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RESEARCH ARTICLE

Novel Digital Twin Deployment Approaches: Local and Distributed Digital Twin

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ABSTRACT The Digital Twin (DT) technology is considered as a backbone in the Industrial 4.0 revolution as it is playing a vital role in the digitization of various industries. A DT is a virtual representation of a physical entity, thus having the ability to simulate real data generated at physical space to optimize, estimate, control, monitor and forecast states/configurations. Despite enormous benefits, DT technology has several implementation challenges. Although deploying DT on edge or cloud platforms yields a plethora of services, its implementation in both spaces faces certain limitations. These limitations include latency, data communication overload, transmission energy consumption, privacy concerns, and communication inefficiencies. It is evident that these shortcomings could significantly impact real-time monitoring and control. Therefore, when considering whether to deploy DT on the edge or on the cloud, it is necessary to make a trade-off, or alternatively, adopt a hybrid approach. However, it is important to acknowledge that even with a hybrid approach, the aforementioned issues will persist to some extent. To address these challenges, this article introduces two innovative approaches. Local DT (LDT) and Distributed DT (DDT). These deployment strategies are designed to mitigate latency, minimize data communication overload, reduce energy consumption, improve communication efficiency, and strengthen privacy measures. Thus, resulting in environmental and economic sustainability. Consequently, these advancements facilitate superior real-time monitoring and control capabilities. Through the utilization of LDT and DDT methodologies, organizations can harness the full potential of DT technology, thereby maximizing its benefits.

INDEX TERMS Digital twin, Industry 4.0, Industrial Internet of Things, latency, cloud computing, edge computing.

I. INTRODUCTION

In recent years, Digital Twin (DT) technology has emerged as a transformative paradigm for accurately modeling, simulating, and monitoring physical systems, enabling real-time control, optimization, and predictive analysis [1], [2].

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By creating a dynamic virtual replica of a physical asset, process, or system, DTs facilitate data-driven decision-making, predictive maintenance, and enhanced operational efficiency [2]. Unlike conventional simulation tools, DTs leverage real-time data streams, typically collected via sensors embedded within physical entities, to enable continuous monitoring, adaptive control, and predictive simulations. This real-time feedback loop allows DTs to not only reflect the current state of physical systems but also predict future behaviors and enable proactive decision-making. As a result, DTs have proven invaluable in optimizing system performance, enhancing fault detection mechanisms, reducing operational downtime, and lowering maintenance costs, thereby revolutionizing the management and operation of physical systems [3].

Furthermore, the integration of DT technology into wireless networks has led to the conceptualization of Digital Twin Networks (DTNs)—an innovative framework for creating virtual representations of communication environments [4], [5]. DTNs enable network operators to simulate, monitor, and optimize wireless communication systems, providing a robust platform for testing and fine-tuning network configurations before real-world deployment. The synergy between DTNs and Artificial Intelligence (AI) presents significant opportunities for enhancing network performance through intelligent resource allocation, improved network management, and accurate prediction of system behavior [5]. This integration empowers communication systems to adapt dynamically to changing network conditions, optimize spectrum usage, and improve overall service quality.

MOTIVATION AND CONTRIBUTIONS

DT technology represents the convergence of advanced sensing, data analytics, and computational intelligence, enabling the development of intelligent virtual representations of physical systems that facilitate seamless interaction between the physical and digital realms. In the era of Industry 4.0, ensuring real-time synchronization between physical assets and their digital counterparts is critical for achieving operational efficiency and driving innovation [6]. However, several challenges impede this synchronization, particularly in Industrial Internet of Things (IIoT) environments, the process of collecting, exchanging, and analysing data in industrial settings via internet-connected smart sensors, gadgets, and machines.The vast volume of real-time data generated by interconnected physical systems places significant strain on communication infrastructure and computational resources.

Furthermore, the limitations of available bandwidth, computational capacity, and latency (the amount of time or delay that occurs in a system while data moves from its source to its destination.)constraints further exacerbate the difficulties of maintaining accurate and timely synchronization between the physical and digital domains [6], [22]. These challenges highlight the urgent need for novel strategies that can efficiently manage large-scale, real-time data streams while addressing the inherent constraints of communication networks and computational resources. Developing such innovative solutions is essential for unlocking the full potential of DT technology in industrial applications, facilitating robust, scalable, and energy-efficient digital-physical interactions.

To fully leverage the potential of DT technology, establishing seamless, real-time, and secure connectivity between the physical and digital worlds is crucial. This connectivity must meet stringent performance requirements in terms of latency and reliability [5], [6]. A critical question arises: *Where should the digital replica of the physical environment be deployed to optimize system performance?* In addressing this question, especially in critical communication scenarios, i.e., smart industries, smart health care, and smart cities there is an inherent risk of data breaches during information exchange. To mitigate these risks, we also propose potential data privacy techniques to ensure secure communication. The primary contributions of this article can be summarized as follows:

- **Proposed Deployment Strategies:** We introduce two novel DT deployment frameworks designed to optimize system performance:
  - *Local Digital Twin* (LDT): A deployment strategy that situates DTs in close proximity to physical assets, aiming to minimize latency, enhance responsiveness, and reduce reliance on remote computational resources.
  - *Distributed Digital Twin* (DDT): A scalable, distributed framework that allocates DT functionalities across multiple nodes, effectively balancing computational loads, reducing communication overhead, and improving overall data efficiency (the best possible use of data by reducing redundancy, increasing accuracy, and making sure information is processed, stored, and sent efficiently in order to get the intended results.).

