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A Short Technical Review on Digital Twins in Smart Manufacturing

KEYWORDS

Digital twin, smart manufacturing, machine learning, Internet of things.

ABSTRACT

The most recent tendencies and breakthroughs in digital technologies have made it possible to implement a new model of manufacturing. By establishing a digital twin of the real environment and basing their judgments on that twin, digital systems are able to monitor, optimize, and manage the processes that they are applied to. This concept is predicated on the creation of a “Digital Twin” for each individual production source that contributes to the overall manufacturing process. In spite of the fact that different real-world applications of digital twin may involve different technical and operational specifics, a significant amount of work was put in over the past few years to recognize and express principal properties, in addition to the primary challenges involved in the practical implementation of digital twins within related industries. The purpose of this article is to review and analyze the fundamental principles, ideas, and technological solutions that comprise the Digital Twin vision for production processes. As a result, the objective of this review is to provide a synopsis of the state-of-the-art regarding digital twin concepts and to analyze their most recent status in terms of their potential application and implementation.

1. Introduction

"Digital twin" is a digital copy of a physical object, system, or process that was designed for, or is now being used in the real world [1]. A digital representation of something that is either meant to exist in the actual world or does in fact exist in the real world is called a "digital twin" or "physical twin" [2]. The digital twin is intended to be the foundational premise for Product Lifecycle Management and it exists throughout the entire lifecycle of the physical entity it represents, including creation, construction, operation/support and disposal [3]. This has been the case since the digital twin's initial introduction. Due to the granular nature of the information, the representation of the digital twin is established by the value-based use cases it is designed to implement. It is possible for the digital twin to exist before there is a physical entity, and this really happens rather frequently. It is possible to model and simulate the full lifecycle of the targeted entity by making use of a digital twin throughout the phase of creation [4]. It is possible to employ the digital twin of an existing entity in real time and keep it frequently synchronized with the physical system it corresponds to, but this is not a requirement [5]. For the purpose of providing an illustration of a real-time digital twin, an object that is being investigated, such as a wind turbine, may be supplied with a variety of sensors relevant to critical aspects of its functionality [6]. These sensors generate information regarding many aspects of the performance of the physical twin [7], such as the exterior weather conditions, and the amount of energy output. After that, the info is transmitted to a processing system, where it is utilized on the digital twin.

Despite the fact that the idea has been conceived earlier, the first operational definition of a digital twin was developed by NASA in 2010, as part of an effort to improve the simulation of spacecraft using physical models [8]. Continual attempts to ensure and improve the quality of the product design and engineering processes finish in the creation of digital twins [9].

Computer-aided drawing and design, model-based systems engineering, and a rigorous relationship to signal from the physical equivalent have largely replaced traditional methods of producing product drawings and engineering specifications [10]. Therefore, the main aim of this technical review is to provide information on concept of digital twins in smart manufacturing. The various approaches like big data, internet of things (IOT), product life cycle management etc. is discussed briefly in section 2. The section 3 describes the importance of machine learning in digital twin. Section 4 shows the importance of digital twin taxonomy in smart manufacturing.

2. Concept of digital twins in smart manufacturing

2.1. Big Data

Big data refers to a vast volume of data, whether regular or irregular, that complicates the operation of day-to-day operations [11]. Better planning and decision-making options for research are supplied as a result of thebig data analysis [12]. When the term “the big data” was relatively new, it took a very long time to collect and store big information for analysis to conclude. The concept gained momentum in the 2000s, when industry analyst Doug Laney defined "Big Data" as 3V consisting of the “volume, velocity and variety” [13]. Big data is more concerned with what to do with it than with how much information is accessible. It analyzes data from any source to uncover solutions that save money and time, new project creation, optimal bids, and smart decision making [14] like in Figure 1. When big data is paired with advanced analytics, business-related benefits include:

- Real-time identification of root causes of mistakes and issues.

- Creating coupons for sale based on the purchase behavior of clients.
- Detecting errors before they have an impact on the operation.
- Recalculating the risks associated with new portfolios.

