empowered intelligent computation offloading for edge computing in the era of 5G and beyond: A state-of-the-art survey

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ABSTRACT

Edge computing has emerged as a promising paradigm for addressing the latency, bandwidth, and scalability challenges associated with traditional cloud-centric architectures. Computation offloading, the process of transferring computational tasks from edge devices to more powerful remote servers or cloud infrastructure, plays a crucial role in optimizing performance and resource utilization in edge computing systems. However, traditional computation offloading techniques often face limitations related to latency, network dependency, and scalability. In this survey, we explore the integration of digital twin (DT) technology into edge computing environments to empower intelligent computation offloading decisions. DTs, virtual representations of physical entities or systems that mirror their real-world counterparts, offer opportunities to enhance situational awareness, optimize resource allocation, and enable more informed decision-making at the edge. We provide a comprehensive overview of DTs empowered intelligent computation offloading, covering the fundamentals of DTs, traditional computation offloading techniques, and their limitations in edge computing. Additionally, we discuss how DTs can address these challenges and improve computation offloading strategies, along with practical applications and use cases across various domains. Finally, we identify open research challenges and opportunities for future exploration in this emerging field. Through this survey, we aim to provide researchers, practitioners, and stakeholders with insights into the potential of DTs to revolutionize computation offloading for edge computing and drive innovation in this rapidly evolving area.

1. Introduction

In the era of 5G and beyond, the landscape of digital communication and computational technology is undergoing a transformative evolution. The advent of 5G networks promises unprecedented improvements in data transmission speeds, connectivity, and latency reduction, which in turn, catalyze the proliferation of Internet of Things (IoT) devices, smart applications, and real-time services. This rapid growth introduces both opportunities and challenges, particularly in the domain of edge computing, where computational resources are strategically positioned closer to the data sources [1,2]. Edge computing, with its promise of low-latency, high-bandwidth processing closer to data sources, has become increasingly integral to enabling a wide range of applications, from autonomous vehicles to industrial automation and beyond [3].

Computation offloading, the process of transferring computational tasks from edge devices to remote servers or cloud infrastructure, plays a pivotal role in optimizing performance, resource utilization, and energy efficiency in edge computing systems [4]. However, as the number of connected devices and the volume of data generated at the edge continue to surge, traditional approaches to computation offloading—where tasks are transferred from resource-constrained devices to more powerful servers—face significant hurdles. The inherent limitations including latency, network dependency, and scalability issues are exacerbated in the context of emerging 5G networks with their ultra-low latency and high-throughput capabilities [5,6]. In addition, these challenges also include dynamic network conditions, varying computational demands, and the need for real-time decision-making to optimize resource utilization. Consequently, the complexity and heterogeneity of edge environments necessitate innovative solutions to ensure seamless, efficient, and intelligent computation offloading.

To address these challenges and capitalize on the opportunities presented by 5G and beyond, researchers and practitioners are increasingly turning to the concept of DTs. Basically, DTs, virtual replicas of physical entities or systems that mirror their real-world counterparts. In recent years, both the academia and industry have shown great interest in the development of DT technology, which benefits in many domains, such as IoT [7,8], real-time remote monitoring and control in industry [9], risk assessment in transportation [10] and internet of

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vehicles (IoV) [11], and the smart scheduling in smart city [12,13]. It is envisioned that DT will significantly reshape cyber application paradigms in terms of efficiency and intelligence in the near future.

In the context of edge computing, DTs hold significant promises. By creating virtual replicas of edge devices, networks, and applications, DTs can facilitate intelligent computation offloading, enhancing the overall performance and efficiency of edge networks. The integration of DTs with edge computing frameworks allows for real-time monitoring, adaptive task scheduling, and optimized resource allocation, thus addressing the inherent complexities of dynamic edge environments. In this way, DT offers a novel approach to enhancing computation offloading decisions in edge computing environments. By leveraging real-time data, predictive analytics, and adaptive decision-making, DT empower intelligent computation offloading strategies that optimize performance, reliability, and resource utilization at the network edge. While traditional optimization models focus primarily on static or semi-static resource allocation techniques, the DT based models enable continuous, real-time updates and predictive analytics. In addition, unlike standard models that may rely on periodic data collection and decision-making, the DT assisted frameworks integrates contextual information to adjust the decisions dynamically based on incoming data from the edge environment, providing adaptive learning and optimization. This dynamic adjustment makes the model more responsive to changing conditions, such as varying network loads or shifts in edge device capabilities, which are crucial in the 5G and beyond context.

DT has the capability to expand its reach by integrating with edge and fog computing technologies, offering a potential solution to mitigate connectivity and latency challenges within networks [14]. DT is not merely a resonant term but is leveraged to create a detailed virtual representation of edge computing processes. We align with the established definition of a DT as a dynamic virtual model that mirrors the real-time states and operational conditions of physical systems. In the context of edge computing, the DT simulates dynamic network conditions, resource usage, and real-time computation tasks at the edge nodes, allowing for more granular analysis and predictions compared to traditional models. In addition, the adequacy of the DT-based model can be enhanced by incorporating detailed network and edge device parameters such as CPU load, bandwidth, latency, and task offloading efficiency. These are continuously updated through the twin, which not only simulates but also interacts with real-time data flows. By doing this, the models can optimize task scheduling, resource allocation, and overall system performance in a 5G edge computing environment, enhancing the decision-making process for intelligent computation tasks. This approach provides real-time insights and adaptability, which is critical in environments where 5G and beyond introduce ultra-low latency and massive connectivity. Thus, this leads to design multiple methodologies for harnessing DT through fog and edge computing, examining suitable use cases such as wind turbine management, product management, healthcare centers, manufacturing [15] and other IoT industrial applications [16].

In this survey paper, we present a comprehensive overview of DT empowered intelligent computation offloading for edge computing in the era of 5G and beyond. We explore the fundamentals of DTs, review existing literature and research efforts, discuss key challenges and opportunities, and identify future research directions in this rapidly evolving field. Through this survey, we aim to provide researchers, practitioners, and stakeholders with insights into the potential of DTs to revolutionize computation offloading strategies and drive innovation in edge computing in the era of 5G and beyond.

In summarize, the paper provides the following contributions:

- Provide an overview of edge computing and computation offloading concepts, challenges, and opportunities.
- Introduce the concept of DTs and their role in enhancing computation offloading decisions and strategies at the edge.
- Review existing literature and research efforts on DTs empowered computation offloading techniques, including optimization algorithms, machine learning (ML) models, and decision-making frameworks.
- Discuss key applications, use cases, and practical implementations of DTs empowered computation offloading in various domains, such as smart cities, healthcare, transportation, and industrial IoT.
- Identify open research challenges, emerging trends, and future directions in the field of DTs empowered computation offloading for edge computing.

The rest of paper is organized as follows. Section 2 provides a review of related works surveying different models and frameworks used to support computation offloading in edge computing. The background and motivation behind the integration of DTs in edge computing environments are discussed in Section 3, highlighting the potential benefits and challenges. Section 4 then delves into the fundamentals of DTs, providing a comprehensive overview of their characteristics, capabilities, and architecture. Subsequently, it explores traditional computation offloading techniques in edge computing, discussing their limitations and paving the way for the introduction of DTs empowered computation offloading strategies in Section 5. The survey further examines the applications and use cases of DTs in computation offloading across various domains, illustrating the practical implications of this approach in Section 6. Finally, Section 7 of the paper concludes with a discussion of open research challenges, future directions, and opportunities for further exploration in this emerging field.

2. Related works

Several recent surveys have extensively explored computation offloading, edge computing, and the role of DTs in optimizing system performance, especially in the context of 5G networks. This section reviews these key survey works, providing insights into how they relate to and differentiate from the DT-empowered intelligent computation offloading framework presented in this paper.

Thes survey by Mustafa et al. (2024) [17] provides a comprehensive taxonomy of computation offloading approaches, particularly focusing on the role of deep neural networks (DNNs) in optimizing offloading decisions within mobile edge networks. The paper addresses key applications, from autonomous vehicles to smart healthcare, and identifies several open issues related to resource allocation and energy efficiency. While this work emphasizes the use of ML, it does not discuss the integration of DTs for real-time task monitoring and optimization, which is the primary contribution of the current paper.

