Digital Twin: An Investigation of the Characteristics, Visions, Challenges, and Opportunities

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Abstract

Emerging technology, known as digital twin (DT) is surrounded by numerous promises and potentials to influence the future of industries and society as a whole. A DT is a system of systems that goes much beyond conventional computer simulations and analyses. It is the process of replicating all of the components, processes, and dynamics of a physical system into their corresponding digital counterparts. Both the physical and digital systems coexist in the same space, sharing all of the inputs and activities via the use of real-time data transfers and the exchange of information. The DT provides a platform for testing and assessing complicated systems, which is not achievable with conventional simulations or modular assessments. This is one of the many benefits offered by the DT. However, the development of this technology faces many challenges, such as the complexities in effective communication and data accumulation, the lack of data available to train machine learning (ML) models, the lack of processing power to support high-fidelity twins, the high need for collaboration between different fields of study, and the absence of standardized development methodologies and validation measures. Due to the fact that DTs are still in the early phases of development, little documentation exists. In this light, the purpose of this survey article is to make attempt to address the significant facets involved in the actualization of the technology. The most important enabling technologies, constraints, and opportunities associated with DTs are discussed. The article presents an in-depth analysis of the technology, includes a list of design aims and objectives, analyses research and commercial advances, details the applications of the technology, and identifies obstacles and constraints associated with design across many sectors.

Keywords: Digital twin; Physical twin; Artificial intelligence; Machine learning; Virtual reality; Augmented reality.

1. Introduction

Digital transformation and intelligent upgrading have emerged as crucial aspects in unleashing massive growth momentum and have emerged as a consensus among nations about future global development. Using the manufacturing sector as an example, a number of nations like the United States of America, Germany, the United Kingdom, and other nations have proposed their very own national manufacturing development plans. The digitization of processes and the application of intelligence are the two most fundamental drivers of technological advancement. As a multidisciplinary technology that makes full use of models, data, machines, and computers, digital twins (DT) have the potential to deliver real-time, efficient, and intelligent services in numerous sectors of smart manufacturing [1]. Additionally, they have the potential to operate as a bridge between the information world and the physical world.

The first time the idea of a DT was presented to the industry was in a study that was written in 2002 by the University of Michigan for the purpose of establishing the Centre for Product Lifecycle Management [2]. As a result of the immaturity of data-collecting technology, computer performance,

Doi: https://doi.org/10.54216/IJAACI.040105
Received: October 27, 2022 Revised: January 25, 2023 Accepted: April 23, 2023

and algorithms at the time, the early notions that were offered by Professor Michael Grieves did not attract much attention at the time, and they were not named DTs. In the year 2010, NASA made the first written proposal for the "DT" concept and continued to develop it. NASA and the Air Force Research Laboratory worked together in 2012 to offer DT examples of future aircraft in order to answer the requirement for future aircraft to be able to carry a large load while being lightweight and to serve for a longer period of time in severe situations. Professor Michael Grieves produced a white paper on DTs in 2014 [3]. In the article, he explicitly defined the three primary components of a DT, which are as follows: data that brings physical things and virtual models together; virtual models that exist in virtual space; and physical entities that exist in real space.

The Fourth Industrial Revolution is now in full swing, and the recent widespread outbreak of the COVID-19 virus has even further sped up the transition to a digital society by several years. Industry executives have been compelled to adjust their company prospects and change their attention from cost-cutting to increased expenditures in digital development as a result of travel restrictions, lockdowns, and the impending economic collapse [4]. These factors have caused executives to modify their business prospects. In addition, the worldwide viral epidemic has placed dynamic uncertainty upon the world's economic system. As a result, businesses have been forced to deal with and rapidly adapt to ever-changing conditions and limits in order to survive or even thrive in spite of the conditions. Despite this, there was a significant amount of work being done toward digitization even before the sanitary crisis. In the first fiscal quarter of 2020, Cisco released its annual Internet report, in which they made several Internet-related forecasts, including a significant increase in the number of people using the Internet globally, the number of networked devices, and a reduction in communication latency that will encourage the development of real-time interactive applications. This anticipated growth in Internet coverage, speed, and connectivity is paving the way for a higher pace of information diffusion, availability, and accessibility, in addition to expanding chances for development and innovation. Figure 1 presents the DT as a provider of numerous services across sectors as part of the Industry 4.0 initiative.