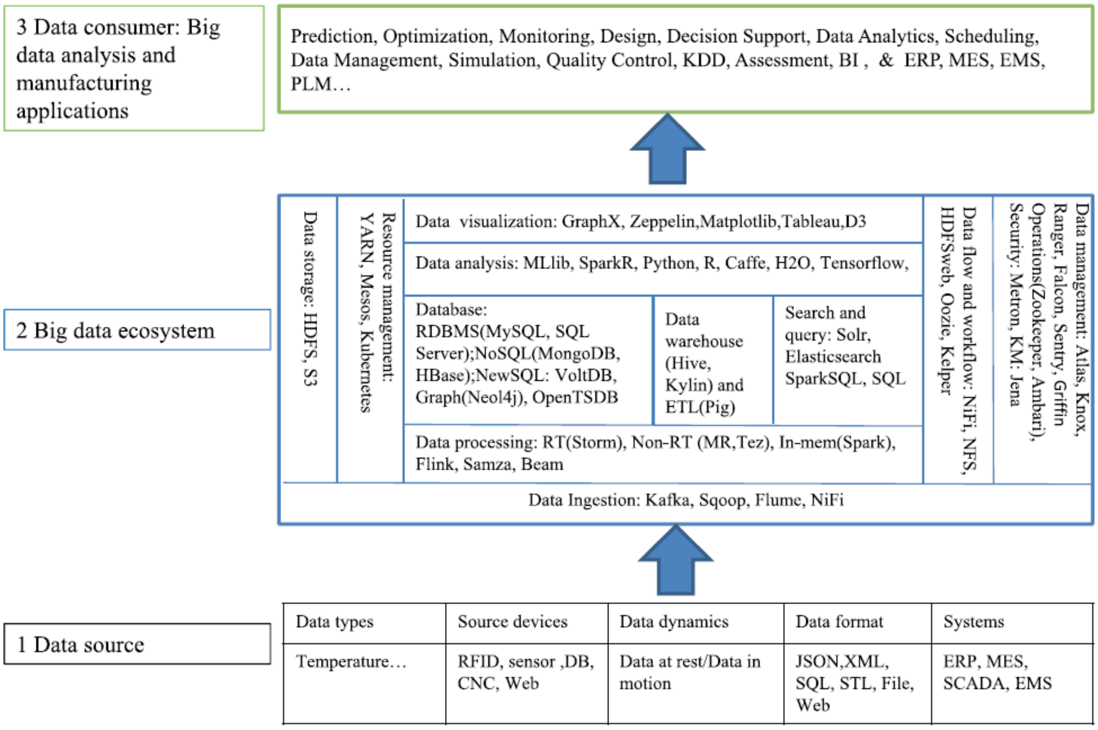

Figure 1. Theoretical structure of Big data [12]

2.2. Internet of Things (IoT)

The applicability of the digital twin (DT) concept has become easier as a result of the integration of the internet of things (IoT), machine learning and artificial intelligence (AI) technologies into the operational models of cyber physical systems (CPS), which have widespread applications in the field of industrial engineering (Figure 2). Persistent perception of physical processes in the virtual environment and making decisions, and taking actions with the data obtained from it are seen as the main difficulties. Cyber physical systems are used in many areas such as manufacturing, health and consumer services, energy systems [15].