  These strategies aim to minimize latency, operational costs, transmission energy consumption, and communication overhead while improving data efficiency and ensuring privacy preservation in DT environments. By reducing unnecessary data transmission between the cloud and the edge, the proposed approach contributes to environmental sustainability through lower energy consumption. Furthermore, the reduction in latency and improvement in communication efficiency lead to optimal resource utilization, thereby decreasing infrastructure usage and maintenance demands. This results in reduced operational costs and supports economic sustainability, making the solution not only technically robust but also environmentally and economically viable.
- **Development of a Five-Layer Architectural Framework:** We propose a structured five-layer architecture that systematically defines the critical functional components required for efficient DT deployment, facilitating effective real-time data synchronization and resource management.
- **Mechanism Analysis and Performance Evaluation:** We conduct a thorough analysis of the proposed LDT and DDT strategies, demonstrating their effectiveness in fulfilling the requirements of efficient DT deployment. The evaluation focuses on key performance metrics such

as latency reduction, data efficiency enhancement, and privacy preservation.

- **Exploration of Critical Application Domains:** We investigate the applicability of the proposed deployment strategies across several critical domains, addressing fundamental challenges associated with DT deployment:
  - *Smart Industries*: Improving real-time decision-making and enhancing operational efficiency in industrial environments.
  - *Smart Healthcare*: Enabling efficient healthcare management through real-time data monitoring and analysis.
  - *Smart Cities*: Facilitating intelligent infrastructure management and resource optimization while ensuring secure, low-latency communication.

The remainder of this article is organized as follows. Section II provides an overview of the existing DT literature, highlighting the gaps and limitations. Section III briefly discusses DT Architecture. Section IV introduces the proposed mechanisms, the LDT and DDT, discussing their deployments. Section V adds distinguished features of the proposed mechanisms, and Section VI presents the use cases. Section VII describes the challenges involved in the proposed mechanisms. Finally, Section VIII concludes the article, summarizing the contributions and outlining future research directions.

II. RELATED WORK

Cloud or edge platforms were suggested for the DT deployment in the literature. Though, edge servers with communication and computational resources provide low latency and high-reliability services [7]. Some researches adopted a hybrid approach to obtain the benefits from both platforms. Ouahabi et al. [8] introduced an architecture that effectively combines the advantages of edge computing and cloud computing. For delay-sensitive applications like production control, cloud computing has certain limitations. To address these limitations, the DT architecture for shop floor monitoring proposed in [8] integrates edge computing, which involves migrating specific DT algorithms, including real-time control, closer to the data sources. In this architecture, edge computing is responsible for data preprocessing and local DT tasks, while cloud computing handles global DT tasks and persistent storage. This integration not only enhances the real-time capabilities of the DT but also alleviates the pressure on the cloud, leading to improved cloud performance. In the work [9], a cloud-edge collaborative framework was introduced for power system regulation, utilizing multi-agent deep reinforcement learning. This approach efficiently decomposes centralized tasks and transfers them to the edge side. This alleviates the load on the cloud center and enhances the robustness of system operation. Moreover, in a few papers, DT was integrated into the system to enhance network management and scheduling. For example, Dai and Zhang [10] proposed the integration of DT into Vehicular Edge Computing (VEC) to enhance the network management and policy scheduling. Various challenges, such as vehicle mobility, dynamic vehicular environments and complex network scheduling, can be addressed by integrating DT into VEC, to reduce latency and alleviate network congestion for vehicular applications and multimedia.

In [11] Campolo et al. have proposed a comprehensive model by using edge-based DT for interacting with remote applications and with the vehicle and Gautam et al. have worked on providing secured communication between vehicle and its DT and also between DTs which is indeed a significant issue in DT based vehicular networks [12]. Wang et al. [13] have explored the unpredictability factor of DT for connected vehicles. They presented their observation by stating that even if the digital model is perfectly derived using cutting edge deep learning techniques it is sometimes difficult to achieve synchronization between the physical object and its digital counterpart. They presented an example and have tried to present their point that small noise or delay in the initial location of vehicle could result in large deviation in vehicle mobility simulation which will result in wrong trajectory prediction. So, as stated by them delay is one of the factors that greatly affect the long term activities. Hence, techniques are needed to eliminate this issue along will the reduction of noise. The study [14] introduces a new approach called DSC-DT, which uses digital twin technology and diversified search techniques to create a more varied and effective top-k service composition in order to overcome service overload and inefficient use of edge resources.

