

Digital Twins in Industry 4.0 Manufacturing: Challenges and Opportunities

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ABSTRACT

As manufacturing advances within the Industry 4.0 paradigm, digital twins have emerged as a key enabler of smart manufacturing. In general, a digital twin is a virtual representation of a physical asset, process, or system that supports data exchange between the physical and digital domains in a manufacturing environment.

Digital twins offer several advantages, including real-time or near-real-time monitoring, process optimization, predictive capabilities, and the ability to integrate and analyze large volumes of system data. By harnessing these data-driven capabilities, these assets transform how industries approach manufacturing.

In this article, digital twins are reviewed alongside traditional engineering modeling techniques, such as computational fluid dynamics and finite element methods. This comparative analysis serves to bridge a gap between established technologies and emerging technologies that shift the scope of manufacturing. Because digital twins are still evolving and their definitions and implementations vary across domains, several challenges and limitations remain to be addressed; these are discussed in the present work.

1. INTRODUCTION

Due to technological advances in recent decades, manufacturers have increasingly implemented integrated optimization and simulation tools in production lines. Within the Industry 4.0 paradigm, which is driven by smart manufacturing, digital twins have emerged as an important enabling concept [1]. The idea of the digital twin is widely associated with Michael Grieves, who introduced the concept in 2002, and it gained broader recognition following later adoption in aerospace and manufacturing contexts, including NASA's technology roadmaps [2]. In general, digital twins act as digital representations of physical products, assets, or processes, often updated in real time or near real time, and can extend beyond the capabilities of traditional offline models. Compared to established engineering models such as finite element analysis (FEA) [3], digital twins are distinguished by their integration with live or continuously

updated data streams through feedback loops [4]. These characteristics have made digital twins an important component of Industry 4.0. Digital twins use data from physical assets to model, predict, and test system behavior using information collected by sensors [2]. Despite their strong potential, many practical challenges continue to limit their large-scale implementation in Industry 4.0 manufacturing [5]. The objective of the present work is to review digital twins in advanced manufacturing. For this purpose, the paper first overviews general modeling approaches in mechanical and manufacturing engineering. Section 4 discusses digital twins in more detail, including their limitations and challenges. Finally, Section 5 presents the conclusions and discusses the future trajectory of digital-twin applications in Industry 4.0 manufacturing.

1.1 Scope and Methodology

Google Scholar was used as the primary search engine to discover relevant peer-reviewed papers. The searches conducted through this engine were filtered from 2000 to 2025, to ensure recent development in technology. Common keywords that were used throughout our search included “Digital Twin,” “Finite Element Analysis,” “Computational Fluid Dynamics,” “Industry 4.0,” and “Smart Manufacturing” to create a scoped review of Digital Twins in Industry 4.0 manufacturing.

2. MODELING AND ENGINEERING

The engineering of digital twins involves the creation of a digital model that serves as a dynamic representation of a physical product, process, or system. This is supported by a two-way flow of data between the digital representation and the physical asset [1]. Before discussing digital-twin modeling in detail, however, it is useful to review more established engineering modeling techniques. This section is divided into three subsections: 2.1 Analytical and Empirical Modeling Approaches, 2.2 Numerical and Computer-Based Techniques, and 2.3 Machine-Learning Techniques.