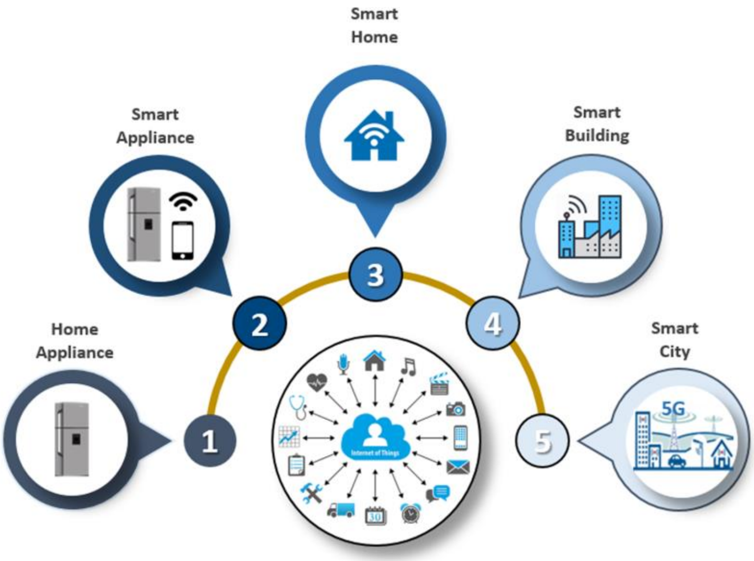

Figure 2. Internet of Things (IoT) smart manufacturing [16]

The term "digital twin" refers to an exact digital replica of a physical object. As an alternative definition, a digital twin is an electronic representation of a physical object or service. The digital twin now incorporates software solutions, artificial intelligence, and the Internet of Things (Industry 4.0) [17]. The employment of sensors has led to a dramatic increase in the amount of data we can obtain from our immediate surroundings. Using sensors, information about the real world is taken in and uploaded to a digital database [18]. A digital duplicate of a real-world process, good, or service is built using the transferred real-time data. This strategy is rapidly gaining prominence as a key tool for improving engineering productivity and creativity in the current day. The sophisticated analysis, monitoring, and inference capabilities of digital twin systems have been put to use by a wide variety of businesses [19]. Although the digital twin model has been around since 2002, the term came to light in 2010. After this date, its popularity has been increasing day by day due to the many benefits it is expected to offer throughout the product life cycle. The concept of the digital twin is currently receiving great attention and continues to be developed by the world's largest companies. Although the digital twin is increasing its usage and prevalence day by day, it is a new concept for many people and businesses. It can be said that this concept emerged with the evolution of the concept of "smart products" introduced in the early 2000s [20]. The digital twin can be seen as a connection between the real world and the virtual one. Integration of smart components with sensors to track data like real-time status, operating condition or location is common in digital twin systems. All the information gathered by the sensors is sent to and stored in a cloud-based system, which is managed by the smart online components [21]. The information gathered here is examined using a number of metrics and parameters. Through this system, many processes such as transforming your work that can be applied to the physical world, performing various tests and analyzes in a virtual environment become applicable [22]. All kinds of improvements that can be made in the production units can be made in the digital twin, which is the electronic copy of the production unit. Improvement may require radical change, such as changing or improving processes or machines. Physical change is always difficult, time consuming and expensive. It is easy and less expensive to make these changes to the digital twin [23].

2.3. Product Lifecycle Management (PLM)

With the digital twin technology, solutions that will eliminate many real-world difficulties have begun to be introduced. It can be found in a wide range of usage examples, from fatigue in marine and wind turbines to testing corrosion resistance, helping to improve efficiency in machining [24]. Thanks to the digital twin, it has become possible to find and research various solutions in the stages of improving production processes, expanding the product life cycle [25] and product development [20] (Figure 3). Here, cost comes first and as it is known, testing or re-establishing a physical environment is a costly process. With the creation of a digital twin with the real data of the physical environment in the real world, these solutions and operations have become very easy to realize in terms of cost and applicability [20].