In comparison to traditional industries, intelligent industries exhibit a greater demand for computing resources and heightened sensitivity to latency. In order to meet these requirements, the study [15] presented a computing platform that integrates edge and cloud resources. The platform primarily consists of edge computing nodes, a cloud system, and an Artificial Intelligence (AI) component. The network and computing offload services are provided by edge computing nodes thereby enabling swift response to industrial tasks. On the other hand, the resource-intensive tasks within the industry are supported by the cloud system providing computing resources and storage services. A noticeable improvement in productivity and accelerated task completion is resulted by the implementation of this platform. A edge-cloud collaborative architecture for 3D printers presented in [16], utilizing the DT for the cloud manufacturing. The proposed architecture addresses the issue of network reliability by deploying time-sensitive services at the edge. In [17], an edge-cloud architecture aimed at driving the sustainable development of intelligent power plants was proposed. It offers a detailed exploration of the edge-cloud architecture from multiple perspectives, including hardware infrastructure, data architecture, and cloud-edge collaboration. The work by Lai et al. [18]

presented the architecture and essential technology of a DT system for helicopter equipment, incorporating edge-cloud integration. It describes how real-time simulation of the helicopter equipment is achieved by harnessing the computational capabilities of edge computing, thereby reducing reliance on cloud computing. This approach enhances the overall system's computational power and minimizes time and costs associated with data transmission processes.

Hence, in the literature, edge-cloud collaboration is used to enhance robustness, computational power and storage and reduce costs, time and load. It is informative to dive deep into the cloud and edge platforms from DT perspective and examine their pros and cons. The data from physical space are transmitted to the cloud servers in cloud-based architectures, where DT models are present, and thereby advanced data analytics are used on the gathered data. However, cloud servers are commonly set up in remote locations, which makes it difficult for cloud-based deployments to meet the latency requirements of different applications because of the large amount of data being transmitted and the significant distance between end-users and the cloud servers [6]. On the other hand, edge computing resources are deployed locally to the physical space, allowing them to establish connections with surroundings and handle large amounts of data locally [19]. Implementing a twin object at a remote cloud location can provide greater computational and storage capacity, but it comes with the trade-off of increased latency as well as high load and costs on infrastructure [20]. Conversely, twin objects deployed at the network edge may have limited computational and storage capabilities but less latency as well as less costs and load on infrastructure [21]. Therefore, a twin at the network edge can be preferably used for latency-constrained applications, whereas a twin deployed at the cloud can be used for the applications that require more computing power and storage [22]. Since different applications have different requirements in terms of reliability, latency, storage, and computation, in general, whether to deploy the DT at cloud or at edge network depends on the application.

A hybrid approach can be used to obtain the benefits of both the cloud and edge based DTs thereby deploying twins at both places, which was briefly discussed by the authors in [22]. However, this approach also has its limitations. The entire data collected from the physical space have to reach edge-cloud platform, creating burden on communication infrastructure and also on both the cloud and edge servers, resulting in reduced data efficiency. In addition to increased cost and time, the data reaching edge or cloud server may contain redundant or missing data, which may be useless and may result in wrong decisions. Therefore, to improve efficiency and to reduce load on platforms and infrastructure, there is a need to intelligently preprocess the data locally at physical space, so that only enriched data is sent to the platforms for action.

Despite the significant advancements in integrating cloud and edge computing within DT environments, existing solutions still face critical limitations concerning latency, communication load, and data inefficiency, particularly when handling massive real-time data streams. While hybrid edge-cloud frameworks attempt to leverage the strengths of both platforms, they often result in increased communication overhead, redundant data transmission, and underutilization of computational resources. Furthermore, these frameworks generally overlook the importance of localized data preprocessing, which is crucial for reducing infrastructure load and improving system responsiveness. Additionally, challenges such as synchronization delays, data privacy concerns, and the effective management of redundant or noisy data remain largely unaddressed. Motivated by these gaps, this paper introduces novel LDT and DDT mechanisms. These approaches aim to intelligently preprocess data at the physical layer, ensuring that only enriched, relevant information is transmitted to edge and cloud platforms. By addressing latency, transmission energy consumption, overloading, and associated costs, our proposed mechanisms offer an efficient and privacy-preserving solution that significantly enhances the performance and scalability of DT deployments in complex industrial and IoT environments.

III. DIGITAL TWIN ARCHITECTURE

Even though DT has been demonstrated to be a paramount enabling technology but there exists insufficient evidence on its' modeling [6]. A four layer reference architecture is proposed in [23] comprised of physical space, network interfaces, sensing and computational infrastructures. In literature, several models presented are based on the five-layer architecture proposed by Tao et al. [24]. Thus, different modeling approaches for DT have been suggested in the literature, with seemingly no consensus on a unified architecture. The reason may be owing to the versatile nature of DT. In our proposed model, we also adopt a five-layer architecture depicted in Fig. 1. Which is based on the concepts provided by Alcaraz and Lopez [25]. We now briefly discuss these five layers.

1. Physical Space Layer (PSL): In the PSL, data collection and dissemination take place using smart devices placed near to a physical object/process/system. In this layer, the technologies that play a role are IIoT and cyber-physical systems.