The survey by Mustafa et al. (2021) [18] investigates the integration of wireless power transfer (WPT) with task offloading in Mobile Edge Computing (MEC) environments. The focus of this paper is on enhancing energy efficiency by leveraging WPT techniques, alongside task offloading. Although it provides detailed insights into energy-efficient task execution in edge networks, it does not explore the real-time dynamic adaptability that DTs offer. The present work distinguishes itself by incorporating DTs for intelligent monitoring and proactive task scheduling, which is critical for 5G-driven applications where latency and system dynamics are paramount.

In the work, Choudhury et al. (2024) [19] reviews the integration of ML techniques, particularly reinforcement learning (RL) and deep learning, to improve offloading efficiency in multi-access edge computing (MEC) environments. The survey highlights how ML-based methods adapt to changing network conditions and device capabilities, but like the previous works, it does not delve into how DTs can enable real-time system updates and predictive analytics for enhanced decision-making.

Peng *et al* [20] focuses on the application of deep RL (DRL) to solve complex computation offloading problems in edge systems. DRL has been shown to effectively manage dynamic offloading scenarios,

Table 1
Summarization of computation offloading models and frameworks in edge computing.

Study	Focus	Contributions	Limitations
[17]	Reviews applications of DNNs in mobile edge networks for computation offloading	Provides insights on ML techniques for offloading but lacks DT integration	Does not explore real-time adaptability or DTs
[18]	Combining WPT with task offloading in MEC environments	Explores energy efficiency in task offloading, but lacks real-time monitoring applications with DTs	Does not incorporate dynamic, real-time monitoring via DTs
[19]	Surveys ML techniques like RL for improving offloading in MEC	Highlights adaptive offloading methods but does not cover DT-driven decision-making	Does not account for the predictive control features enabled by DTs
[20]	DRL approaches for solving complex offloading problems in edge systems	Complements DRL with DT-driven predictive modeling for offloading decisions	Limited to DRL, no discussion of DTs and real-time feedback mechanisms
[21]	DT applications in smart manufacturing, predictive maintenance	Provides an early overview of DTs for monitoring industrial IoT systems	Introduces foundational DT concepts but lacks the offloading aspect in edge computing or 5G

making it suitable for 5G networks where device heterogeneity and mobility pose significant challenges. However, the survey is limited to ML-based approaches and does not discuss the predictive and real-time control aspects that DTs bring to the table. The current paper extends these ideas by showing how DTs can complement DRL approaches to further enhance real-time task offloading and resource management.

The study, conducted by Soori et al. (2018) [21] provides an early but insightful look at the application of DTs in smart manufacturing and IoT systems. The paper primarily addresses how DTs enable predictive maintenance and performance monitoring in industrial settings. However, it does not cover computation offloading or the integration of DTs with edge computing, leaving a gap that this paper aims to fill by focusing on the 5G era and intelligent task management through DTs.

While the existing surveys provide extensive overviews of computation offloading and the use of ML in optimizing edge computing, they largely overlook the emerging role of DTs in facilitating real-time decision-making and predictive task offloading. Moreover, none of the existing surveys fully explore the interplay between DTs and 5G networks, a critical component in modern edge computing environments. The current paper aims to bridge this gap by offering a comprehensive review of how DTs can be harnessed to empower intelligent computation offloading, with a focus on real-time adaptability, low-latency task management, and the capabilities afforded by 5G and beyond technologies.

Table 1 summarizes the key features of computation offloading models and frameworks in edge computing in the literature.

3. Computation offloading in edge computing

Edge computing is an emerging paradigm that brings computation and data storage closer to where it is needed, reducing latency and bandwidth use compared to traditional cloud-based models [22]. By processing data at or near the source, edge computing enables real-time analytics and decision-making, crucial for applications in the era of 5G and beyond, such as autonomous vehicles, smart cities, and IoT devices. This approach enhances performance and responsiveness while reducing the strain on central data centers and networks. The architecture of edge computing typically includes several key components: edge devices (sensors, actuators, and IoT devices generating data), edge nodes or gateways (handling data aggregation and processing), edge servers (providing computational resources close to data sources), and cloud data centers (offering extensive computational power and storage for less time-sensitive tasks) [23]. Communication networks (like 5G, Wi-Fi, and Ethernet) facilitate data transfer among these components. This layered architecture ensures efficient, scalable, and responsive data processing, though it presents challenges such as managing distributed resources, ensuring security and privacy, and maintaining consistent service quality across diverse environments [24].

Computation offloading in edge computing refers to the process of transferring computational tasks from edge devices to nearby edge servers or cloud resources for execution [25]. This strategy aims to alleviate the computational burden on edge devices with limited processing capabilities and battery life while leveraging the higher computational capacity and resources available at the edge or cloud. The fundamental concept involves determining which tasks should be offloaded, where they should be offloaded, and how to manage the offloading process efficiently. Offloading decisions may consider factors such as task characteristics, network conditions, resource availability, energy constraints, and user preferences [26]. Various offloading strategies, including static and dynamic approaches, can be employed based on application requirements and system constraints [27]. Static offloading involves predefining offloading policies [28], while dynamic offloading adapts decisions based on real-time conditions [29]. Challenges in computation offloading include minimizing latency, optimizing resource utilization, ensuring data privacy and security, and managing network congestion. Effective offloading strategies play a crucial role in enhancing the performance, scalability, and energy efficiency of edge computing systems, making them vital for realizing the full potential of edge computing in various domains.

Computation offloading in edge computing presents several challenges that need to be addressed to maximize its potential [4]. One of the primary issues is latency and network variability, as real-time applications require minimal delay, but network instability and congestion can introduce significant latencies. Efficient resource management is another challenge, involving the allocation and scaling of computational resources among diverse and heterogeneous edge devices. Security and privacy are critical concerns, given the risks of data transmission to edge servers and the need to protect sensitive information from unauthorized access. Additionally, energy efficiency is paramount, as offloading tasks must be managed to avoid quickly draining the battery life of devices. Interoperability and standardization pose difficulties due to the diverse ecosystems and lack of universal standards, complicating the integration of different systems. Reliability and fault tolerance are also crucial, requiring mechanisms to ensure continuous operation despite device failures or connectivity issues. Task partitioning and scheduling present complexities in determining which tasks to offload and dynamically adjusting schedules based on real-time conditions. Quality of Service (QoS) assurance is challenging due to the need to maintain high service levels under varying workloads. Finally, economic and cost considerations involve balancing the additional costs for data transfer and resource usage while developing viable monetization models for edge computing services. Addressing these challenges is essential to fully leverage the benefits of computation offloading in edge computing.

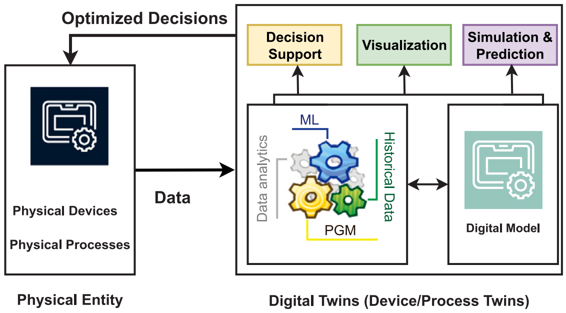

Fig. 1. DT modeling methodology and core features.

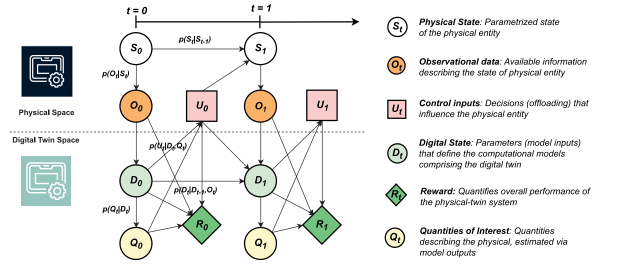

Fig. 2. An example of PGM to model, and build a DT.

4. Digital twins

4.1. DT concepts

The physical-virtual interaction is of the most important in the DT-based systems. The physical side informs the virtual one of the updates of parameters at an appropriate frequency to maintain the synchronization and effectiveness of the model. Meanwhile, the virtual side feeds back the analysis results to the physical end in real-time to assist decision-making. With this sense, the physical-virtual interaction gives DT models the characteristic of dynamicity, enabling them to simultaneously match the work progress and working status of the product to assess its quality, life span, and health status [30]. To fully exploit the potential of DT, DT networks (DTNs) are defined as a many-to-many mapping network constructed by multiple one-to-one DTs [31]. Basically, DTN leverages advanced communication technologies to facilitate real-time information exchange between a physical object and its virtual twin, among multiple virtual twins, and between various physical objects. DTN achieves dynamic interaction and synchronized evolution between multiple physical objects and their virtual twins through precise DT modeling, communication, computing, and physical data processing technologies. Within DTN, physical objects and virtual twins can communicate, collaborate, share information, and complete tasks together, forming an information-sharing network by connecting multiple DT nodes.