2.1 Analytical and Empirical Modeling

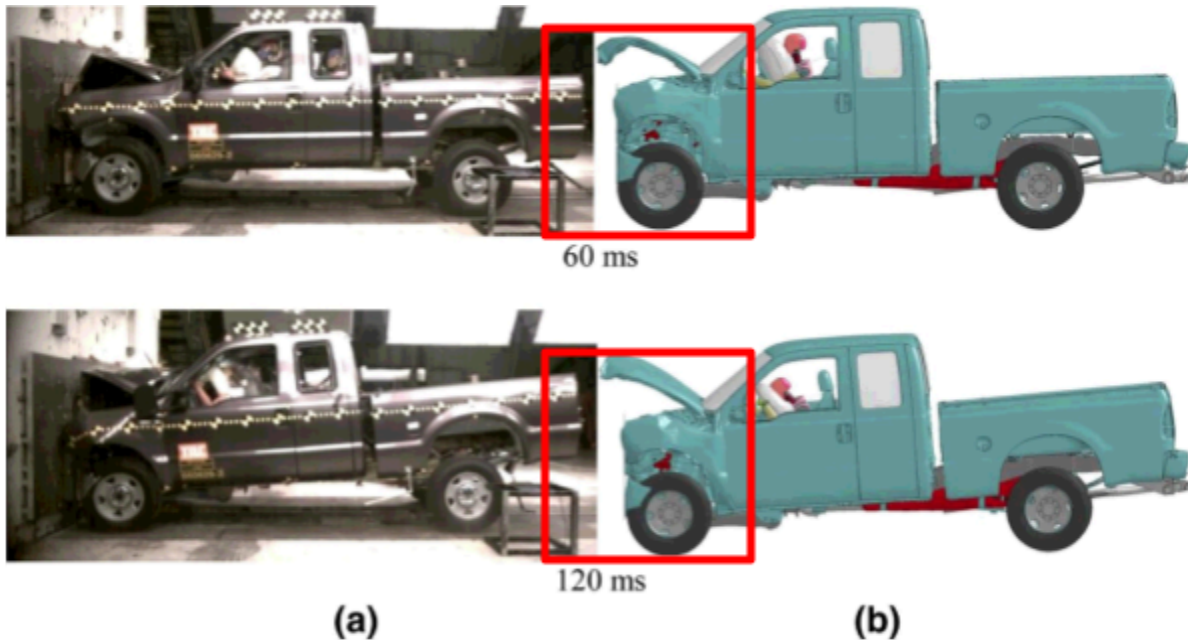
Digital Twins rely on modeling techniques that could include analytical, empirical, and semi-empirical models. Analytical techniques are derived from logical and scientific principles, forming theoretical frameworks. Examples include elasticity theories to model the stresses in structural engineering [1], heat transfer and thermodynamic relationships to predict the thermal changes in thermo-hydraulic systems [1], vibration theories used to predict the modal behavior of structures [1], etc. In contrast, empirical and semi-empirical modeling techniques utilize experimental data, often through Design of Experiment (DOE) and curve-fitting to formulate relationships between parameters, when theory alone could not explain the behavior, often due to nonlinear and chaotic behavior of the system. Well-known examples include solid-particle erosion theories used in predicting the material removal rates due to impact of abrasive particles [6].

2.2 Numerical and Computer Based Techniques

Numerical modeling techniques in engineering are computational methods that use discretized mathematical representations of physical systems to approximate and analyze behavior when analytical solutions are impractical or impossible. Well-known numerical and computer-based techniques in mechanical engineering include finite element analysis (FEA) and computational fluid dynamics (CFD). FEA is primarily used in structural and manufacturing engineering to model the elastic, plastic, and thermal behavior of solids by discretizing the domain into deformable elements. CFD, on the other hand, is used to model flow and heat transfer in steady and transient thermo-fluid systems by discretizing the domain into control volumes and numerically solving the governing equations until convergence is achieved.

Composite materials are extensively used in the aerospace and automotive industries due to their high strength, light weight, and anisotropic properties [3]. Despite their unique advantages such as high strength, light weight, and anisotropic properties, several issues might occur when processing these materials. For instance, drilling of composite materials could lead to an undesirable phenomenon, called delamination, in which, different layers of material detach from each other and structural integrity is jeopardized [3]. FEA has been used to identify the mechanisms of delamination and determine solutions to prevent its occurrence, such as through the application of active back up force [3]. Furthermore, FEA has been used to optimize manufacturing processes such as deep drawing [7]. In a study to produce micro square cups from stainless steel 304 foils, the FEA code Abaqus was utilized to predict the forming outcome and tune the process parameters for optimized parts. FEA has also been extensively used as an effective tool in simulating crash and impact and structural design in the automotive industry [3, 9]. Fig. 1 shows the application of FEA in simulating a crash test.

In the study of Abrasive Slurry Jet micro-machining (ASJM), Moghaddam et. al [6] used CFD to simulate the transient flow of turbulent jets and predict the underlying physics of the process and provide solutions to improve the quality of micro-features. CFD has also been extensively utilized in aerodynamics modeling and aerospace design [8, 10]. Fig. 2 shows the implementation of CFD in aerospace design. CFD has also been used in the analysis of the aerodynamics of a train passing a windbreak transition under crosswind. CFD analysis was used to simulate the environment of a CRH2 train passing through a transition zone to discover how its trajectory may shift due to the sudden change in atmospheric pressure [11].