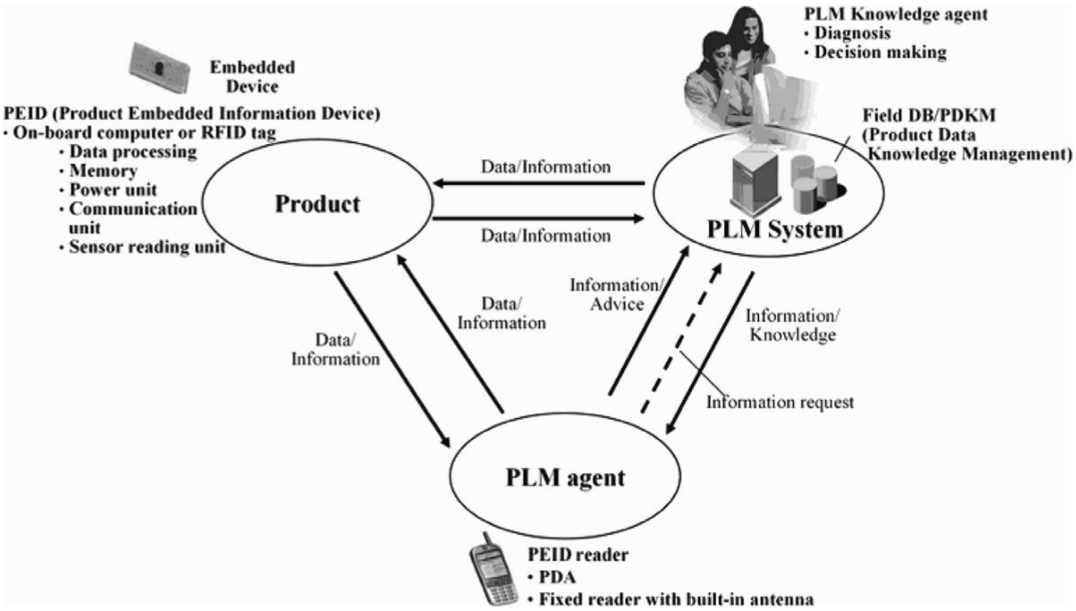

Figure 3. Product Lifecycle Management (PLM) [20]

2.4. Continuous Acquisition and Life cycle Support (CALS)

CALS technology has the potential to dramatically minimize the amount of design effort. Many components of previously established equipment, machinery and systems are described. A single format for data transfer network servers that is available for all CALS technology users is significantly less difficult (Figure 4) [26]. Solve maintenance issues, integrate goods into various types of systems, and it is expected that the following factors will lead to success in the market of complex technical products: the environment, adaptation to changing operating circumstances, and specialization of the design organization [27].

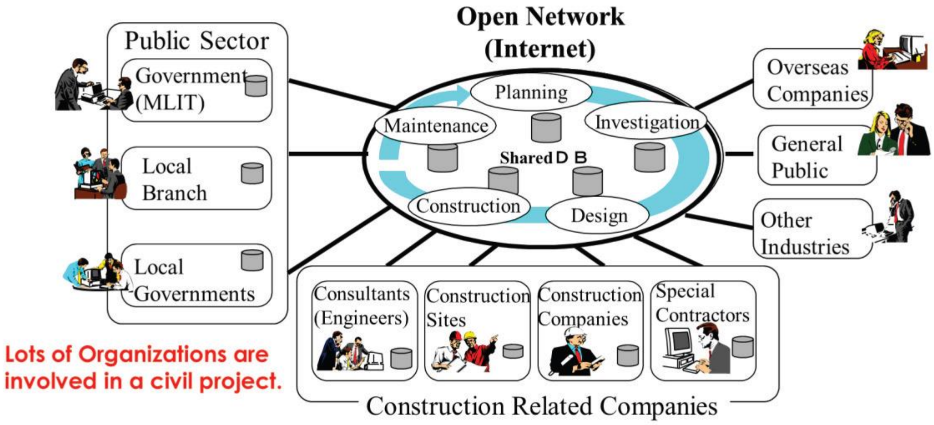

Figure 4. Example of Continuous Acquisition and Life cycle Support (CALS) [26]

Advances in CALS technology should result in the phenomenon known as virtual emergence. Manufacturingis in charge of the process of developing software specifications [28]. In terms of time and space, enough technological equipment to manufacture a product may be installed between several companies and self-contained design studios. Among CALS-technologies' accomplishments is the simplicity of deployment of sophisticated design solutions; it is part of a project such as a new development [29]. The foundation of current CALS technology is the construction of an open distributed automation design and management system in the industry. The fundamental issue with their design is guaranteeing homogeneity. Data description and interpretation, wherever and whenever it was received a generic system that grows to become a global system. Design, technology, and operation are all intertwined. Standardization of documents and presentation languages is required. Then it is truly effective. Time and space are separated and various tools are used to work on a single project by different teams CAD/CAM/CAE systems. The same design document can be reused in many settings. Projects and integrated technical documents adapted to various manufacturing situations reduce the overall cost of design and production by a significant amount. Besides the system's functioning has been simplified [30].