A DT is a digital representation of a physical product, and process with required accuracy and fidelity to simulate, and predict the physical performance, thus supporting the optimized decisions as shown in Fig. 1.

In particularly, Device Twin and DT are related concepts, but they serve different purposes within modern systems. A Device Twin focuses on replicating the state and behavior of individual devices or components, such as sensors, engines, or control systems, providing detailed data about the operation of those specific elements. In contrast, a DT encompasses a broader scope by integrating data from multiple Device Twins to represent and simulate the behavior of an entire system, such as a connected car, smart city, or manufacturing process. The relationship between the two lies in how Device Twins supply the granular, component-level data that feeds into the larger, system-level analysis and optimization performed by the Digital Twin.

4.2. DT modeling

Despite their potential, the development of DTs is still very challenging, since it requires the collaboration of experts in multiple fields and the use of robust and affordable computational tools, able to integrate multiple physics as well as diverse solving technologies. The kind of resources that are only available to original equipment manufacturers (OEMs) or Tier-1 manufacturers [31].

Table 2
State-of-the-art models developed to support DT implementation.

Model	Focus
Autodesk Tandem [35]	Modeling physical movements and characteristics within engineering structures, residential, and office spaces
Eclipse Ditto [36]	Designed for IoT-based DTs. By enabling real-time monitoring and comparison of the current state of IoT devices with their expected state, Ditto supports predictive analysis
MCX Framework [37]	Modeling the interaction between physical processes and their digital counterparts, facilitating the development of cyber–physical system DTs
Twinbase [38]	Used for deploying DTs on web networks and streamlines the process of integrating, updating, and scaling DT models across distributed systems
Ayla [39]	Used for the integration of IoT sensors with HTTPS, MQTT, and CoAP protocols, offering compatibility with Android, Linux, and cloud providers
iTwin.js [40]	A robust framework for developing web applications for DT infrastructure.

However, predictive DT models can be built by ML and data analytics approach fed the historical data of physical entity, and probabilistic graphical models (PGMs) to accurately estimate the future states and performance of physical entities [32,33].

As illustrated in Fig. 2, a PGM is constructed as a formal mathematical representation of a DT and its associated physical asset [34]. The declarative and general nature of the proposed DT model make it rigorous yet flexible, enabling its application at scale in a diverse range of application areas.

Currently, there are DT models developed to support specific applications as shown in Table 2

4.3. DT models enhanced by AI

DT modeling enhanced by artificial intelligence (AI) represents a significant advancement in the field of DT technology, offering unprecedented capabilities for simulating, monitoring, and optimizing complex systems in real-time [41]. By integrating AI techniques, such as ML and deep learning, into DT modeling, it becomes possible to enhance the fidelity, accuracy, and predictive capabilities of DT representations. AI-powered DTs can learn from historical data, adapt to changing conditions, and autonomously make decisions to optimize system performance and efficiency. These AI-enhanced DTs can provide valuable insights into the behavior and dynamics of physical systems, enabling better understanding, diagnosis, and control of processes across various domains, including manufacturing, healthcare, transportation, and smart cities. Moreover, AI-driven DTs enable proactive maintenance, predictive analytics, and scenario-based forecasting, empowering organizations to anticipate and mitigate potential issues before they occur, ultimately leading to improved operational efficiency, cost savings, and innovation. As AI continues to advance, the integration of AI techniques into DT modeling holds immense promise for revolutionizing how we design, monitor, and manage complex systems in the digital age.

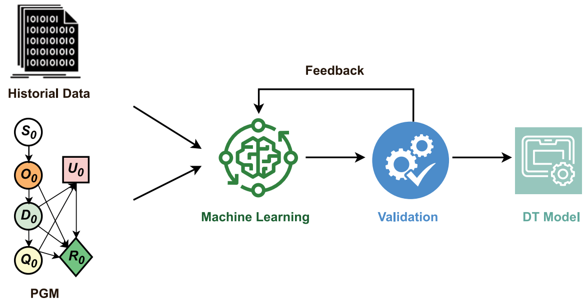

Fig. 3. DT modeling by ML and PGM.

When fed with the historical data of physical entities, ML algorithms can be developed to create the efficient DT models for physical twins [42] (Fig. 3).

4.4. *Standards and organizations in DT development*

In the rapidly evolving landscape of DTs, the establishment of standards and the work of key organizations have been instrumental in driving innovation, ensuring interoperability, and addressing the challenges of scalability and security. This section highlights the role of prominent organizations and the standards they have developed or are currently working on, which serve as the backbone for Digital Twin technologies across industries.

4.4.1. *DT consortium*

The DT Consortium (DTC) [43] is the largest organization dedicated to advancing the use of DT technologies. Founded by key industry players such as Microsoft, Dell, and GE Digital, the consortium brings together various stakeholders from different industries, including manufacturing, healthcare, aerospace, and telecommunications. DTC focuses on creating an ecosystem that promotes the development of best practices, reference architectures, and frameworks to ensure the broad adoption of DTs.

The consortium also plays a crucial role in identifying cross-industry use cases and providing guidelines for the development of scalable and secure DT implementations. By facilitating collaboration between industry, academia, and government, DTC acts as a central hub for the dissemination of DT standards and resources.

4.4.2. *oneM2M*

oneM2M is a global standards initiative that focuses on developing technical specifications to ensure interoperability between machine-to-machine (M2M) systems, which is crucial for DT deployments in IoT environments. As DTs often rely on real-time data from IoT devices, oneM2M's contributions in standardizing communication protocols and data exchange frameworks are essential for building robust DT systems [44].

oneM2M provides a horizontal platform that integrates various IoT applications and services, allowing for seamless data flow and management, which are critical for the operational success of Digital Twins, especially in sectors such as smart cities, manufacturing, and transportation.

4.4.3. *ETSI (European Telecommunications Standards Institute)*

ETSI plays a significant role in defining the standards for emerging technologies such as 5G, edge computing, and IoT, which are foundational to the success of DT implementations [45]. The ETSI Industry Specification Group on cross-cutting Context Information Management (ISG CIM) provides specifications that enable context-aware services in IoT, an essential feature for Digital Twin ecosystems where real-time contextual data is vital.

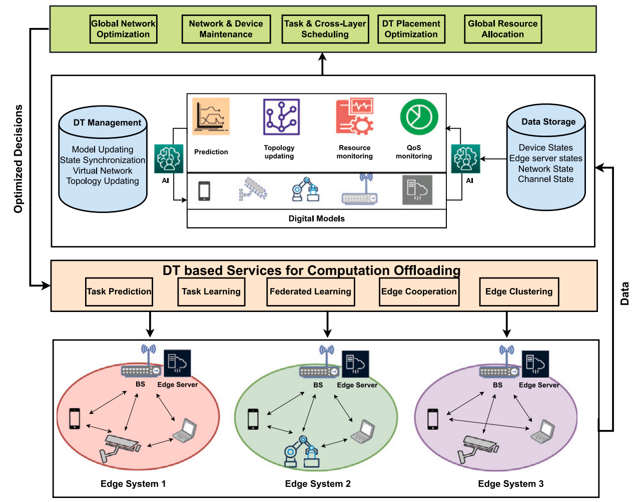

Fig. 4. DT: Features and roles to support computation offloading in edge computing systems.

ETSI's Multi-access Edge Computing (MEC) standards also align closely with the needs of DT environments by allowing low-latency data processing at the edge of the network, reducing response times and enhancing the performance of DTs in real-time applications.

4.4.4. *3GPP (3rd Generation Partnership Project)*

As the primary organization responsible for the development of 5G standards, 3GPP's work is essential to the growth of DTs, particularly in applications requiring ultra-low latency, high bandwidth, and massive connectivity. The integration of 5G into DT frameworks enables advanced use cases such as real-time simulation, remote monitoring, and control of physical assets in industries like healthcare, manufacturing, and automotive.

