Digital Twin in Manufacturing: A Review of Definitions and Applications

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Abstract: The Digital Twin (DT) concept is one of the key enabling technologies for the realization of Smart Manufacturing (SM) and Industry 4.0. However, industry and academia define a DT in several different ways and there is not yet a consensus about the concept and how it can be implemented in real manufacturing ecosystems. This paper summarizes some perspectives that have been reported in the literature on how the DT concept is defined and applied by both industry and academia.

Keywords: Digital Twin, Modeling, Smart Manufacturing, Industry 4.0

1. Introduction

New smart manufacturing (SM) strategies can be important tools as we move forward to address current and emerging challenges in the production industry. The SM initiatives integrate manufacturing assets with sensors, computing platforms, communication technology, control, simulation, and data-intensive modeling to move toward comprehensive reactive, predictive, and proactive technologies. Among the many tenets of SM, "Digital Twin (DT)" solutions represent a significant opportunity for manufacturers to leverage existing and emerging technologies to improve quality and throughput and reduce variability and cost. A DT uses data collected from the plant floor, operations, and enterprise environments to create replicas and advanced analytics for physical assets, systems, or processes while focusing on key behaviors such as life, efficiency, or flexibility. DT technologies promise several opportunities to improve manufacturing systems operation. DTs can be applied in a variety of scenarios such as tracking and visualizing the performance of the manufacturing system in real-time, evaluating production decisions based upon analytics, troubleshooting manufacturing equipment remotely to reduce resolution times, and commissioning new and change requests to automation processes and industrial equipment from remote service locations to reduce service costs.

To date, no consensus has been reached on a DT definition in manufacturing. The DT label is often applied to any capability that replicates some aspect of a system, e.g., simulation of anything in manufacturing. This paper synthesizes different perspectives that have been reported in the literature on how the DT concept is defined and applied in both industry and academia.

2. Digital Twin Definitions

Digital Twins were anticipated by David Gelernter's 1991 book *Mirror Worlds* [1]. Mirror Worlds" are computer-generated models of urban regions where a whole city could show up on a screen, in a single condensed, live, and changing representation. Mirror Worlds provide complete views of the broader urban ensemble, while also allowing the user to deep dive into the data while retaining its spatial context. In manufacturing, the concept of DT was first introduced by Michael Grieves, then of the University of Michigan, in his presentation about Product Lifecycle Management (PLM) in 2002 [2]. Grieves presented a conceptual model for a virtual, digital representation equivalent of a physical product that includes the real space, virtual space, and the data and information flow between the two spaces. Since then, the "Digital Twin" concept has been defined in many ways in academia and industry.

A widely accepted DT definition is that of NASA and the US Air Force Research Laboratory, that defined a DT as an integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system, which incorporated the best available physical models, updated sensors data, and historical data to mirror the life and condition of the corresponding flying twin [3]. General Electric (GE) defines DTs as software representations of components, assets, systems, and processes that are used to understand, predict, and optimize performance in order to achieve improved business outcomes [4]. The Industrial Internet Consortium defines DT as "a digital representation of an entity, including attributes and behaviors, sufficient to meet the requirements of a set of use cases [5]. Siemens defines a DT as a virtual representation of a physical product or process, used to understand and predict the physical counterpart's performance characteristics. Digital twins are used throughout the product lifecycle to simulate, predict, and optimize the product and production system before investing in physical prototypes and assets [6]. According to Deloitte, a digital twin can be defined, fundamentally, as an evolving digital profile of the historical and current behavior of a physical object or process that helps optimize business performance [7]. Similar definitions exist in academia. The CIRP Encyclopedia of Production Engineering defines DT as a digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases [8]. Alam and El Saddik define a DT as an exact cyber copy of a physical system that truly represents all of its functionalities, [9]. Ding et al. define a DT as the process of building twins of the physical objects and systems in the cyber world and establishing data channels for cyber-physical interconnection and synchronization, [10]. Plattform Industrie 4.0 defines the Asset Administration Shell, which could play the role of a DT, as a digital representation (information that represents characteristics and behaviors of an entity), sufficient to meet the requirements of a set of use cases [11]. Table 1 summarizes these definitions of DT in the literature.

3. Digital Twin Applications

DT technology has been implemented in several ways in industry. Oftentimes the technology is not referred to as "digital twin", and, in many cases, it has existed long before the term "digital twin" was coined. For example, Model-Based Process Control (MBPC), virtual metrology, virtual sensing, sensor fusion, and model-based Predictive Maintenance (PdM) are technologies commonly used in manufacturing today that fit most DT definitions, or use DT capabilities align with most of the DT properties to achieve an objective. These technologies replicate some aspect of a physical thing, have a purpose of improving some aspect of their application environment, use data to maintain some level of synchronization with their real counterpart, and employ modeling technology to achieve their goals, e.g., increase availability and efficiency of equipment, extend its useful life, and reduce its life cycle cost [12], [13], [14], [15], [16].