Structural Deformation at 60 ms vs 120 ms

Figure 1: FEA simulation of car crash (b) vs actual crash tests (a). Adapted from [9].

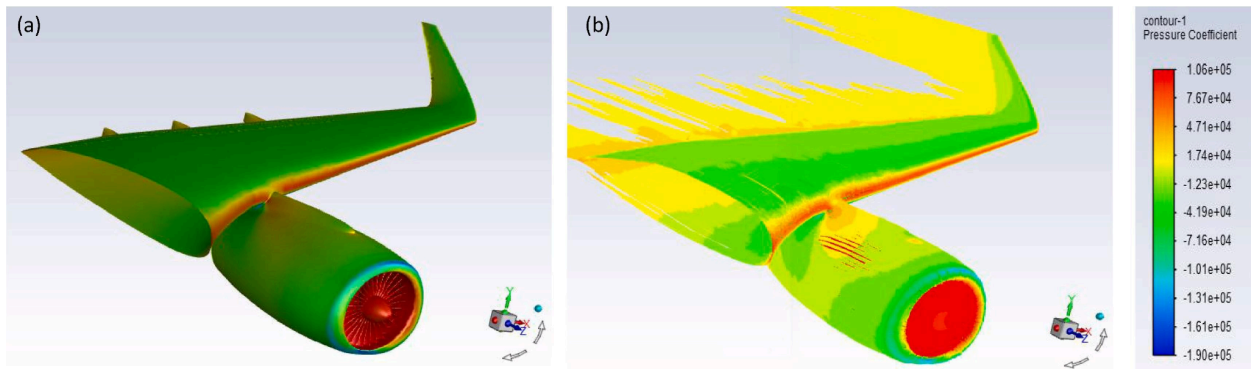


Figure 2: CFD modeling of pressure over a commercial plane wing [10] *Reproduced under a Creative Commons License.*

2.3 Machine Learning Techniques

Data-driven models, such as machine-learning (ML) models, are trained on large datasets to learn underlying patterns and relationships and then use these patterns to predict system behavior for previously unseen data [12]. These models include artificial neural networks (ANNs) [13], random forests (RF) [13], deep neural networks (DNNs) [13], and regression models. In many cases, such models function as black boxes because they do not directly reveal physically interpretable relationships between inputs and

outputs. However, they can be highly effective for prediction and classification tasks and may be computationally efficient once trained. Fig. 3 shows the schematics of a typical ANN architecture

Some common uses of machine-learning models in manufacturing include predictive maintenance and inventory management [13]. Deep learning models consist of multiple hidden layers and can provide the predictive intelligence required for advanced digital-twin applications. Prominent deep-learning frameworks in Industry 4.0 manufacturing include convolutional neural networks (CNNs) and deep recurrent neural networks (DRNNs) [13]. Digital twins are often categorized as data-driven simulation models because of their reliance on data to function [1]. Their dependence on information from physical systems distinguishes them from purely theoretical analytical techniques.