3GPP's Release 16 and beyond includes features such as Ultra-Reliable Low Latency Communication (URLLC) and enhanced mobile broadband, which are critical for supporting the vast data flows and real-time requirements of DTs [46].

4.4.5. *Other notable organizations and standards*

In addition to the major organizations mentioned, several other standards bodies contribute to the ecosystem of Digital Twin technologies:

- ISO/IEC JTC 1 (Joint Technical Committee) has been working on standardization in the areas of IoT and artificial intelligence, both of which are essential components of DT systems [47].
- IEEE P3144 defines a DT maturity model for industry, including DT capability domains and corresponding subdomains [48].

5. DTs empowered computation offloading for edge computing

Existing literature and research efforts on DT empowered computation offloading techniques have made significant strides in leveraging DT technology to optimize the offloading process in edge computing environments. These efforts encompass a wide range of approaches, including optimization algorithms, ML models, and decision-making frameworks, which represents the key features and roles of DT to facilitate computation offloading processes as illustrated in Fig. 4.

5.1. DT-aided optimization algorithms

Researchers have developed optimization algorithms to efficiently allocate computational tasks to edge devices based on factors such as resource availability, network conditions, and application requirements. These algorithms consider various constraints, including computational capacity, energy consumption, and latency, to ensure that offloading decisions are both effective and feasible in real-world edge computing scenarios.

In [49], the paper discusses a study on a MEC architecture with the assistance of DT for industrial automation, focusing on reducing end-to-end latency by offloading computing tasks from IoT devices to MEC servers. The authors propose a practical end-to-end latency minimization problem in the MEC model with the support of DT technology and have developed a novel DT framework to assist in task offloading for IoT devices in industrial IoT networks with MEC. They address the latency minimization problem by iteratively optimizing parameters such as the transmit power of IoT devices, user association, intelligent task offloading policies, and estimated CPU processing rates of the devices. Finally, simulation results are conducted to validate the efficacy of the proposed approach in terms of latency performance compared to conventional methods. The limitations of the study include the non-convex nature of the optimization problem, which can be challenging to solve for large-scale scenarios.

MEC serves as a crucial technology for enabling smart industry solutions by offering flexible and readily available services to mobile devices (MDs) by transferring latency-sensitive tasks to edge service providers. However, ensuring optimal decisions regarding computation offloading and resource allocation while safeguarding the privacy and security of MDs poses a significant challenge. Hence, in [50], the authors propose a novel approach of leveraging DT empowered edge networks, wherein the optimization problem is addressed through a two-stage incentive mechanism. Initially, the resource allocation strategy is determined via interactions among DTs based on credit-based incentives. Subsequently, a distributed incentive mechanism is employed, utilizing the Stackelberg-based alternating direction method of multipliers to derive optimal offloading and privacy investment strategies simultaneously. Numerical findings demonstrate that this two-stage incentive mechanism effectively achieves resource allocation and computation offloading while enhancing the privacy and security of MDs.

In the work [51], the authors investigate the issue of intelligently offloading tasks from mobile users (MUs) to cooperative mobile-edge servers (MESs) with the support of DT. Specifically, they propose a DT-assisted task offloading scheme (DTTOS) that involves the selection of MESs and intelligent task offloading. Channel state information (CSI) and blockchain technology are leveraged for MES selection. Subsequently, we introduce a method to facilitate MU's task offloading, formulated as a Markov decision process (MDP) with intelligent considerations. Additionally, they devise a mathematical optimization model to minimize power and time overhead, which is decomposed into two sub-optimization models and solved using the decision tree algorithm (DTA) and double deep-Q-learning (DDQN), respectively, to address complexity issues. Simulation results demonstrate the effectiveness of the proposed scheme in ensuring data security and enhancing network performance.

5.2. DT-aided ML models

ML techniques have been applied to predict workload characteristics, resource demands, and network conditions, enabling more informed offloading decisions.

Researchers have developed supervised learning models, such as regression and classification algorithms, to predict offloading outcomes based on historical data and input features. Additionally, unsupervised learning techniques, including clustering and anomaly detection, have been used to identify patterns and anomalies in offloading behavior, enabling adaptive decision-making in dynamic edge environments.

5.3. Decision-making frameworks

Decision-making frameworks have been proposed to formalize the offloading process and provide a structured approach for making offloading decisions.

These frameworks typically involve a series of steps, including data collection, analysis, optimization, and decision-making, to systematically evaluate offloading options and select the most suitable strategy. Examples include Markov decision processes (MDPs), RL algorithms, and game theory-based approaches, which model the offloading process as a decision-making problem and aim to find optimal policies for task allocation and resource utilization.

The work [52] introduces a new vision of DT Edge Networks (DITEN) for mobile offloading, which effectively reduces latency, failure rate, and service migration while saving costs. With the assistance of DT, the offloading optimization poroblem is solved by applying Lyapunov optimization and Actor–Critic deep RL.

Given the mobility of users and the unpredictable nature of MEC environments, the study [53] investigates the intelligent task offloading issue in unmanned aerial vehicle (UAV)-enabled MEC with the support of DT technology. The objective is to minimize the energy consumption of the entire MEC system by optimizing mobile terminal users (MTUs) association, UAV trajectory, transmission power distribution, and computation capacity allocation, while adhering to the constraints of mission maximum processing delays. Initially, a double deep Q-network (DDQN) algorithm derived from deep RL is introduced to effectively address the problems of MTUs association and UAV trajectory. Subsequently, a closed-form expression is utilized to manage the transmission power distribution issue, and the computation capacity allocation problem is further tackled using an iterative algorithm. Numerical findings indicate that our proposed approach can converge and substantially decrease the total energy consumption of the MEC system compared to benchmark methods.

In the study [54], they introduced a DTN architecture tailored for Industrial Internet of Things (IIoT), employing DT technology to establish the network structure and stochastic task arrival model within IIoT networks. Subsequently, we devised a formulation for the stochastic computation offloading and resource allocation issue to collectively optimize offloading decisions, transmission power, bandwidth, and computation resources. Given that the formulated problem entails a non-convex stochastic programming challenge, we employed the Lyapunov optimization technique to transform the original problem into a deterministic per-time slot problem equivalently. Finally, we applied the AAC algorithm to address the computation offloading and resource allocation problem. Evaluation via numerical experiments illustrates the superior performance of our proposed algorithm compared to benchmark methods.

To better facilitate the emergence of vehicular applications and multimedia services, vehicular edge computing (VEC) offers computing and caching services in close proximity to vehicles. This approach aims to reduce network transmission latency and alleviate network congestion. However, current VEC networks may encounter several implementation hurdles, including the high mobility of vehicles, dynamic vehicular environments, and complex network scheduling. DT technology, as an emerging solution, enables the creation of virtual representations of physical networks to predict, estimate, and analyze real-time network conditions. In this study [55], they integrate DT technology into VEC networks to dynamically manage network resources and policy scheduling. Initially, they introduce the framework of VEC networks and outline the primary challenges encountered within these networks. Subsequently, they introduce the concept of DT and propose an adaptive DT-enabled VEC network. In this proposed network, DT technology facilitates adaptive network management through two closed loops between physical VEC networks and DT representations. Moreover, they formalize a DT empowered VEC offloading problem, incorporating vehicle digital models and road side unit (RSU) digital models. They design a deep RL (DRL)-based offloading scheme aimed at minimizing total offloading latency. Numerical results demonstrate the efficacy of the proposed DRL-based algorithm for VEC offloading.

The sixth-generation (6G) is anticipated to feature pervasive connectivity, significantly reduced latency, and improved edge intelligence. However, incorporating these attributes into 6G networks necessitates addressing novel, distinctive, and intricate challenges, particularly at the network's edge. In this paper [56], they introduce a wireless DT edge network model by integrating DT technology with edge networks, thereby enabling novel functionalities such as hyper-connected experiences and low-latency edge computing. To effectively establish and maintain DTs within the wireless DT network, they formulate the edge association problem considering dynamic network states and varying network topologies. Furthermore, we decompose the problem into two subproblems based on different operational stages, namely DT placement and DT migration. Additionally, they devise a deep RL (DRL)-based algorithm to determine the optimal solution for the DT placement problem, followed by leveraging transfer learning to address the DT migration problem. Numerical simulations demonstrate that the proposed approach offers reduced system costs and improved convergence rates for dynamic network states.