2. Communication Layer (CL): The CL plays a crucial role in facilitating the exchange of data and information between the physical entity and its digital counterpart. It serves as a bridge that connects the physical world with the virtual world, enabling real-time monitoring, control and analysis.

3. Data Preprocessing Layer (DPL): This layer carries out data management and synchronization. Preprocessing of data is performed here. Data received is normalized and enriched before further processing. Dealing with missing or duplicate data is also the responsibility of this layer. Moreover,

it is critical to keep both the physical and digital worlds synchronized, so as to maintain a true virtual representation of the physical object/process/system.

4. Twin Layer (TL): This layer contains logical twin objects that are virtual representations of the physical object/phenomenon, i.e., the digital models of physical counterparts. AI and big data techniques are used here, providing application programming interface, predictive maintenance, anomaly detection, diagnostics analysis, and other services. Furthermore, cyber security services may also be added here.

5. Services Layer (SL): The SL provide an interface for users to use DT for their required tasks. It enables users to visualize simulation results and contain interfaces for applications that allow user to request a service from the DT system.

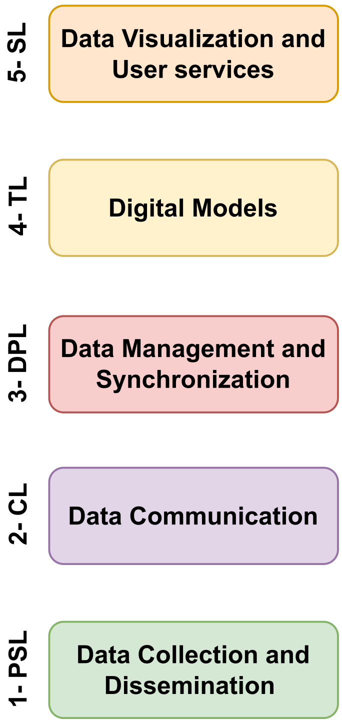

FIGURE 1. Schematic representation of the digital twin architecture, featuring a hierarchical structure across five layers— physical space layer, communication layer, data processing layer, twin layer, and service layer —facilitating seamless data flow and synchronization.

After this brief discussion on the different layers of the DT architecture, we move to the presentation of our proposed deployment mechanisms in the next section.

IV. PROPOSED MECHANISMS

As the scope and complexity of DT applications expand, several challenges arise, particularly in terms of latency, data communication load, data efficiency, and privacy. The advent of autonomous vehicles, smart cities, and industrial automation has accentuated the need for efficient and privacy-preserving DT deployment techniques. In certain critical applications, even a slight delay can have severe consequences, such as causing accidents in autonomous cars. Moreover, the centralized approach to DT implementation raises concerns about privacy leakage due to the transfer of end-devices' data to a centralized cloud server. To address these challenges, this article proposes two novel mechanisms, the LDT and DDT.

The LDT concept focuses on creating digital replicas within the physical space, leveraging computational resources available within the objects or systems themselves. This approach is particularly suited for the scenarios where only low computational resources are required for DT realization, or where enough computational resources are available in physical space. The LDT results in minimized data communication load on infrastructure and reduced latency, caused by the long distance between the physical space and cloud server. Hence, leads towards overall efficiency improvement and paving the way for real-time monitoring and controlling of physical environment. Additionally, privacy is enhanced due to the coexistence of the LDT and its physical counterpart thereby eliminating the need for transferring sensitive data to external servers [22].

On the other hand, DDT technique utilizes local computational resources in addition to the edge and cloud servers for DT deployment. It is pertinent to mention here that DDT is a suitable candidate for both low-resource-demand and resource-intensified DT applications, hence offering a more flexible and scalable deployment approach. By distributing the DT functionalities among the physical entity, edge layer, and cloud layer, DDT optimizes resource utilization based on the complexity of processes. Complex tasks can be offloaded to the cloud, while simpler computations can be performed locally or on the edge. This distributed architecture not only reduces latency but also improves data communication efficiency, leading to reduced data communication overload and improved overall system performance. Furthermore, real-time data synchronization is achieved through the integration of IoT devices and sensors, which continuously capture and transmit data from the physical environment to the DT. For example, in industrial settings, sensors such as temperature, vibration, and pressure monitors provide real-time feedback, enabling the DT to simulate and predict system behavior. This continuous interaction ensures that the DT remains an accurate and up-to-date representation of the physical entity, facilitating real-time monitoring, predictive maintenance, and control. In addition, to improve the accuracy of the DT, sensor fusion techniques are used to combine data from multiple sources. For example, Kalman filtering integrates data from temperature, vibration, and pressure sensors to create a unified and accurate representation of the physical system. In addition, AI-driven sensor fusion uses machine learning algorithms to dynamically weigh and combine sensor input, accounting for noise and inconsistencies. This results in a more robust DT capable of supporting advanced analytics and decision making.