3. Importance of machine learning (ML) in digital twinning of smart manufacturing

It is possible to carry out difficult or costly transactions in the real world in the virtual environment and apply them in the real world by looking at the results. It has paved the way for these transactions to be done more easily and at lower cost by processing and interpreting real-time data in the virtual environment. By making various simulations, it will be possible to test the innovations digitally before they are tried in the physical environment. Artificial intelligence [18] and machine learning [31] are two examples of how many operations can be enhanced through the application of these techniques. Identifying issues in the digital twin before bringing them into the physical production space saves time and money. Predictions can be made with tools like machine learning and artificial intelligence, allowing us to provide not only analysis of the current situation but also forecasts for the future. This creates an effect that can make serious contributions to the costs of businesses (Figure 5) [32,33].

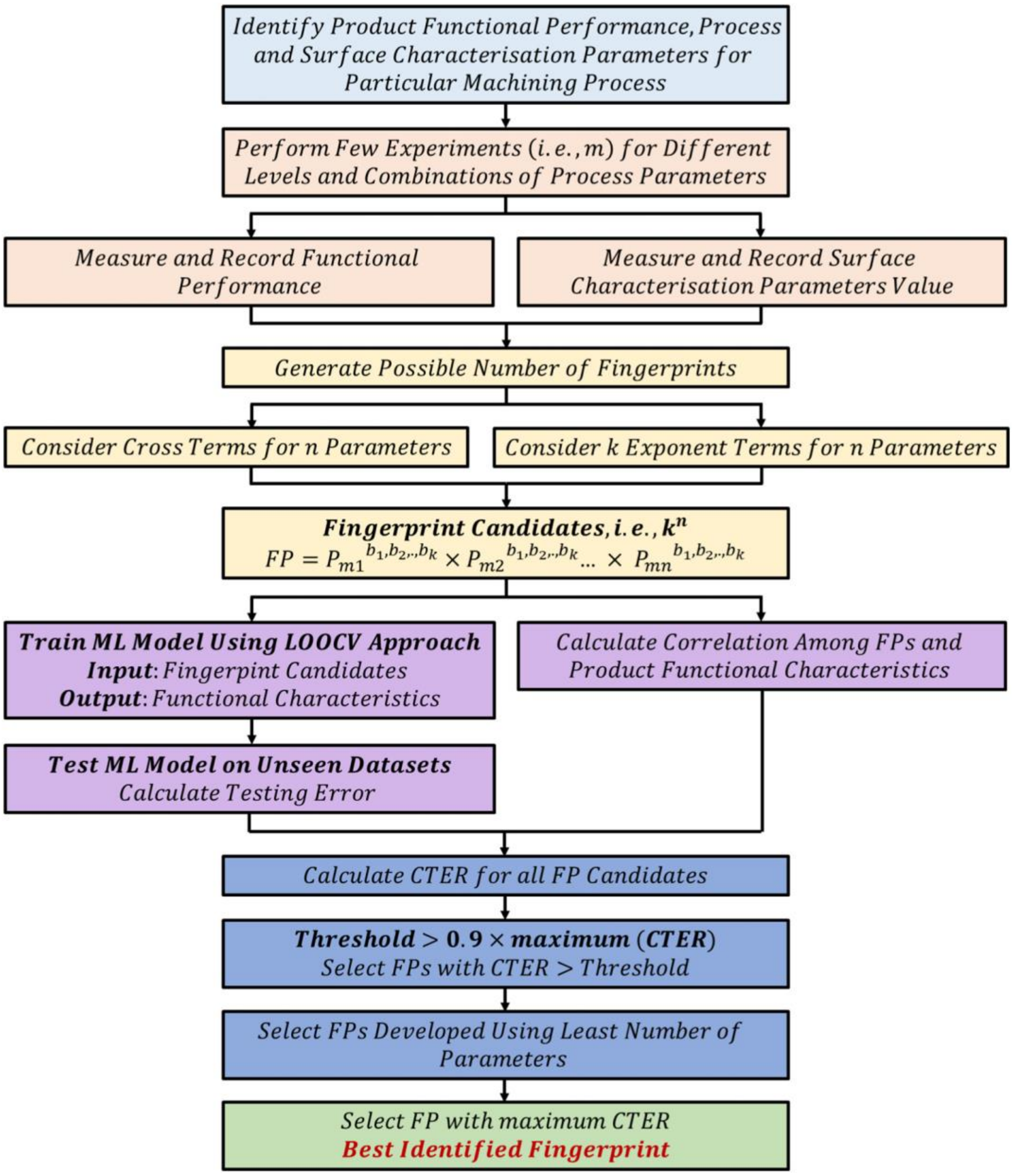

Figure 5. Machine Learning (ML) based manufacturing process [32]

4. Digital twin taxonomy and its importance in smart manufacturing

4.1. Digital twin prototype (DTP)

In particular, performing all these processes in a digital environment is extremely important in terms of R&D costs. In this way, business processes are accelerated and healthier simulation results are obtained. However, for this process, the prototype of the product, the sensors and the data it produces, and the digital twin (virtual copy) of the product are required. Computer Aided Design (CAD) software is used while preparing the virtual copy [34]. While performing the task of the prototype, analog data is taken with the help of sensors, digitized and applied on the virtual model. In this way, simulations in accordance with real operating conditions can be made and more reliable simulations of products developed especially for critical missions are made [35].

4.2. Digital twin instance (DTI)

A DTI (formed from the DTP) is a physical asset's doppelganger. Throughout the duration of a physical asset, the DTI remains connected to it. Typically, the DTI comprises data pertaining to in-use conditions as acquired by sensors, previous state, expected state, asset and warranty information, service records, and so on. While a DTI begins with the baseline information from its prototype, the DTI is enhanced by operational data over the course of its existence. Throughout its life cycle, this sort of DT is