In this paper [57], the authors present the concept of DT wireless networks (DTWN), where DTs are integrated into wireless networks to facilitate real-time data processing and computation at the edge level. Subsequently, they introduce a federated learning framework empowered by blockchain technology within the DTWN environment. This framework promotes collaborative computing, thereby enhancing system reliability, security, and data privacy. Furthermore, to address the trade-off between learning accuracy and time efficiency inherent in the proposed approach, they devise an optimization problem for edge association. This problem jointly considers factors such as DT association, training data batch size, and bandwidth allocation. They employ multi-agent RL techniques to identify an optimal solution. Numerical experiments conducted on real-world datasets demonstrate that the proposed scheme outperforms benchmark learning methods in terms of efficiency and cost reduction.

In the realm of IoVs, stringent requirements for ultralow network response latency are commonplace. Addressing this challenge involves integrating IoV with MEC, thereby enabling edge devices to pool their communication, computation, and caching (3C) resources through intelligent cooperation at the edge. However, allocating 3C resources with the aid of artificial intelligence (AI) necessitates an extensive dataset and substantial computational capabilities, which are unattainable on resource-constrained on-board units (OBUs) or road-side units (RSUs). To address this issue, the authors in [58] propose a DT supported edge intelligent cooperation scheme, facilitating optimal 3C resource allocation and intelligent cooperation at the edge. Their focus lies in minimizing response delays to cater to the needs of latency-sensitive applications in the IoV domain. To this end, they formulate mathematical expressions for network response times by modeling the edge server workflow as an M/M/1/N/FCFS queuing process. Additionally, we conduct an in-depth analysis of deviations in 3C resources between the physical realm and the DT space, and discuss their impact on offloading decisions. Furthermore, they develop a mathematical optimization model to minimize latency. Given its complexity, they employ a deep deterministic policy gradient algorithm to solve it, treating the cooperation process between edge nodes as a Markov decision process. Finally, through simulations, they validate the superiority of our algorithm over existing schemes in terms of network response latency.

The work [59] introduce an innovative DT framework supported by the notion of the metaverse, incorporating a holistic model encompassing communication, computation, and storage. This framework leverages MEC and ultra-reliable and low-latency communications (URLLC) to create an MEC-based URLLC DT architecture. This architectural design is focused on enhancing the resilient computing infrastructure through the utilization of methodologies like task offloading and task caching on proximal edge servers in order to reduce latency. Furthermore, the proposed DT scheme ensures stringent reliability and low-latency requirements, aligning well with the anticipated needs of future networked systems in the metaverse. Notably, this study is the first of its kind in the literature to tackle the optimal latency/reliability problem in DT-enabled metaverse environments. This is achieved by optimizing various communication and computation parameters, including offloading strategies, edge caching policies, bandwidth allocation, transmit power, and computation resources of user devices and edge servers. The proposed scheme is designed to enhance the quality of experience of DT applications within the metaverse, particularly in terms of latency and reliability.

In this research paper [60], the focus revolves around optimizing the decision-making process concerning computation offloading (DCO), channel access arrangement, and downlink power allocation. Given the asynchronous multi-stage (UL-DL) nature of our problem, they introduce a novel algorithm called Asynchronous Actors Hybrid Critic (AAHC) that builds upon the Advantage Actor–Critic structure, aiming to approach a near-optimal solution. To address the sequential and multi-stage nature of our problem, we devise two interactive RL agents tasked with optimizing the two transmission stages. Moreover, recognizing the sequential nature of problem, which is divided into stages, we break down the reward into stage-specific rewards along with an overarching global reward.

In [61], the authors tackle the challenge of reducing latency in computation offloading within DT wireless edge networks in the industrial Internet-of-Things (IoT) landscape, leveraging URLLCs links. This latency reduction is achieved through the joint optimization of communication and computation variables, including transmit power, user association of IoT devices, offloading proportions, and the processing rate of both users and edge servers. To address this complex issue, they introduce an iterative algorithm based on an alternating optimization approach integrated with an inner convex approximation framework. Simulation results underscore the effectiveness of the proposed algorithm in latency reduction when compared to alternative benchmark schemes.

In this study [62], they address the task of minimizing end-to-end (e2e) latency in DT-assisted offloading within edge networks, augmented by unmanned aerial vehicles (UAVs) equipped with multiple antennas, all within the strict constraints of ultra-reliable low-latency communications (URLLC) links. The objective of minimizing latency is achieved through the joint optimization of transmit power, offloading parameters, and the processing rate of both Internet of Things (IoT) devices and edge servers (ES). To tackle this intricate problem, they employ an alternative optimization approach coupled with suitable inner approximations. Various simulation scenarios are conducted to demonstrate the efficacy of the proposed DT solution in supporting IoT applications.

A series of studies have proposed innovative solutions for improving the reliability and latency of DT-enabled metaverse communications. [59,63] both emphasize the potential of mobile edge computing (MEC) and URLLC in this context. [59] specifically introduces a DT scheme that leverages MEC and URLLC to optimize various communication and computation variables, while [63] discusses the role of 6G edge intelligence-based URLLC in achieving the full potential of the metaverse. [60] further enhances these ideas by proposing a multi-agent deep RL approach for DT over 6G wireless communication, which optimizes computation offloading and channel assignment to ensure reliability and low latency. [61] extends these concepts to the industrial IoT environment, presenting an algorithm that minimizes latency in DT wireless edge networks through the joint optimization of communication and computation variables. These studies collectively highlight the potential of edge intelligence-based URLLC in enhancing the performance of DT-enabled metaverse communications. [62] explored the use of DT technology in 6G aerial edge computing with a focus on URLLC. To address the challenge of minimizing end-to-end latency in DT-aided offloading, [62] proposes a joint optimization approach for transmit power, offloading factors, and processing rate.

Within MEC-enhanced intelligent transportation systems (ITS), latency-sensitive computing tasks are shifted to Roadside Units (RSUs) for execution, thereby diminishing transmission latency compared to cloud-based solutions. Nonetheless, the repetitive execution of identical tasks, contingent upon input data, contributes to additional system latency. An alternative approach involves preemptively caching requisite services on RSUs. By jointly considering computation offloading and service caching, the demands of latency-sensitive computing tasks are fulfilled. Additionally, leveraging DT technology, a virtual representation mirroring the real-world environment is constructed in real-time to efficiently devise offloading strategies. This paper [64] introduces a novel approach, named CODT (Computation Offloading and Service Caching using Decision Theory), for computation offloading and service caching in ITS with DT. Initially, computation offloading and service caching in ITS are modeled utilizing DT. Subsequently, a Mixed-Integer Nonlinear Programming (MINLP) problem is formulated to minimize system latency. Decision theory is then applied to evaluate the utilities of offloading strategies across various RSU states and determine the optimal strategy. Extensive simulations, based on real-world datasets, demonstrate that CODT outperforms other baseline methods.

Combining edge computing with DT-enabled IoVs offers promising prospects for deploying computationally intensive applications, thereby enhancing intelligent transportation capabilities. By continuously updating DTs of vehicles and offloading services to edge computing devices (ECDs), the limitations of vehicles' computational resources can be effectively supplemented. However, the computational intensity of DT-empowered IoV poses challenges, as excessive service requests can overload ECDs, leading to degraded Quality of Service (QoS). To mitigate this issue, this paper [65] analyzes a multiuser offloading system in which QoS is evaluated based on service response times. Subsequently, we propose a Service Offloading (SOL) method utilizing deep RL for DT-empowered IoV in edge computing. SOL utilizes deep Q-network (DQN) to derive optimized offloading decisions, leveraging the value function approximation of deep learning and RL. Experimental evaluations conducted against comparative methods demonstrate the effectiveness and adaptability of SOL across diverse environments.

This research [66] addresses the collaborative optimization of computation offloading, service caching, and resource allocation within the DT Edge Network (DTEN), framing the issue as a Mixed-Integer Non-Linear Programming (MINLP) challenge aimed at minimizing long-term energy consumption. To tackle this optimization task, we introduce a novel Deep Deterministic Policy Gradient (DDPG) algorithm tailored to determine optimal strategies for computation offloading, service caching, and resource allocation. Simulation outcomes affirm the significant reduction in long-term energy consumption achieved by the proposed DDPG-based algorithm, showcasing its superior performance over various benchmark algorithms across diverse scenarios.