A. LOCAL DIGITAL TWIN

In the situations where only low computational resources are required, e.g., DT for a simple object, or where there are

FIGURE 2. Illustration of the local digital twin framework, demonstrating localized data processing for autonomous vehicles, smart cities, and industrial systems, with cloud-based duplicates for backup and control continuity.

sufficient computational resources residing with the physical object/process/system, the DT model can be created locally within the physical space to perform simulations locally and respond promptly to the physical space. Consider the case that an automotive car is moving in an unplanned area and an unexpected scenario arises. The LDT would be a better option in responding to such an scenario in real-time, particularly if connectivity is unavailable in the area.

An LDT will not overload the infrastructure as it only needs the minimal data transfer. This is extremely attractive, particularly in the future when massive introduction of DTs for industry, smart cities, automotive and healthcare, etc. occur, which requires transferring massive amount of data. LDTs will not compete with these vital DT applications for resources. The minimal data transfer implies that nearly all data generated in the physical space will be processed locally so that there is nearly no need for data transfer. Additionally, a duplicate or image DT for LDT can be created on the cloud which only needs concise data. If the LDT is corrupted or the local hardware/software system is updated, the duplicate DT on cloud can be used as a backup and it can also control the physical space until the LDT is made functional again. Hence, this duplicate/image of LDT is beneficial in two ways. It can control the physical space in the absence of LDT, and it provides all the necessary data after the local hardware/software is reinstated. However, the LDT for complex systems will only be possible if high computational resources matching the needs are available within the physical space.

An application deployment for the LDT is depicted in Fig. 2. Where the LDTs for autonomous cars, smart city and industry are shown on Local Digital Twin Layer and their duplicates/images are shown on the cloud. Here, the data generated in real environment will be communicated to the LDT where simulations will be done and possible decisions will take place. So, because of its first-hand availability, an LDT in each environment will process all data locally, and this results in improved real-time monitoring and controlling. Moreover, in case that an LDT becomes malfunction or local hardware/software needs repair or upgradation or new hardware/software installation is underway, its duplicate/image DT will control all the processes, and after the necessary repair or upgradation, the same responsibility is dropped back to the LDT.

B. DISTRIBUTED DIGITAL TWIN

Khan et al. [22] discussed that a hybrid approach can be used to obtain the benefits of both the cloud and edge-based DTs thereby deploying twins at both places, keeping in mind that edge has limited storage and computation capacities as compared to cloud. For a system, such as DT-enabled infotainment system in an automotive car where low latency is essential, edge-based twin can be used, while for other systems, e.g., an industrial water boiler where latency is not an issue, cloud-based twin can be used.

Our proposed architecture goes one step further. A DDT is distributed among the physical entity as well as in the edge and the cloud. Therefore, the proposed DT deployment is split into three parts. One is with the physical space, the second part is on the edge, and the third is on the cloud. This distribution can be based on the level of the processes' complexities in a system. Specifically, the complex part is implemented on the cloud, the moderate part on the edge, and the simple part is with the physical object. In the case that sufficient computation and storage resources are available especially with the physical space, this distribution can also be based on the latency for achieving real-time monitoring and controlling. Additionally, the physical layer DT can decide which data need to be sent to edge or cloud. Thus, the physical layer DT only sends needful data to other DT part on edge or cloud, and this can be achieved based on a number assigned to each process similar to the port number in data communication.

The proposed DDT architecture can be well explained by the scenario presented in Fig. 3, where three-tier architecture is shown. The physical layer DT part is shown within the industrial setting, smart city and automotive, while the second part of DT is shown on the edge layer, and the final part of DT is shown on the cloud layer. In this environment, data processing will done in physical layer DT, where urgent or lesser complex tasks will take place. On the hand, moderate processes will be forwarded to edge layer DT and complex processes will take place at cloud layer DT. Moreover, physical layer DT will be authorized to make decisions regarding dealing of data on either platform. As aforementioned, the reason for introducing this DDT architecture is to reduce latency, data communication overload and transmission energy as well as increase data efficiency between DT and its physical counterpart but in a much more viable way than other DT deployment approaches. For those parts of physical objects/processes/systems that only require

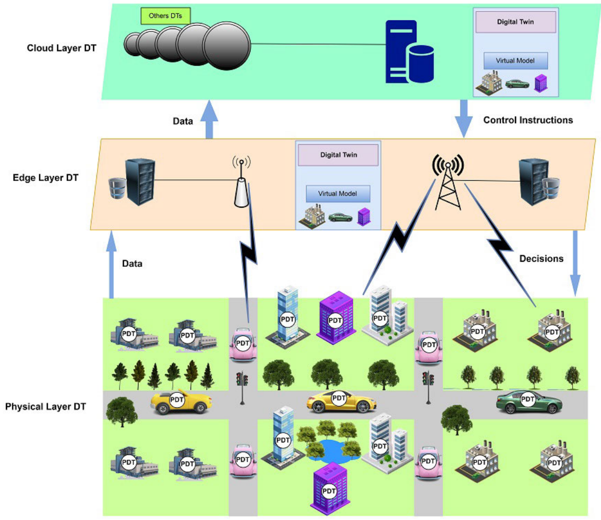

FIGURE 3. Distributed digital twin architecture featuring a three-tier structure with physical, edge, and cloud layers, enabling efficient task distribution based on computational complexity to optimize latency, data efficiency, and energy consumption.

low computation resources, models for them are created locally, i.e., within objects/processes/systems, while for those parts that demand high computational resources to perform functions, i.e., simulations, etc., DT models are created on edge or remotely on a cloud. As mentioned earlier, a function can be added to the physical layer DT to empower it for making the decisions regarding which data is worthy to be sent to remote DT models. As the entire data collected from the physical space is gathered at the physical layer DT, it has the decision power to send only needful data to remote DT models and discard redundant or useless data. This improves data efficiency, saves data transmission energy as well as reduces the burden on the communication infrastructure and also on the remote DT models.