linked to its physical counterpart. DTI was formed during the production process. Once a physical system is established, data from the actual world is transported to the virtual world and vice versa in order to monitor and forecast system behavior. These data may be used to determine if the system is displaying the expected desired behavior or not, as well as whether the projected unwanted scenarios have been successfully removed. Because the connection between the two systems is bidirectional, any changes made in one will be replicated in the other [19]. The authors refer to a collection of DTIs as Digital Twin Aggregate (DTA).

4.3. Digital twin aggregate (DTA)

A DTA is a collection of numerous DTIs. DTIs can be colocated inside a single entity (for example, 100 motors in a single manufacturing) or across businesses. It is commonly understood that collective behavior does not equal the sum of individual conduct. Similarly, in the future, DTAs may offer previously undiscovered and surprising insights [36].

4.4. Digital twin environments (DTE)

The Digital Twin Environment (DTE) is a virtual depiction of the real surroundings in which the item lives. The DTE is the application space for DT simulation, modeling, and assessment for a number of reasons [37].

5. Conclusions

So far, it has not been determined whether or not there is a position that is consistent regarding the methods and technologies that may be utilized to execute the concepts of digital twins in production scenarios that take place in the real world. Following from what was covered previously, it appears that there are still some issues that need to be addressed. Despite the fact that many recently bought machines and plants have sensors and communication capabilities, this prevents organizations from planning investments on the adoption and integration of digital twin-based solutions. According to some research, this is due to the fact that virtually all businesses are undertaking digital transformation right now. Given the immaturity of some key elements of the digital twin, this target appears ambitious at best. On the other hand, the digital twin is currently showing up in the design, management, and optimization of manufacturing facilities and is one of the most prominent innovation trends in this area. The scientific community and industry actors are making significant efforts to develop standards, designs, methodologies, and deployable systems. This is evidence of the topic's acknowledged relevance and optimism that existing problems may be surmounted in a few years.

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