The integration of MEC and DT technologies holds promise for enhancing mobile application service quality in the 6G era. However, existing research often neglects considerations such as service caching and task interdependency, potentially leading to a degradation in system performance. Additionally, edge servers (ESs) face constraints in computing resources and caching capacities, necessitating collaborative efforts to meet user demands effectively. To overcome these challenges, a DT-empowered MEC architecture is proposed [67] to facilitates mobile users (MUs) in offloading dependency-aware tasks, while also accounting for service caching and edge collaboration. The aim is to jointly optimize computation offloading and resource allocation to minimize overall system energy consumption. Consequently, the offloading problem is formulated as a Mixed Integer Non-linear Programming (MINLP) challenge and employ an Asynchronous Advantage Actor–Critic (A3C)-based method for resolution. Through extensive simulations, the results demonstrate the superiority of proposed approach over alternative benchmark algorithms across various scenarios, notably reducing energy consumption.

The use of computation offloading and service caching in ITS with DT technology is a growing area of research. [65,66] both propose methods that jointly optimize these processes, with [65] using decision theory and [66] using a Deep Deterministic Policy Gradient (DDPG) based algorithm. [67] extends this work by considering task dependency and edge collaboration, and proposes an Asynchronous Advantage Actor–Critic (A3C)-based method for joint optimization. These studies collectively demonstrate the potential of these techniques in improving system performance and reducing energy consumption in ITS with DT.

A range of studies have proposed innovative resource scheduling schemes for intelligent vehicular systems. [68] introduces a parallel intelligence-driven scheme that reduces system cost and improves load balance. [69] presents a DT-driven approach that adapts to dynamic service demands and vehicle mobility. [70] focuses on latency minimization, using a DT Supported Resource Allocation Scheme. [71] establishes a dynamic DT for aerial-assisted IoVs, and designs a two-stage incentive mechanism for resource allocation. These studies collectively highlight the potential of DT technology and artificial intelligence in enhancing the efficiency and performance of intelligent vehicular systems.

Real-time DT technology has the potential to enhance traffic safety in intelligent vehicular systems and offer systematic strategies for intelligent traffic management. However, achieving real-time DT functionality relies heavily on robust computation spanning from vehicle-side to cloud-side platforms. To address challenges arising from the dual dependency of timing and data in computation tasks, as well as the issue of uneven workload distribution among MEC servers, the authors in [68] propose a parallel intelligence-driven resource scheduling scheme for computation tasks in intelligent vehicular systems (IVS). Firstly, the authors formulate delay and energy consumption models for each computing platform, taking into account the dual dependence of sub-tasks. Subsequently, they define an allocation model for computing and communication resources based on the auction algorithm's bidding concept, alongside formulating a load balancing model for the MEC server cluster considering the load status of each MEC server. Secondly, they formulate a joint optimization problem encompassing offloading, resource allocation, and load balancing. Finally, they propose an adaptive particle swarm optimization algorithm with genetic components to solve this optimization problem. Simulation results demonstrate that the proposed scheme effectively reduces the system's total cost while meeting maximum tolerable delay requirements, and significantly enhances the load balance of the edge server cluster.

This research [69] introduces a pioneering approach to managing computing resources of edge servers within vehicular networks, leveraging DTs and artificial intelligence (AI). Specifically, we develop two-tier DTs tailored for vehicular networks, designed to capture networking-related characteristics of both vehicles and edge servers. Exploiting these features, we propose a two-stage computing resource allocation scheme. Initially, the central controller periodically generates reference policies for real-time computing resource allocation based on network dynamics and service demands captured by the DTs of edge servers. Subsequently, computing resources of the edge servers are dynamically allocated to individual vehicles in real-time through a low-complexity matching-based allocation mechanism that adheres to the reference policies. By harnessing DTs, the proposed scheme exhibits adaptability to dynamic service demands and vehicle mobility in a scalable manner. Simulation results showcase that the DT-driven scheme enables the vehicular network to accommodate a greater number of computing tasks compared to benchmark schemes.

In this research paper [70], they introduce a novel Resource Allocation Scheme (RAS) supported by DT technology, known as DTS-RAS. This scheme facilitates intelligent collaboration among edge nodes in the IoV context. Their primary objective is to minimize latency within the DT-IoV framework. To achieve this, they first derive a mathematical expression to quantify the response time of vehicle offloading tasks to collaborative edge nodes, treating the edge server as an M/M/1/N queue model. Subsequently, they devise an optimization model aimed at reducing this response time. Given the complexity involved, we employ a Double Deep Q-learning Network (DDQN) to train the edge server, enabling it to determine optimal allocation actions by modeling the collaboration process as a Markov Decision Process (MDP). Simulation results illustrate that the proposed scheme surpasses existing approaches in terms of execution latency.

The IoVs empowered by aerial communications, facilitates seamless connections and nearby computing services for vehicles. However, the dynamic network dynamics of aerial-assisted IoV present challenges in resource allocation. The study [71] proposes the establishment of a dynamic DT (DT) for aerial-assisted IoV to capture the fluctuating resource supply and demands, enabling unified resource scheduling and allocation. A two-stage incentive mechanism for resource allocation based on the Stackelberg game is devised, where the DT of vehicles or roadside units (RSUs) acts as the leader, and the RSUs providing computing services are the followers. In the initial stage incentive, the computing resources that RSUs are willing to offer are determined based on vehicles' preferences. To further enhance vehicle satisfaction and overall energy efficiency, a distributed incentive mechanism based on the alternating direction method of multipliers (ADMMs) is designed, optimizing the resource allocation policy for each vehicle. Leveraging ADMM, the incentive mechanism can operate concurrently at multiple RSUs to reduce delays and alleviate the computational burden of UAVs. Simulation results demonstrate that the proposed scheme effectively enhances vehicle satisfaction and energy efficiency simultaneously.

As sixth-generation (6G) networks continue to advance, virtualization emerges as a pivotal aspect. The future of virtualization hinges on both the network's service provisioning capability and the service requirements of end users, paving the way for network and end user virtualization. Hence, this study [72] introduces a comprehensive network virtualization architecture that amalgamates DT technology and network slicing to realize service-centric and user-centric network management. With the proliferation of latency-sensitive and computationally intensive in-vehicle applications, the limited computing resources within vehicles struggle to meet diverse network demands, thereby making vehicle edge computing (VEC) a promising solution. However, computation offloading encounters challenges such as excessive upload traffic and prolonged upload times. Consequently, to minimize the overall response time (ORT) of the system, we propose a novel environment-aware offloading mechanism (EAOM) leveraging the integrated sensing and communication system (ISAC) to address the joint optimization problem of task scheduling and resource allocation. Considering vehicle mobility and environmental dynamics, the optimization problem is formulated as a Markov decision process, with an enhanced algorithm incorporating Shapley-Q value and deep deterministic policy gradient (DDPG) utilized for solving it. Simulation results underscore the effectiveness and superiority of our proposed scheme.

[50,72] both propose resource allocation schemes for integrated sensing and communication in DT-enabled IoVs. [72]'s work focuses on minimizing overall response time through an environment-aware offloading mechanism, while [50]'s scheme uses a distributed incentive mechanism to maximize vehicle satisfaction and energy efficiency. [71] extends this work by introducing a dynamic DT for aerial-assisted IoV, further improving satisfaction and energy efficiency. [58] presents a resource allocation scheme for the IoV environment, leveraging intelligent edge cooperation and a DT-supported approach to minimize latency. These studies collectively contribute to the development of efficient resource allocation strategies for DT-enabled IoV.

DTs and edge computing offer compelling solutions for supporting computing-intensive and service-sensitive applications in the IoVs. While existing solutions for IoV service offloading primarily focus on edge–cloud collaboration, the potential collaboration among small cell eNodeBs (SCeNBs) is often overlooked. By fostering collaborative computing among nodes, service delays significantly lower than offloading tasks to the cloud can be achieved. In this paper [73], the authors propose a framework that facilitates and maintains simulation of collaboration between SCeNB nodes by constructing a DT that encapsulates SCeNB nodes within the central controller. This enables the determination of user task offloading positions, sub-channel allocation, and computing resource allocation. Subsequently, an algorithm named AUC-AC, grounded in the dominant Actor–Critic network and the auction mechanism, is introduced. To enhance the global information processing capability, the convolutional block attention mechanism (CBAM) is incorporated into the DT of each SCeNB node to observe its environment and learn strategies. Numerical results demonstrate the superiority of the proposed scheme over several baseline algorithms in terms of service delay reduction.