The objectives of the Industry 4.0 initiative are completely congruent with this rapid and ongoing process of digital change [5]. Industry 4.0 aspires to achieve its goal of fully automating all of the conventional, bare-metal manufacturing processes, and it plans to do so by digitizing as much of the physical equipment as possible and moving it into the digital realm. The role that DTs play in all of this will now become clear. DTs originated as an experimental collection of technologies that enabled the reproduction of components, functions, operations, and dynamics of physical systems into the digital realm. This allowed for increased levels of control during testing, analysis, prediction, and hazard avoidance for processes that were particularly sensitive. However, up until very recently, the enabling technologies were not sufficiently developed to enable the development of DTs for complex systems or systems-of-systems. Recent advancements in areas such as machine learning, artificial intelligence, data integration, virtual and augmented reality, sensing, security, cloud storage, transfer learning, data visualization, and ultra-reliable low-latency communications have made it possible to implement DT and its extended applications in a variety of different industries. The DT is a technology that was supposed to be capable of dealing with isolated operations and processes; nevertheless, it may now provide possible applications that will ultimately replicate the processes, elements, dynamics, firmware, connections, and operations of physical systems in the digital world.

The creation of a digital mirror copy of a physical system opens up a world of potentially limitless possibilities. It is possible for the virtual system to coexist with the physical system by first interlinking the physical and digital systems in order to carry out flawless data transfers between the two [6]. Communication of data in real time between the digital and physical systems enables the actual and virtual equivalents to operate in a synchronized and consistent manner. After being moved into the digital realm, it is much simpler to combine optimized learning, information transmission, analysis, visualization, optimization, and planning in order to see the potential for improvement along with modifications that have been proposed. Therefore, the DT is a useful tool for evaluating, observing, and validating the physical system, making suggestions for adjustments, and visualizing the potential for improvements. Previously thought to be impossible, DTs have recently emerged as one of the most important technologies that have the ability to radically alter the future.

The objective of this study is to provide an overview of the recent developments in the DT paradigm through a comprehensive review of the literature published in the past few years. The purpose is to establish a shared understanding of this technology, investigate its market potential and trends,

Doi: https://doi.org/10.54216/IJAACI.040105
Received: October 27, 2022 Revised: January 25, 2023 Accepted: April 23, 2023

identify its most significant enabling technologies, examine various applications, frameworks, and case studies that have been extensively documented, and ultimately analyze the lessons learned and remaining challenges of this innovative technology.