Table1: Definitions of Digital Twin in industry and academia

	Reference	Definition
Industry	NASA (2012) [3]	An integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system, which incorporated the best available physical models, updated sensors data, and historical data to mirror the life and condition of the corresponding flying twin
	GE (2018) [4]	Dynamic digital representations that enable companies to understand, predict, and optimize the performance of their machines and their business.
	Industrial Internet Consortium (2019) [5]	A digital representation of an entity, including attributes and behaviors, sufficient to meet the requirements of a set of use cases
	Siemens [6]	A virtual representation of a physical product or process, used to understand and predict the physical counterpart's performance characteristics. Digital twins are used throughout the product lifecycle to simulate, predict, and optimize the product and production system before investing in physical prototypes and assets.
	Deloitte (2017) [7]	A digital twin can be defined, fundamentally, as an evolving digital profile of the historical and current behavior of a physical object or process that helps optimize business performance.
Academia	Grieves (2017) [2]	A set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin.
	Alam & El Sadik (2017) [9]	An exact cyber copy of a physical system that truly represents all of its functionalities.
	CIRP (2019) [8]	A digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases
	Ding et. al (2019) [10]	The process of building twins of the physical objects and systems in the cyber world and establishing data channels for cyber-physical interconnection and synchronization
	Plattform I4.0 (2018) [11]	A digital representation (information that represents characteristics and behaviors of an entity), sufficient to meet the requirements of a set of use cases

DTs are used today in many industrial areas such as product design, production, health monitoring, and human machine collaboration. In product design, Tao et al. propose a DT-based product design approach that connects the physical and virtual products to improve product customization [17]. Schleich et al. propose a DT reference model that ensures that the required geometrical features of the product are satisfied regardless of the presence of geometrical part deviations [18]. In the manufacturing process, Leng et al. propose a DT conceptual framework for monitoring and optimizing physical manufacturing workshops based on context data [19]. Tao and Zhang propose a digital twin shop-floor to realize the convergence between physical and virtual spaces in cyber physical production systems [20]. In health monitoring, Liu et al. propose a DT approach for the evaluation of process plans with dynamic changes of machining conditions and DT-related uncertainties is presented in [21]. GE uses DTs for real-time monitoring, timely inspection, and predictive maintenance of engines [22] as well as to monitor running states of wind turbines through sensory data, and control their operations through digital models [23]. Guerra et al. present a DT method for the optimization for ultra-precision motion systems. The DT combines virtual representations of mechanical and electrical components to emulate non-linearities (backlash and friction) and the corresponding control system [24]. Some studies have investigated the connections between humans and DTs in the production area. A DT approach that enables the communication and coordination of operators with the production system was proposed in [25]. De Magistris et al. propose a dynamic digital human model that is capable of computing dynamic, realistic movements and internal characteristics in quasi-real time, based on a simple description of future work tasks, in order to achieve reliable ergonomics assessments of various work task scenarios [26]. Such DTs facilitate the integration of humans in the decision-making process for self-controlling systems. Other example applications of DTs can be found in [27]. Table 2 shows some DT applications in the fields of product design, production, health monitoring, and human machine collaboration.

Table2: Some DT applications in the literature

DT application environment	Reference	Description
Product design	Tao et, al. (2018) [17]	The DT-based product design approach connects the physical and virtual products to improve product customization
	Schleich et al. (2017) [18]	The DT reference model ensures that the required geometrical features of a product are satisfied regardless of existing geometrical part deviations
Production	Leng et al. (2018) [19]	The DT conceptual framework monitors and optimizes physical manufacturing workshops based on context data
	Tao and Zhang (2017) [20]	The DT shop-floor enables the convergence between physical and virtual spaces in cyber physical production systems
Health monitoring	Liu et al. (2019) [21]	The DT enables the evaluation of process plans with dynamic changes of machining conditions and DT-related uncertainties
	GE (2015, 2016) [22], [23]	DTs are used for real-time monitoring, timely inspection, and predictive maintenance of engines. DTs are used to monitor running states of wind turbines through sensory data and control their operations through digital models.
	Guerra et al. (2019) [24]	The DT combines virtual representations of mechanical and electrical components to emulate backlash and friction and the corresponding control system
Human machine collaboration	Graessler and Poehler (2017) [25]	The DT enables the communication and coordination of operators with the production system. The DT facilitates the integration of humans in the decision-making process for self-controlling systems.
	De Magistris et al. (2015) [26]	The DT computes the human's dynamics, realistic movements in quasi-real time, based on a simple description of future work tasks, in order to achieve reliable ergonomics assessments of various work task scenarios

4. Conclusion

Digital Twin is one of the key concepts of smart manufacturing , which allows to exploit data collected from the manufacturing operations to monitor and analyze performance of machines and equipment, develop predictive strategies, and manage the manufacturing system expectations to support decision making. Since the "Digital Twin" concept was coined, it has been defined in many ways in academia and industry. The aim of this paper was to provide a literature search of common DT definitions and associated applications including efforts from both industry and academia.

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