In the era of 6G networking, the development of IoV is being driven by the integration of DT and Intelligent Reflective Surface (IRS) technologies, which enhance resource utilization and wireless channel quality. However, the future of autonomous driving demands robust networking resources and high-quality wireless communications to ensure Quality of Service (QoS). This becomes particularly critical given the dynamic physical operating environments of IoV, necessitating improvements in resource utilization and wireless channel quality. To address these challenges, the authors in [74] propose a DT-Driven Vehicular Task Offloading and IRS Configuration Framework (DTVIF) for efficient monitoring, learning, and management of the IoV. Specifically, MEC and IRS are leveraged to augment computing capacities for vehicles and enhance transmission performance during communication with MEC servers. DT facilitates real-time data collection and digital representation of the IoV's physical operating environments to support decision-making processes. To minimize overall delay and energy consumption in DTVIF, they introduce a Two-Stage Optimization for Jointly Optimizing Task Offloading and IRS Configuration (TSJTI) algorithm based on DRL and Transfer Learning (TFL). In the first stage, Double Deep Q-learning Networks (DDQN) are employed to determine optimal offloading decisions. In the second stage, parameters learned from the first stage are transferred to optimize IRS configuration using the Deep Deterministic Policy Gradient (DDPG) method. Simulation results demonstrate the effectiveness of the proposed algorithm in reducing task offloading latency and average energy consumption in DTVIF.

Table A.3 summarize the key features of DT-empowered computation offloading approaches in edge computing (see Appendix).

6. Challenges

While DTs have the potential to revolutionize the field of intelligent offloading in edge computing, there are several challenges that need to be addressed. Some of the key challenges include:

6.1. Data management

DTs generate vast amounts of data, which must be collected, stored, and analyzed in real-time. This requires sophisticated data management techniques and infrastructure, which can be expensive and complex.

6.2. Modeling accuracy

The accuracy of the DT model is critical to its effectiveness in predicting the behavior of the physical system. However, building an accurate model can be challenging, especially for complex systems with multiple interacting components. In particular, creating accurate and high-fidelity DTs for dynamic and diverse physical entities is inherently complex. This involves capturing detailed physical, environmental, and operational data, which requires sophisticated modeling techniques and substantial computational resources.

6.3. Security and privacy

DTs are vulnerable to cyber-attacks and must be secured to prevent unauthorized access or modification. Additionally, privacy concerns may arise if the data collected by the DT includes sensitive information. Sensitive information must be protected against unauthorized access, breaches, and cyber-attacks, especially in critical applications such as healthcare and industrial automation.

6.4. Real-time performance

For edge computing systems that require real-time processing, the DT must be able to provide real-time feedback and analysis. This requires high-performance computing infrastructure and optimized algorithms. Maintaining real-time synchronization between physical entities and their DTs is challenging due to the latency and bandwidth limitations of current networks. Ensuring low-latency communication and high throughput is essential for real-time updates and decision-making.

6.5. Resource management

Efficiently managing computational resources at the edge is critical to handle the varying demands of different applications. Balancing the load, optimizing resource allocation, and ensuring the availability of edge servers pose significant challenges.

6.6. Scalability and interoperability

As the number of interconnected devices and DTs increases, the system must scale seamlessly. Additionally, ensuring interoperability between diverse devices, platforms, and standards is crucial for the widespread adoption of DT technologies.

6.7. Network reliability and latency

Despite the advancements in 5G technology, network reliability and latency remain challenges, particularly in densely populated areas or remote locations. Ensuring consistent and reliable connectivity is vital for the continuous operation of DTs.

6.8. Dynamics and heterogeneity of environments

Edge computing environments are highly dynamic, with constantly changing network conditions, user demands, and resource availability. Adapting to these changes in real-time for optimal offloading decisions is a complex task. In addition, edge devices vary widely in terms of computational power, storage capacity, and communication capabilities. Managing this heterogeneity to provide a seamless and efficient offloading process is a significant challenge.

6.9. Integration with existing system

Integrating DTs with existing edge computing systems can be challenging due to differences in hardware and software configurations. This requires careful planning and coordination to ensure compatibility and interoperability.

Addressing these challenges will require a multidisciplinary approach that combines expertise in areas such as data science, cybersecurity, systems engineering, and software development. However, overcoming these challenges will be critical to realizing the full potential of DTs in intelligent offloading for edge computing.

7. Open issues

Applying DT technology for intelligent computation offloading in edge computing, especially in the era of 5G and beyond, presents several open issues.

7.1. Interoperability and standardization

The integration of DT technology with edge computing and 5G networks requires standardized protocols and frameworks. Current lack of interoperability standards poses significant challenges for seamless communication and operation across diverse platforms and devices.

7.2. Scalability and performance

Managing the scalability of DTs and maintaining high performance in computation offloading is critical, especially as the number of connected devices and DT instances grows. Ensuring that systems can scale without degradation in service quality or increased latency is a major concern. In addition, there is a need for research on the scalability and interoperability of DTs in edge computing. As the number of edge devices and applications grows, it becomes increasingly challenging to manage and coordinate the DTs used for modeling and optimization. Thus, there is a need for developing standards and frameworks for managing and sharing DTs across different edge computing platforms and applications.

7.3. Real-time data synchronization

Achieving real-time synchronization between physical entities and their digital counterparts is essential for accurate decision-making. Ensuring low-latency, high-reliability communication is challenging, especially in dynamic and distributed edge environments.

7.4. Resource management and allocation

Efficiently allocating and managing resources such as computing power, storage, and network bandwidth among multiple DTs and edge devices is complex. Dynamic and intelligent resource management strategies are needed to optimize utilization and performance.

7.5. Data privacy and security

Protecting sensitive data exchanged between physical objects, DTs, and edge servers is paramount because DTs can potentially expose sensitive information about the behavior and performance of edge devices, which could be exploited by malicious actors. Thus, there is a need for developing robust security and privacy mechanisms that can protect the confidentiality and integrity of DT data. This includes developing robust security measures such as encryption, secure communication protocols, and advanced authentication mechanisms to prevent unauthorized access and breaches.

7.6. Energy efficiency

Reducing the energy consumption of DTs and edge computing infrastructures is crucial for sustainability. Innovative solutions to enhance energy efficiency without compromising performance are necessary to make these systems viable in the long term.

7.7. Network reliability and latency

Despite the advancements of 5G, maintaining consistent network reliability and minimizing latency in edge computing environments remain challenging. Techniques to ensure stable and low-latency communication are essential for real-time applications.

7.8. Complexity of DT modeling

Creating accurate and detailed DT models that reflect the real-time state and behavior of physical objects is complex and resource-intensive. Simplifying the modeling process while maintaining accuracy is an ongoing challenge. This involves designing models that accurately capture the dynamics of edge devices, such as their processing capabilities, energy consumption, and communication bandwidth, as well as the workload demands and quality of service (QoS) requirements of the applications running on them.

7.9. Development of accurate model

One of the key challenges in using DTs for intelligent offloading is developing accurate models of the edge devices, their capabilities, and their interactions with the cloud. This requires understanding the dynamics of the edge devices, including their processing capabilities, energy consumption, and communication bandwidth, as well as the workload demands and QoS requirements of the applications running on them.

7.10. Optimizing offloading strategies

Another research issue is optimizing the offloading strategies based on the models developed. This involves designing algorithms that can dynamically adjust the workload distribution between edge devices and the cloud based on real-time measurements and predictions of their performance. It also involves developing new metrics for measuring the effectiveness of different offloading strategies.

7.11. Integrating ML techniques

ML techniques can be used to improve the accuracy of DT models and offloading strategies. For instance, ML models can be trained to predict the performance of edge devices and cloud resources based on historical data. However, this requires developing new ML algorithms that can operate effectively in the constrained computing environments of edge devices. The combination of DT and ML, AI, and data analysis provides great potentials to improve the system performance. For instance, the study [75] introduces DT Edge Networks (DITEN) to connect physical systems and digital spaces in IIoT, utilizes federated learning for creating DT models of IoT devices, and demonstrates improved communication efficiency and reduced transmission energy costs. DT and federated learning (FL) are novel technologies extensively employed in IIoT, IoVs, and Internet of Devices (IoD) [76]. DT offers a virtual representation of networks, while FL facilitates collaborative learning, bolstering network privacy and security. The implementation of DT and FL could pose various ongoing research obstacles, including concerns regarding security, privacy, effectiveness, and adaptability.