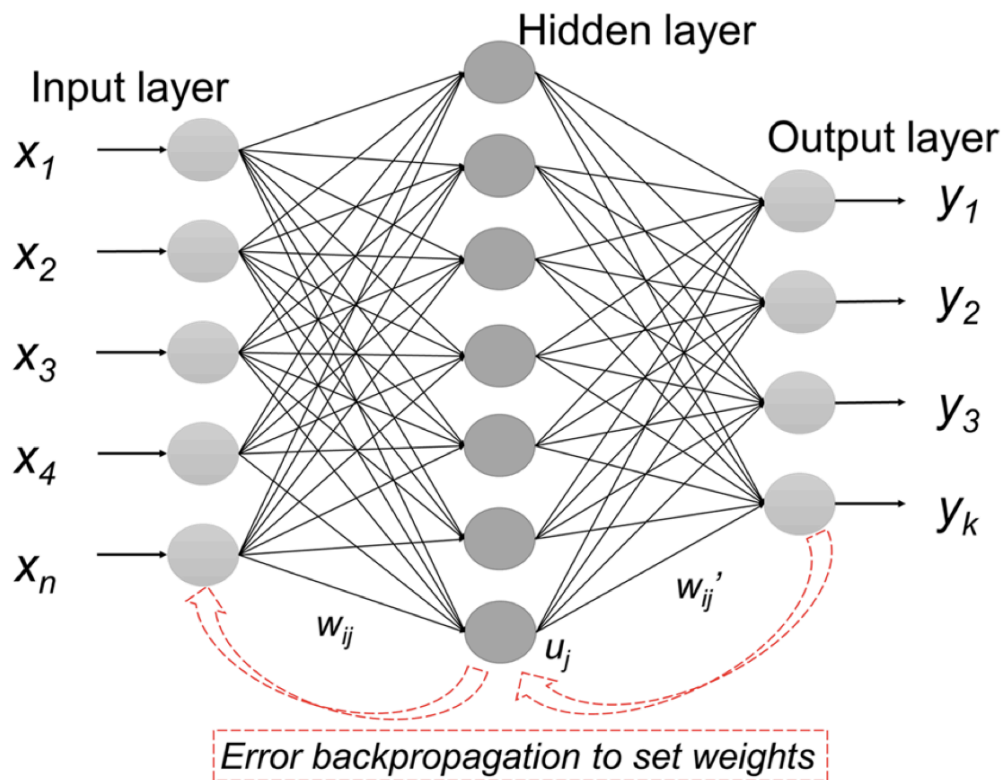


Figure 3: Schematic representation of a typical ANN Architecture [14]

In the Function-Structure-Behavior-Control-Intelligence-Performance (FSBCIP) framework [1], machine learning is essential to the Intelligence Model, which defines the components that give a digital twin its cognitive capability. This framework, proposed by Leng et al. [1], is intended to guide the development of smart manufacturing systems using digital twins. Artificial intelligence enables digital-twin models to go beyond simple predictive modeling and recognize complex nonlinear patterns in data where analytical, empirical, and numerical techniques may become less accurate.

Training of ML models can be performed through either supervised or unsupervised learning [15]. Supervised learning techniques, in which models are trained using labeled data, are often used in manufacturing for predictive maintenance because of their ability to classify failures [15]. These models can be used to predict machine failure or the remaining useful life of equipment. Support vector machines (SVMs) and random forests are examples of ML techniques that utilize supervised learning [15]. Unsupervised learning models are trained on unlabeled data and can be used to identify hidden patterns in data [15]. Common applications of unsupervised learning include anomaly detection and clustering [2], which benefit from the ability to discover useful structures in data.

A key advantage of ML techniques is their ability to handle high-dimensional, multivariate data [13]. In Industry 4.0 environments, various processes such as the Internet of Things (IoT), cloud computing, and digital twins require large amounts of data to function and communicate efficiently in real time. Another major advantage of ML modeling is adaptability [13]. Because Industry 4.0 environments are subject to frequent changes in machine state and operating conditions, machine-learning techniques can adapt to new information more readily than many rigid traditional models.

Despite their advantages, ML techniques also suffer from important limitations, one of which is data acquisition and quality [13]. ML models rely heavily on the collection of large volumes of representative data to produce accurate predictions. Data collection and processing may be time-consuming and expensive. Furthermore, models often do not perform well outside the range of the training data. Another challenge is the difficulty of interpretation [13]. Model outputs must be verified for accuracy, and results may be overfitted, meaning that the model has learned noise or random fluctuations rather than useful patterns. This can be particularly problematic when such information is applied to physical processes in real time.

While these foundational methods work well for isolated simulations, creating live representations requires massive computational power which is explored in the following section of Industry 4.0.

3. INDUSTRY 4.0

Industry 4.0 refers to the era of smart manufacturing, in which production systems become increasingly connected, data-driven, and adaptive. Key technological pillars of Industry 4.0 include the following:

Cyber Physical Production Systems (CPPS):

CPPS are systems in which physical and digital processes are integrated within a continuous loop. The physical layer represents machines, sensors, and production processes, while the digital layer stores data, algorithms, and learned patterns. Digital twins operate within such systems by supporting the exchange of information between these domains [16].

Internet of Things:

IoT is an overarching connectivity that enables efficient transfer of data across the physical and digital domains. Digital Twins are based on real-time connectivity and data transfer for which, the IoT is essential for maintaining updated flow of information. This extensive connectivity is across various sensors and machines, allowing the Digital Twin to manage a heavy load of information from different physical assets in real-time. [16]

Big Data and Cloud Computing:

Big Data and Cloud Computing are applications which function as the intelligence of Industry 4.0. Big Data aims to analyze data collected from sensors through IoT, by constructing crucial patterns in data. Cloud Computing acts as the storage and processing center of the factory. Instead of storing information in individual machines, Cloud Computing acts as an overarching network of servers that allows efficient communication [16]. In oil and gas industries, the usage of Cloud Computing in Digital Twins has shown to be a prominent and useful alternative for scalability, pricing, and security [17]. The most prominent clouds used in these industries are IaaS and PaaS services, which store information such as reservoir modeling and seismic processing [17]. As a result, cloud computing has proven itself to be an essential part of the Digital Twin in Industry 4.0 manufacturing due to its high data storage and processing capacity.