V. DISTINGUISHED FEATURES OF PROPOSED MECHANISMS

We now discuss the eminent features of the presented deployment approaches, which are achieved by implementing the proposed techniques.

1) Reduced Latency: By deploying LDTs and DDTs, a significant reduction in latency is achieved compared to centralized approaches. LDTs enable prompt response within the physical space without relying on remote cloud severs, while DDTs distribute the computational load among the local space, the edge and the cloud, minimizing the latency based on the system's requirements.

2) Decreased Data Communication Load: LDTs minimize data transfer on the communication infrastructure by processing data locally within the physical space. This reduces the burden on the infrastructure, preventing overload as DTs become more prevalent across industries. DDTs also optimize data communication by distributing the processing among physical layer, the edge and the cloud, avoiding unnecessary data transfer.

3) Increased Data Efficiency: Both LDTs and DDTs improve data efficiency. LDTs process data locally, avoiding the need to transfer all data generated in the physical space but only sends essential data to image DT for recovery. The DDTs empower the physical layer DT to decide which data is worth sending to remote DT models, ensuring that only useful data is transmitted. This reduces the burden on communication infrastructure and improves overall data efficiency.

4) Improved Privacy: LDTs enhance privacy by keeping the DT and its physical counterpart together. This avoids privacy leakage when end-device data is transferred to a centralized cloud or edge server. By processing data locally, LDTs minimize the risks associated with data transfer, thus improving privacy. DDTs transfer much less data from end devices to remote servers than centralized approaches, which also improves data privacy.

5) Backup and Redundancy: LDTs have duplicate or image counterparts created on the cloud. This backup functionality ensures that if a LDT becomes non-functional or requires maintenance, the duplicate/image DT can control the processes and provide necessary backup data. This redundancy helps maintaining continuity and minimizing downtime. Similarly, in DDTs, if physical space DT starts malfunction, edge/cloud servers can work to control the entire situation.

6) Resource Optimization: LDTs fully utilize available computational resources within the physical space. DDTs allocate tasks based on complexity or latency requirements. This resource optimization ensures that the right level of computational power is dedicated to each part of the system. Thus, the distribution of computational resources in DDTs allows for efficient utilization of available resources.

7) Real-Time Monitoring and Controlling: LDT and DDT both can achieve real-time monitoring and controlling. For LDT, virtual twin resides within physical space and the time required for data transmission is nil. If sufficient computational resources are available within physical space, then real-time monitoring and controlling can be achieved. For DDT, latency constrained applications are dealt locally, which help achieving real-time decision making.

8) Cost and Energy Reduction: The proposed architectures can result in significant cost and energy savings. By reducing data communication, optimizing data transfer, and leveraging available computational resources, the overall cost and transmission energy can be reduced. This has considerable benefits to industries and systems that rely on DTs.

VI. USE CASES

Various industries can benefit from implementing LDT and DDT. Below some use cases for LDT and DDT are discussed.

A. SMART INDUSTRY

In the context of the smart industry, the deployment of the proposed LDT and DDT can bring numerous benefits. Some potential use cases are listed here.

1) Equipment Monitoring and Predictive Maintenance: By creating LDTs/DDTs for machinery and equipment, real-time monitoring of their performance and condition can be achieved. LDTs/DDTs can simulate the behavior of the physical counterparts and detect anomalies or signs of potential failures. This enables predictive maintenance, where maintenance actions are scheduled based on the LDT's/DDT's insights, reducing downtime and minimizing maintenance costs.

2) Process Optimization: LDTs/DDTs can be used to model and simulate complex industrial processes. By leveraging the computational resources available, these LDTs/DDTs can perform real-time simulations, identify bottlenecks, and propose optimization strategies. This allows for continuous process improvement, increased efficiency, and cost reduction.

3) Supply Chain Management: Implementing DDTs in the smart industry domain can improve supply chain visibility and coordination. By creating DDTs that span across different entities in the supply chain, such as manufacturers, distributors, and retailers, real-time data sharing and synchronization can be achieved. This enables better inventory management, demand forecasting, and collaborative decision-making, resulting in optimized supply chain operations.

4) Automotives: LDTs/DDTs can be implemented for cars. The available computation resources within the car can be utilized for LDTs/DDTs to reside. By processing data locally, safety can be improved. For more complex processes/systems, such as vehicular networks, the benefits of cloud/edge can be leveraged while using DDTs.