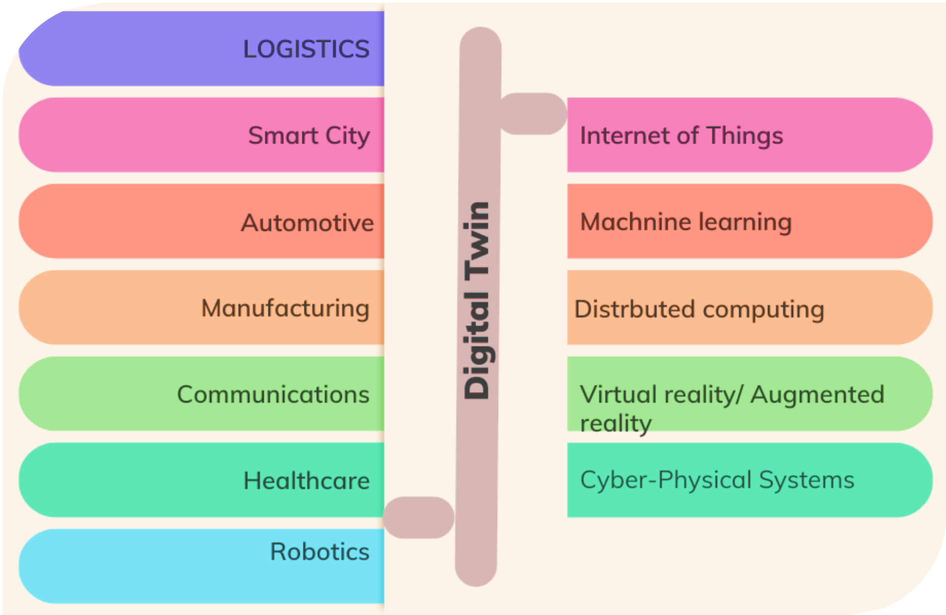

Figure 1: The pivotal significance of the DT in the epoch of Industry 4.0.

2. Technologies that support digital twins

DT is commonly perceived as a technological artefact, however, it can be more precisely conceptualized as a complex system of systems. It integrates multiple enabling technologies to create an intelligent virtual model of a physical entity, facilitating a continuous and reciprocal exchange of information between the twin components. Simultaneously, the enabling technologies can manifest in various forms contingent upon the use case of digital technology.

2.1 Machine learning

DT offers the benefit of raising awareness for a physical asset that may otherwise be overlooked. The reference here pertains to a distinct form of intelligence that is proficient in comprehending substantial numerical data and deducing domain-specific inferences at a faster pace than an expert human could. It is important to note that this intelligence is not synonymous with the conventional human interpretation of "awareness". Therefore, it is imperative for the DT to possess the capability to deduce significant and practical insights from the data that is produced by its physical counterpart and the surrounding milieu. The utilization of machine learning techniques serves as the fundamental basis, or cognitive center, of a digital transformation.

2.2 Cloud, edge and fog computing

The utilization of DT is versatile and can be applied to replicate systems of varying degrees of complexity, ranging from individual components, such as the motion axis of a Computerised Numerical Control machine tool, to an entire collection of aircraft [7]. The process of virtualizing composite heterogeneous machines or services necessitates significant computational power. The requirement for real-virtual synchronization, which is a distinctive feature of the DT, along with the need for nearly instantaneous responsiveness, underscores the necessity for distributed and parallel computing. Cloud, fog, and edge computing are commonly discussed in the literature related to digital transformation for various purposes.

2.3 Cyber–Physical Systems

The concept of Cyber-Physical Systems (CPS) has recently received a lot of interest from both academic institutions and businesses due to the progress being made toward the digitization of traditional physical systems. In the conception of CPS that came first, they were meant to symbolize the pervasive and comprehensive convergence of actual complex systems composed of heterogeneous systems and the intelligent control instances of their virtual counterparts [5]. An ecosystem of physical

Doi: https://doi.org/10.54216/IJAACI.040105
Received: October 27, 2022 Revised: January 25, 2023 Accepted: April 23, 2023

equipment, sensors, actuators, and human operators all working together towards the same objective may be thought of as the representation of the physical space. This paradigm is sometimes referred to as cyber-physical production systems. The cyber elements are the virtual representations of the physical components, and they offer a layer of intelligence that provides self-configuration, self-adaptation, and self-preservation to each physical instance. This ensures that the ecosystem is resilient to changes and failures that would affect its ability to reach its goals.

2.4 Virtual Reality and Augmented Reality

It would seem that the objective of the DT, which is the merger of virtuality and reality, is ideally aligned with the driver behind two growing technologies: virtual reality (VR) and augmented reality (AR). Indeed, the goal of VR is to better human-machine interactions by using computer-generated three-dimensional simulations with which the user may intuitively engage by means of electronic wearables. In other words, VR may assist in fully submerging human operators into a digital setting. AR technologies, on the other hand, make use of wearable devices in order to render 3D digital pictures onto a backdrop that is based on the actual environment. In its most basic form, AR helps integrate virtual information into the real world.