Digital Twins utilize specific Edge-Cloud optimization for IoT to overcome certain limitations regarding latency found within these applications [1]. Edge-Cloud optimization is the combination of cloud computing and edge computing to form a cloud-edge framework [1]. In the same proposed framework, Raspberry Pi Card machines [1] are also used as processing units in scenarios where multi-tasking is required. They are low cost computers (Raspberry Pi) that can be plugged into manufacturing equipment [1]. Additionally, an edge-cloud algorithm is proposed by Leng et al. [1] to control and evaluate incoming tasks to avoid latency issues. Fig. 4 shows the link between Edge-Computing and the new generation of Information Technology.

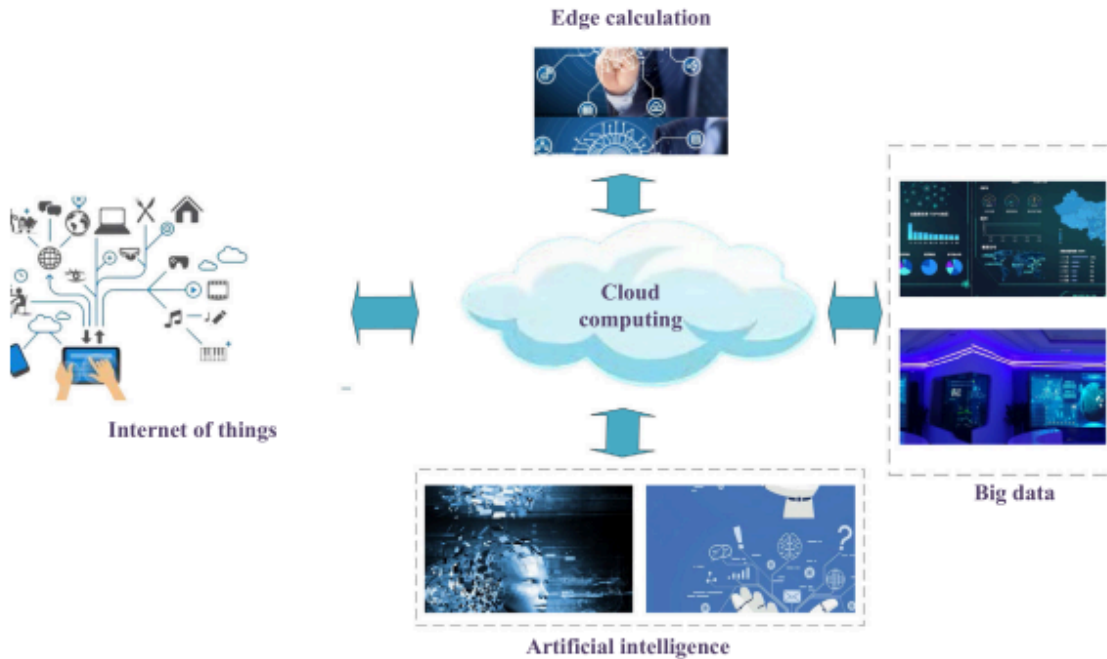


Figure 4: Link between Edge-Computing and the new generation of Information Technology [18]

The advanced frameworks for connecting physical and digital realms are defined, but include various limitations. The following section discusses the broad scope of a Digital Twin, including the challenges that follow.

4. DIGITAL TWINS

As previously mentioned in the introduction, a Digital Twin by definition is considered “one of the pillars of Industry 4.0” [1]. In this section, first, common types of Digital modeling in manufacturing will be discussed to distinguish Digital Model, Digital Shadow and a Digital Twins.

Digital Model:

A representation of a physical asset which does not include an automated exchange of data between a physical and digital object. Any form of data exchange is done manually by users. These models have been used in 3D CAD modeling in product design [15], FEA, and CFD, as discussed in Section 2.