7.12. Adaptability to diverse applications

DT-empowered computation offloading must be flexible enough to adapt to various applications across different industries. Customizable solutions are needed to address specific requirements of sectors like healthcare, manufacturing, and smart cities.

7.13. Integration with legacy systems

Integrating DT and edge computing technologies into existing infrastructures can be difficult due to compatibility issues with legacy systems. Strategies to facilitate smooth integration without significant disruptions or costs are required.

8. Conclusion and discussion

In conclusion, this survey has provided a comprehensive overview of the emerging research area of DTs empowered intelligent computation offloading for edge computing. By leveraging DT technology, edge computing systems can achieve greater levels of efficiency, scalability, and intelligence in their computation offloading strategies. Throughout the survey, we have explored the fundamentals of DTs, discussed traditional computation offloading techniques and their limitations in edge computing, and examined how DTs can address these challenges and enhance computation offloading decisions. Additionally, we have presented various applications and use cases of DTs in computation offloading across different domains, illustrating the practical implications and benefits of this approach. Looking ahead, there are several opportunities for further research and development in this field, including the exploration of advanced optimization algorithms, ML models, and decision-making frameworks for intelligent computation offloading. Moreover, addressing key challenges such as privacy concerns, scalability issues, and interoperability barriers will be essential for the widespread adoption of DTs empowered computation offloading in real-world edge computing scenarios. Overall, this survey serves as a valuable resource for researchers, practitioners, and stakeholders interested in understanding the potential of DTs to revolutionize computation offloading strategies and drive innovation in edge computing.

CRediT authorship contribution statement

Hoa Tran-Dang: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Investigation, Formal analysis, Conceptualization. **Dong-Seong Kim:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table A.3
Comparison of DT task offloading models.

Study	DT-based model	Pros	Cons	Application
[49]	DT-assisted edge collaboration model for task offloading	Improved edge collaboration, enhanced resource utilization	Complexity in synchronization and management of multiple DTs	DT edge networks, collaborative edge computing
[50]	Incentive-driven resource allocation and offloading using DTs	Optimized resource allocation, fair incentive distribution, adaptability in smart industries	Requires robust incentive models, may not scale well with extremely large industrial networks	Smart industry, DT-driven resource allocation
[51]	DT-enabled edge computing for reducing offloading latency in 6G networks	Low latency, optimized edge resource usage for real-time applications	High reliance on 6G infrastructure, potential scalability issues in large-scale environments	6G-based Healthcare
[52]	DT integrated with aerial edge computing for dynamic task offloading	Flexibility in aerial edge computing, efficient resource allocation for mobile environments	Limited battery life of aerial devices, potential communication issues between aerial and ground nodes	Aerial edge networks, mobile and dynamic edge computing
[53]	DT integrated with aerial edge computing for dynamic task offloading	Flexibility in aerial edge computing, efficient resource allocation for mobile environments	Limited battery life of aerial devices, potential communication issues between aerial and ground nodes	Aerial edge networks, mobile and dynamic edge computing
[54]	DRL-based computation offloading model for DT networks	Optimized decision-making in dynamic environments, supports stochastic task offloading	High computational complexity, requires large datasets for training the model	Stochastic task offloading in DT networks
[55]	Adaptive DT model for dynamic task offloading in vehicular edge computing networks	High adaptability in vehicular environments, real-time optimization of edge resources	Potential communication delays between vehicles and edge nodes, complexity in managing high-speed mobility	Vehicular edge computing, automotive networks
[56]	Adaptive edge association model leveraging DTs for wireless networks in 6G	Low latency, enhanced edge association strategies for seamless handover in 6G environments	High dependency on 6G infrastructure, possible scalability issues in large-scale networks	Wireless DT networks in 6G
[57]	Federated learning with blockchain integration for low-latency edge association in DT networks	Improved data privacy and security, low latency through federated learning, decentralized control	Blockchain overhead, potential challenges in synchronizing distributed edge nodes	6G DT networks with secure and decentralized control
[58]	DT-assisted resource allocation for IoVs through edge intelligence	Improved vehicular resource utilization, low-latency communication for IoV	Complexity in dynamic resource allocation for fast-moving vehicles, communication overhead	IoVs, edge-intelligent cooperation
[59]	Edge intelligence-based URLLC model in DT-enabled metaverse	URLLC suited for immersive metaverse environments	High demands on edge infrastructure, challenges with real-time data processing at scale	Metaverse, ultra-reliable low-latency communications
[60]	Multi-agent deep reinforcement learning (MADRL) for DT task management in 6G-enabled metaverse	Efficient task management, scalability through decentralized agents	High computational complexity, communication delays between multiple agents	6G wireless communication in the metaverse
[61]	DT-assisted URLLC in industrial IoT	High reliability and low latency, suitable for mission-critical applications in industrial settings	High infrastructure demands, potential latency in large-scale networks	Industrial IoT, ultra-reliable and low-latency edge networks
[62]	DT integrated with 6G-enabled aerial edge computing model	Enhanced flexibility for aerial systems, optimized task offloading in dynamic environments	Battery and energy limitations of aerial devices, high reliance on 6G infrastructure	Aerial edge networks, 6G-enabled edge computing
[64]	DT-driven computation offloading and service caching for ITSs	Efficient resource allocation for intelligent transport, reduced latency	Complexity in managing fast-moving vehicles and dynamic resource demand	ITSs, edge computing
[65]	Deep Q-network-based service offloading model for DT-enabled IoVs	Improved decision-making in dynamic environments, low latency for vehicular networks	High computational complexity, scalability issues in large-scale vehicular networks	IoVs, edge computing
[66]	DT-assisted task offloading and service caching model for mobile edge computing	Efficient service caching and reduced latency for mobile applications	Complexity in managing multiple edge nodes, high dependency on accurate DT models	Mobile edge computing, service caching
[67]	A3C-based (Asynchronous Advantage Actor–Critic) computation offloading and service caching model	Optimized task scheduling and resource utilization, aware of task dependencies	High computational complexity, training overhead for A3C model	DT edge networks, task dependency-aware computing
[68]	Parallel intelligence-driven resource scheduling for DT-enabled intelligent vehicular systems	Efficient scheduling and resource optimization for vehicular systems, scalable for dynamic environments	Complexity in coordination among multiple parallel agents, communication overhead	Intelligent vehicular systems, DT resource scheduling
[69]	DT-assisted computing resource management for vehicular networks	Efficient resource allocation, enhanced performance for vehicular applications	High computational complexity, challenges in handling fast-moving vehicles	Vehicular networks, computing resource management

(*continued on next page*)

Table A.3 (*continued*).

Study	DT-based model	Pros	Cons	Application
[70]	Edge cooperation-based resource allocation in DT-enabled IoVs	Improved resource utilization, low-latency cooperation between edge nodes	Complexity in synchronization between edge devices, overhead in maintaining multiple DTs	IoVs, edge cooperation
[71]	Dynamic DT and distributed incentives for resource allocation in aerial-assisted IoV	Flexible and dynamic resource allocation, efficient use of aerial resources	Limited battery life for aerial devices, complex incentive mechanisms	Aerial-assisted IoV, dynamic resource allocation
[72]	Integrated sensing and communication-based resource allocation in DT-enabled IoV	Optimized communication and sensing, supports real-time vehicular applications	High dependency on accurate real-time data, communication delays in large-scale networks	IoVs, integrated sensing and communication
[73]	Collaborative offloading model for DT-assisted cloud–edge computing in IoV	Efficient offloading between cloud and edge, optimized resource usage for vehicular tasks	High infrastructure cost, complexity in managing cloud–edge synchronization	IoVs, cloud–edge collaborative offloading
[74]	DT-driven vehicular task offloading and IRS (Intelligent Reflecting Surface) configuration	Improved signal quality with IRS, optimized offloading for vehicular tasks	High dependency on IRS infrastructure, complexity in real-time configuration	IoVs, IRS configuration, vehicular task offloading
[75]	Federated learning model for communication-efficient DT edge networks in IIoT	Enhanced data privacy, reduced communication overhead, efficient learning across edge devices	Federated learning synchronization overhead, complexity in large-scale industrial environments	IIoT, federated learning, DT edge networks

Appendix. Table of comparison

See Table A.3.

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