3. Challenges and Limitations

In the process of implementing DT technology, it was discovered that there are five primary problems that are universal to all sectors.

3.1 Challenges and limits

- This text pertains to a range of topics related to data, including but not limited to trust, privacy, Cybersecurity, convergence and governance, as well as acquisition and large-scale analysis. Designers face challenges in replicating or simulating behaviours that lack quantifiable explanations. Instances of social conflicts, socio-political concerns, social disparity, and environmental sustainability are prevalent. The aforementioned advancements in the spheres of social and environmental domains will be directed towards societal readiness levels that are relatively lower, wherein there exists a lucid comprehension of the plausible repercussions on the stakeholders, the society as a whole, and the environment.
- The application of DT suffers from a lack of standards, guidelines, and rules. Particularly in the realm of manufacturing, there is a deficiency of standards as well as interoperability that is recognized, which has resulted in a restriction of DT implementations. Articles that investigate the advantages of DTs, describe the ideas and architectures of DTs, and examine the state of the art in terms of the technology are essential if a general, tangible knowledge of DTs and their significance is to be adopted.
- High expenses associated with the implementation as a result of the increasing number of sensors and processing resources that are required. Due to the high cost of DT implementations, access to them is restricted by the availability of such resources, which is often lacking in underdeveloped nations. This is because of the high cost of DT implementations. The need for a greater number of sensors brings with it a rise in the complexity of data transmission and processing, which makes it difficult to get to level 3 on the maturity spectrum (which requires the digital model to be augmented with real-time information).
- The use of AI and big data in order to meet the needs for data analysis on a massive scale and over the long term. Big data algorithms and Internet of Things technology are strong friends that may give significant assistance to successful implementations of DT due to the massive amounts of data that are created and analyzed in DT systems. In addition, the information that is coming from the many levels of indicator systems poses a barrier to the process of defining uniform rules and standards.
- Obstacles pertaining to communication networks. The imperative exists to construct communication interfaces that are swifter and more effective, exemplified by the advent of 5G technology. The text highlights the pressing need to incorporate 5G technology in the development of smart cities. This is due to the technology's ability to facilitate the connection of numerous sensors and devices, provide high-speed and ubiquitous connectivity, enhance reliability and redundancy, and minimize power consumption. The authors contend that leveraging these capabilities would be instrumental in enabling real-time data connectivity and operational efficiency for the DT.

3.2 Benefits and implications

Doi: https://doi.org/10.54216/IJAACI.040105
Received: October 27, 2022 Revised: January 25, 2023 Accepted: April 23, 2023

- A more tangible and broad knowledge of the advantages and consequences of this technology is made accessible after it is understood how different DT applications may vary in terms of their needs, data collection strategies, data processing, and simulation and prediction capabilities.
- In order to attain a wider deployment, businesses and other organizations need to have a solid understanding of the advantages that come with incorporating DTs into their workflows. In this regard, the essay provides a comprehensive summary of the ways in which this emerging technology affects each and every sector. In addition, a comprehensive assessment of the advantages, problems, and future agenda for DT research is offered. This is done in order to address DTs in a general approach, which is essential in order to make these insights transferable throughout other domains. The difficulties that are discussed in this part provide an unmistakable illustration of the constraints that now exist for more developed and intricate applications of DTs in every conceivable field. When it comes to creating the DT technology, the issues that have been addressed provide a framework for academics and practitioners to follow so that they may concentrate on certain elements that are encountered in real-world applications.