Digital Shadow:

A one-way flow of information of either the physical or the digital affecting the other, but not vice versa is defined as a Digital shadow. One shadows the work of the other and processes the information [19].

Digital Twin:

The two-way flow of data between a physical and a digital object may be categorized as a Digital Twin. A Digital Twin is defined accurately when both variables affect the other through a constant flow of information [19]. Fig. 5 shows the connection between the cyber and digital worlds. Fig. 6 shows the various applications of Digital Twins in manufacturing and its evolution. Digital Twins have had impact throughout multiple domains that aren't limited to manufacturing as well as seen in Fig. 6.

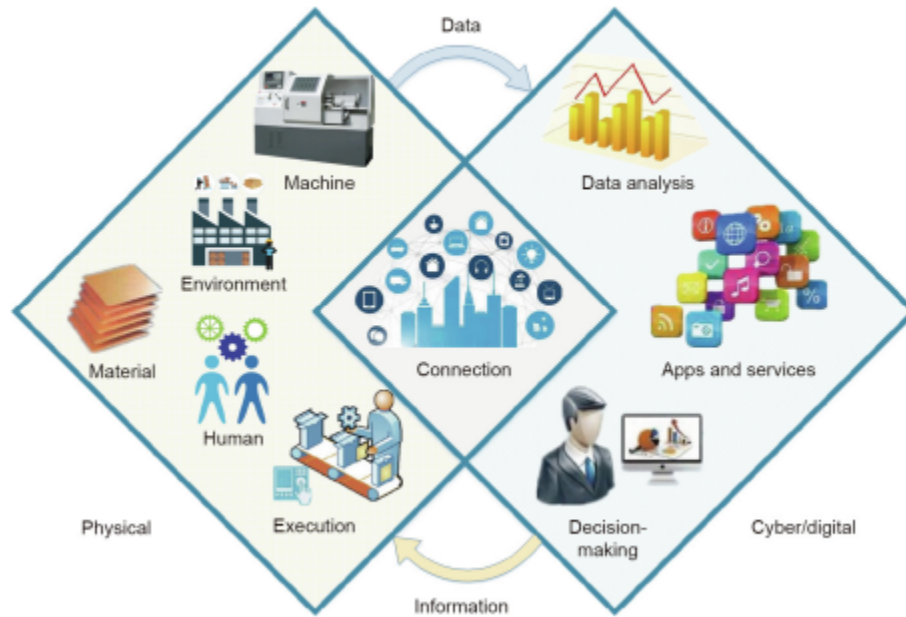


Figure 5: Mapping between Physical and Cyber/Digital Worlds [20] *Reproduced under a Creative Commons License.*