The use cases identified in this subsection highlight the potential role of LDTs and DDTs in the Industry 4.0 revolution.

B. SMART HEALTHCARE

The utilization of LDTs and DDTs for smart healthcare can revolutionize healthcare delivery and improve patient outcomes. Here are a few potential use cases.

1) Remote Patient Monitoring: LDTs/DDTs can be used to create virtual representations of patients, capturing their physiological data from wearable devices or sensors. This enables remote patient monitoring, where healthcare providers can continuously monitor patients' vital signs, detect abnormalities, and provide timely interventions. LDTs/DDTs allow for real-time simulations and analysis of patient data, facilitating early detection of health issues and proactive care.

2) Personalized Treatment Planning: DDTs can be deployed to the healthcare domain to facilitate patients. By doing so, treatment plans can be simulated and optimized by creating patient-specific models. DDTs also help to generate personalized treatment options by integrating data from electronic health records, medical imaging, and genetic information. Healthcare department also gets benefit from DDTs to predict treatment outcomes and ultimately select the most appropriate one.

3) Healthcare Resource Optimization: LDTs and DDTs assist healthcare departments by optimizing healthcare resource allocation and utilization. LDTs aid in minimizing the potential bottlenecks of inefficiencies. They also model and simulate the hospital operations and patient flow respectively. LDTs help to optimize resource allocation in real-time by leveraging healthcare computational resource facilities. DDTs have the ability to integrate data from multiple healthcare facilities that coordinate resource sharing and allocation, thus improving resource optimization.

C. SMART CITIES

The implementation of LDT and DDT can assist in different aspects of urban management to facilitate the quality of life for citizens. Some potential use cases are as follows:

1) Urban Infrastructure Management: By utilizing LDTs/DDTs, different urban infrastructure entities such as buildings, roads, bridges, and utility networks can be managed. This will also enable real-time monitoring of structural health, energy consumption, and maintenance needs. City authorities can monitor the system by making informed decisions regarding maintenance, repairs, and infrastructure upgrades by simulating and analyzing data from LDTs and DDTs. This will help ensure the optimal performance and safety of smart cities.

2) Traffic and Transportation Optimization: DDTs can also aid the transportation sector by modeling and simulating the traffic flow, transportation systems, and public transit networks within a city. DDTs play a significant role in traffic management and optimization by integrating real-time data from sensors, cameras, and connected vehicles. It will enable city planners to enhance the efficiency of public transportation routes, lessen congestion and improve mobility.

3) Environmental Monitoring and Sustainability: LDTs and DDTs can play a crucial role in monitoring and managing the environment within a smart city. By integrating data from various sensors and environmental monitoring devices, LDTs/DDTs can provide real-time insights into air quality, noise levels, waste management, and energy consumption. City authorities can leverage LDTs/DDTs to identify the areas for improvement, develop sustainable initiatives, and implement policies to reduce environmental impact and promote a healthier living environment for citizens.

4) Citizen Engagement and Participation: LDTs/DDTs can serve as platforms for citizen engagement and participation in decision-making processes. By creating LDTs/DDTs that represent public spaces or specific projects within the city, citizens can virtually explore and visualize proposed developments or changes. LDTs/DDTs can facilitate public consultations, allowing citizens to provide feedback, express concerns, and actively participate in shaping their city's future.

5) Emergency Management and Resilience: LDTs and DDTs assist emergency management and city resilience planning by providing a better understanding of potential risks, the impact of natural disasters or incidents, and evacuating

plans through modeling and simulating emergency scenarios. LDTs and DDTs can also facilitate coordination among different agencies and enable real-time information sharing during emergency situations.

The use cases discussed in this subsection highlight the potential of LDTs and DDTs in enabling data-driven decision-making, optimizing urban services, enhancing sustainability, promoting citizen engagement, and improving overall city management and resilience. By leveraging DT technologies, smart cities can achieve greater efficiency, sustainability, and livability for their residents.

VII. CHALLENGES

While we have demonstrated several potential benefits of deploying LDTs and DDTs, there are also research challenges and considerations that need to be addressed in order to fully realize the benefits of LDTs and DDTs. The key challenges associated with the proposed approaches are as follows.

1) Computational Resources Limitations: Creating and deploying LDTs within physical objects or processes may be limited by the availability of computational resources. Complex systems or processes may require high computational capabilities that are currently not feasible to have locally. Lightweight methods like pruning and quantisation can reduce processing demands for systems with limited resources without compromising efficiency. For DDTs, the physical layer DT also requires sufficiently high computational resources to deal with the enormous data generated at the physical space and to decide which data should be dealt locally and which should be sent to edge/cloud DTs. Computational loads in local and remote environments can be balanced by hierarchical scheduling and dynamic task allocation. Additionally, by facilitating decentralised model training, federated learning minimises data transfer.

2) Data Synchronization and Consistency: When using distributed DTs across different locations or layers (physical, edge, and cloud), ensuring data synchronization and consistency becomes crucial. It is vital to develop effective and efficient mechanisms and protocols for managing data updates, maintaining coherence between multiple twin instances, and handling potential inconsistencies caused by delays or other network issues.