4. Digital Twin

A digital twin is an electronic copy or simulation of a real-world product, procedure, or infrastructure. It entails building a computer program that behaves and performs similarly to its physical analogy in real-time or over time. The idea of digital twins has received a lot of attention and has been used in many different fields, such as manufacturing, construction, healthcare, and transportation[8], [9].

Data from sensors, IoT devices, and other data streams that pertain to the physical item or system are all part of what makes up the digital twin notion. With this information, a digital representation may be made of the physical object, allowing for analysis, simulation, and performance forecasting.

Digital twins' most important characteristics and uses are:

The design and development phases of a product or system are ideal times to use a digital twin. Engineers and designers may speed up development and optimization by building a digital model simulating real-world circumstances and testing alternative configurations. Time to market, expenses, and product performance are all improved as a result[10], [11].

Control and Monitoring: Digital twins make it possible to monitor and manage physical assets and systems in real-time. The digital twin may provide information about the performance, health, and condition of the physical counterpart by continually collecting and analysing data from sensors and IoT devices. The ability to spot problems quickly, foresee the need for repairs, and fine-tune operations are all made possible by this.

Utilizing both historical and real-time data, digital twins can carry out predictive analytics. The digital twin can optimize performance, anticipate behaviour, and detect problems by modelling and analysing a variety of situations. Decisions may be made ahead of time, risks can be reduced, and operational planning can be enhanced[12], [13].

Digital twins also make it possible to conduct operations and training from a distance. Remote monitoring, control, and troubleshooting of the physical model is made possible via interaction with the virtual representation by operators and technicians. This is especially helpful in high-risk and complicated settings since it improves both safety and productivity. Digital twins have further use in training, giving operators a chance to hone their skills without risking damage to the real-world asset[14], [15].

Lifecycle management: Digital twins are useful over a product's or system's whole lifespan. The digital twin helps with visibility and insights across the whole process, from design and development through operation and maintenance. As a result, assets may be managed more effectively, their performance optimized, and wiser choices can be made at every stage of their existence[16], [17].

The many parties engaged in a product's or system's lifetime are able to more easily collaborate and communicate because to digital twins. By creating a virtual space where all parties involved can communicate and share data, you can ensure that everyone involved has a thorough grasp of the asset or process at hand before making any judgments[18], [19].

All things considered, digital twins are a potent resource for learning about and improving the performance of physical assets and systems. Digital twins, which help bridge the gap between the digital and physical worlds, may lead to increased productivity, better decision-making, and new forms of creativity in many different fields[20], [21].

5. Conclusion

In this study, we conducted an in-depth analysis of the current and growing body of literature pertaining to DTs, and from that analysis, we derived several lessons that will assist scholars in this area consolidate their knowledge of DTs and determine future avenues that need further development.

Doi: https://doi.org/10.54216/IJAACI.040105
Received: October 27, 2022 Revised: January 25, 2023 Accepted: April 23, 2023

Overall, it seems that the DT is making rapid progress towards Industry 4.0, and the almost infinite potential that it has helps to position it as a key and more popular participant in the competition. The technology that enables it is always advancing, and every step we take towards improving them takes us that much closer to a world in which actual DTs are a reality. As more people become interested in doing research on the DT, there has been an increase in the amount of effort made to build it. These endeavours have run across certain common and enduring hurdles. In this day and age of artificial intelligence, the emphasis is on the data, and the DT finds itself in the center of an information loop: it needs to be given well-researched data in order to fuel its complicated ML algorithms, and then it further allows for a deeper comprehension of that data through its interactive and predictive accomplishments. The DT is slowly making its way towards the automation of industrial processes, but not before encountering a few difficult issues along the road.

Funding: “This research received no external funding.”

Conflicts of Interest: “The authors declare no conflict of interest.”

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Doi: https://doi.org/10.54216/IJAACI.040105
Received: October 27, 2022 Revised: January 25, 2023 Accepted: April 23, 2023

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Received: October 27, 2022 Revised: January 25, 2023 Accepted: April 23, 2023