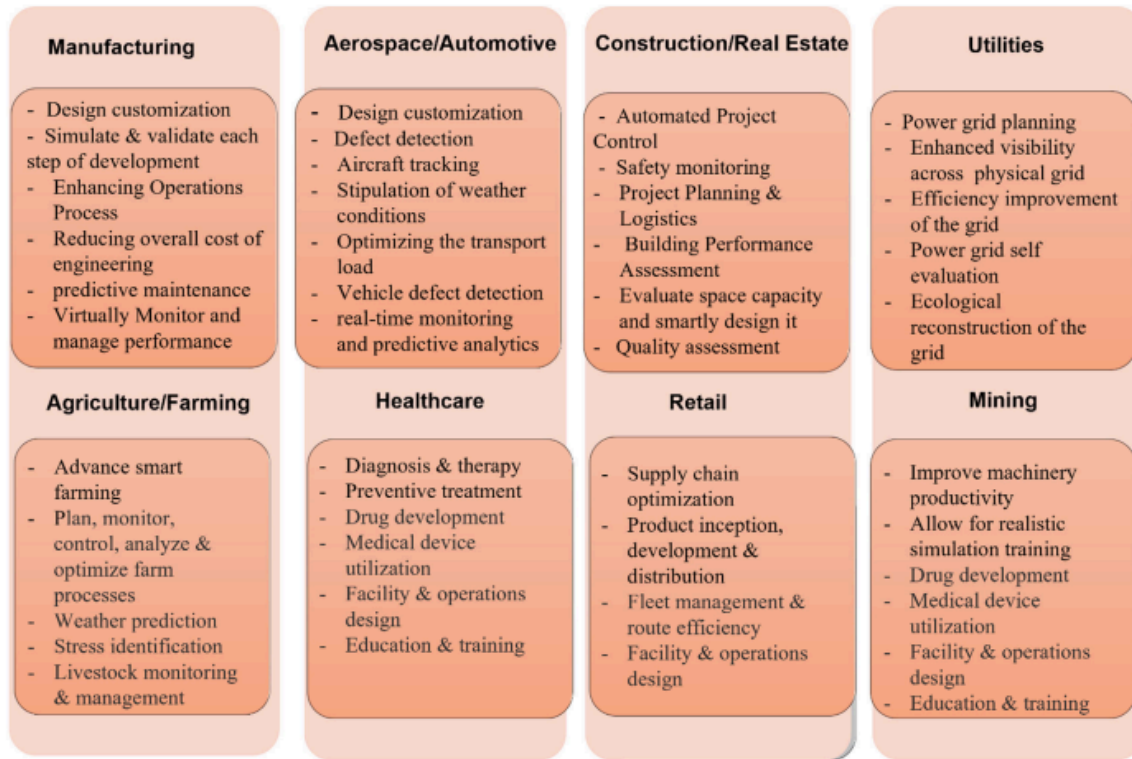


Figure 6: Evolution of Digital Twins in Manufacturing [2] *Reproduced under a Creative Commons License.*

4.1 Comparative Analysis with Traditional Engineering Models

To understand the dynamic shift from traditional engineering models to Industry 4.0 innovations, contrasting well-established techniques found in section 2 with Digital Twins would be beneficial. FEA and CFD function more as Digital Models compared to Digital Twins which interact with the environment and are automated.

Table 1 below provides a brief comparison of CFD, FEA, and Digital Twins across multiple domains.

Table 1: Comparison of FEA, CFD, DT

Metric	Finite Element Analysis (FEA)	Computational Fluid Dynamics (CFD)	Digital Twins (DT)
Primary Scope	Structural integrity, thermal behavior of solids.	Flow of fluid, heat, and behavior of gases.	Live optimization, simulation, and monitoring between

			physical and digital domains.
Data Dependency	Reliant on physics. Boundaries set by the user, including material restraints.	Reliant on physics, including fluid properties.	Updated by user, alongside real-time self optimization.
Update Frequency	Offline/Static. Updated manually per simulation run or design iteration.	Offline/Static. Updated manually per simulation run or design iteration.	Live/Real-time. Automatically updated in real time via IoT data.
Computational Cost	Substantial. High in demand for CPU/GPU power when simulation is running.	Extremely high. Requires high processing power to achieve accurate fluid simulation.	High-upfront, but continuous. Requires significant resources, but execution is highly efficient once established.

4.2 Limitations and Current Challenges of Digital Twins

Although Digital Twins offer significant technological potential, their implementation remains challenging due to several obstacles. Various limitations and bottlenecks of Digital Twins will be discussed in this section, including cost, speed, data management, cybersecurity, and trust issues. Such limitations are crucial and should be addressed before implementing Digital twins in manufacturing setups.

4.2.1 Cost of Digital Twins Implementation

Implementation of Digital twins in traditional manufacturing setups could be highly expensive due to required complex infrastructure and high fixed costs. Setting up a Digital Twin within a traditional factory includes the costs of technologies and infrastructures capable of transmitting and processing data in real-time, and rigorous testing to ensure the Digital Twin is working as intended [2]. The applications required by the Digital Twin itself could significantly vary case by case. As discussed in section 3, Digital Twins utilize Artificial Intelligence, Internet of Things, and Cloud storage. However, due to these high capabilities it requires a large amount of software and data, customized towards a specific cause. Internet of Things requires delicate and costly sensors to ensure a constant flow of information between the physical and digital world. Companies are also required to invest in a high amount of Cloud Storage to keep up with the constant flow of data that a Digital Twin requires [2]. Furthermore, production would often be disrupted due to the installation of new machines and infrastructures and updating the current system.

4.2.2 Speed and Latency

A true Digital Twin is categorized by its ability to transfer data in real-time, a characteristic that is impacted by its processing speed and latency. The efficient interoperability depends on its ability to maintain a bi-directional flow between virtual and physical environments. According to Francisco K. [17], round-trip delays pose a threat to the functionality of Digital Twin because of cloud computing. Although due to the high volume of data, cloud storage is a fundamental aspect of Digital Twins, transmitting data to and from cloud servers poses the risk of creating a latency gap. Leng et al. [1] suggests that high-accuracy models require massive computational power, which often jeopardizes real-time synchronization between the physical and digital assets. As a result, some industrial protocols such as MQTT (Message Queueing Telemetry Transport) [21] have been proposed to improve speed quality for Digital Twin. MQTT is a lightweight network protocol, utilized within the manufacturing industry as a communication bridge across machines. According to Gonzalez et al. [21] MQTT is preferred due to its low bandwidth usage, ensuring rapid communication.