3) Bidirectional Communication: Bidirectional communication is a critical feature of DT technology, enabling the DT to influence the physical entity. Through feedback loops and control mechanisms, the DT can send actionable insights and commands back to the physical system. For example, in a smart manufacturing setup, the DT can adjust machine parameters in real-time to optimize performance or prevent failures. This two-way interaction ensures that the DT is not merely a passive replica but an active participant in system control and optimization.

4) Network Infrastructure and Connectivity: Successful deployment of DTs relies on reliable and robust network infrastructure. However, in some areas, especially remote or underdeveloped regions, network connectivity may be limited, unstable, or even unavailable. Moreover, the current infrastructure may not be able to handle the massive data generated by smart industries, smart cities, and smart healthcare, etc. Research is needed to address the challenges related to connectivity, network latency, and bandwidth limitations, particularly when real-time or near-real-time responses are required.

5) Security and Privacy Concerns: While LDTs can offer enhanced privacy by keeping data within the physical space, there are still security challenges associated with DT deployments. Ensuring secure communication and protecting sensitive data within the distributed twin architecture is crucial. These difficulties include the possibility of unauthorized access, data breaches, and communication vulnerabilities between dispersed elements. Strong encryption techniques for data in transit and at rest, as well as secure communication protocols (such as TLS and DTLS), are essential for reducing these hazards. Advanced threat detection systems and tamper-proof technologies are necessary in DDTs due to the possibility of man-in-the-middle attacks or data tampering during communication between remote nodes. Furthermore, distributed designs are vulnerable to cloud or edge node compromise, which could cause system disruptions or expose sensitive information. In order to address this, multifactor authentication techniques and access control policies (such as role-based or attribute-based access control) should be put in place to regulate access to crucial system components. Researchers need to explore secure communication protocols, encryption mechanisms, access control, and authentication methods to mitigate potential security threats.

6) Scalability and Interoperability: As the adoption of DTs increases across various industries and domains, ensuring scalability and interoperability becomes a significant challenge. Dynamic resource allocation approaches, in which storage and computational resources are modified in real-time according to system demands, can be used to address scalability in high-complexity systems. Furthermore, complicated systems can be divided into smaller, more manageable sub-twins that can function independently while coordinating with one another by implementing modular digital twin (DT) design principles. This modular strategy streamlines the integration process while simultaneously increasing scalability. Developing standardized interfaces, data models, and communication protocols that can facilitate the integration and interoperability of different DT instances is essential. This requires extensive research efforts to define common frameworks and standards that enable seamless interactions between local and distributed twins.

7) Real-time Simulation and Processing: Achieving real-time or near-real-time simulation and processing capabilities within DTs can be challenging, especially for complex systems. High-fidelity simulation models and algorithms may require significant computational resources and may not be feasible to run in real-time. Researchers need to explore techniques such as parallel computing, optimization

algorithms, and distributed computing to overcome these challenges and enable efficient real-time simulations within DTs.

8) Cost and Energy Efficiency: The implementation of DTs requires additional cost and energy constraints. Further research is needed to develop new approaches to minimize the overall cost and environmental impact of DT implementation. The proposed techniques should cover the cost-effective, energy-efficient, and resource-optimization barriers.

VIII. CONCLUSION

In this paper, we have presented two novel DT deployment approaches, called LDT and DDT. Both techniques offer appreciable improvements in enhancing data efficiency, minimizing latency, and reducing data communication load on the infrastructure. Hence, reducing overall transmission energy and the cost related to it in comparison to the current deployment mechanisms for DT. By utilizing, the available computation and storage resources in physical space, the LDT technique particularly enables the implementation of DTs within the local environment. As a result, it will reduce latency and data communication load consequently, will result in real-time monitoring and decision-making. However, the LDT has a potential constraint of the availability of limited resources in the local environment. To ensure the scalability and flexibility of LDT implementation, organizations must be vigilant to evaluate the available computation and storage capacity. On the other hand, the DDT approach addresses challenges in large-scale and in complex systems by distributing features across different platforms. This will enable efficient data processing and decision-making. Hence, minimizing latency, data communication load, and improving efficiency. However, the burden of bifurcating the features of the physical space for distribution and the allocation of computation resources within the physical layer DT can pose additional challenges. In short, the LDT and DDT can assist organizations to overcome the barriers related to data communication load, latency, and communication efficiency in the implementation of DT. Both approaches help optimize operations, improve decision-making, and enable predictive maintenance. It is pertinent to consider the resource constraints and carefully allocate resources to ensure the successful implementation of the LDT and DDT. Key metrics like energy consumption, latency, communication overhead, efficiency, and privacy will be analyzed in a future study to highlight our techniques' strengths. Additionally, AI-driven sensor fusion and edge computing offer promising enhancements for DT systems by improving real-time interaction and data flow. Future research will explore their integration to enhance responsiveness and scalability.

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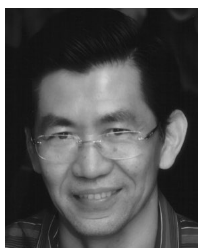

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