4.2.3 Data Management

Digital Twins require a vast amount of storage due to their reliance on communication and processing of large data-sets. Data is managed with methods such as cloud computing, one of the main pillars in Industry 4.0 to accommodate the demands of Digital Twins. The main challenge presented with data management is managing its life cycle. The effort required to filter and normalize data is significant and necessary in Digital Twins applications [13]. A Digital Twin is required to clean data as fast as it produces information to avoid data back-logging, a phenomenon where unprocessed data piles up and interferes with latency. Additionally, many industries fail to manage data correctly with the use of relational databases (SQL) that are a mismatch for Digital Twins, which rely on “Big Data.” [21]. Switching to non-relational databases such as MongoDB is necessary to ensure Digital Twins work at full capacity. Non-relational databases function with Big Data due to their flexibility in storing information, which is a conflict for relational databases that are more rigid. The difference is in the formatting structure, where relational databases organize data while non-relational databases do not have such requirements.

4.2.4 Cyber Security

Due to the bi-directional flow of data between the digital twin and the physical environment, malicious manipulation can be devastating. The heavy reliance of digital twins on data transmission can increase the opportunity for a cyber attack and compromise the manufacturing operation. Communication between Digital Twins and other applications (i.e. cloud computing, IoT) requires constant maintenance and monitoring to avoid interception or tampering [5]. This includes overall interconnectivity between applications and Digital Twins. The high amount of applications used in the manufacturing sector can pose safety issues due to increased exposure to cyber threats. Furthermore, Digital Twins rely on trained Artificial Intelligence that themselves are composed of massive datasets. As noted by Goncalves et al. [5],

data poisoning can lead to malfunctioning of AI models when data is manipulated. Internal workers with authorized access could also manipulate parameters or increase possibilities for security concerns, due to the high amount of data and control that a Digital Twin has on the manufacturing environment.

4.2.5 Trust Issues and Human Capabilities

Digital Twins are a relatively new concept that has not been widely implemented. Oftentimes, the reliability of Digital Twin could be questionable for investors and many have taken the safer and more conservative approaches. For instance, Digital Twins do not always provide the logic behind its outputs [13]. According to Thorsten Wuest [13], the information produced by the Digital Twin cannot be trusted if the results are not interpretable. Finally, the integration of Digital Twins is extremely complex. With the example of Gonzalez et al.'s [21] approach to constructing a digital twin, setting up the sufficient parameters for a Digital Twin can discourage its usage due to it being extremely complex and new.

LIMITATIONS OF THIS REVIEW

While this literature review deals with advancements in Digital Twins and in Industry 4.0 manufacturing, several limitations in the process should be noted. First, the paper heavily relied on a small group of highly cited papers, particularly the works of Leng et al. [1] and Mohsen & Bilge [2], to cite definitions and portray key diagrams. Secondly, the paper emphasizes certain engineering fields, such as automotive and aerospace, due to the common use of CFD and FEA. Finally, the paper relies on Google Scholar as the primary search engine which may not cover all of Digital Twins in Industry 4.0 manufacturing.

CONCLUSION

Digital twins are expected to play an increasingly important role in Industry 4.0 manufacturing as industries move toward more connected, data-driven, and adaptive production systems. While current adoption is still limited by high implementation cost, latency, data-management complexity, cybersecurity concerns, and limited trust in model outputs, these barriers are likely to be reduced as supporting technologies continue to mature. In particular, advances in edge-cloud computing, lightweight communication protocols, improved sensor networks, and better data-processing frameworks will help improve real-time performance and scalability. At the same time, stronger cybersecurity practices, more interpretable machine-learning models, and hybrid approaches that combine physics-based and data-driven methods are likely to improve reliability and user trust. Therefore, the future trajectory of digital twins in manufacturing will likely be toward broader, more practical deployment in applications such as predictive maintenance, process optimization, and quality control, with adoption increasing as these technical and organizational challenges are progressively addressed.

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