Digital Twin-Driven Design: A Framework to Enhance System Interoperability in the Era of Industry 4.0

Safaa Lebjioui, Mamadou Kaba Traoré, and Yves Ducq

Abstract Product development and manufacturing is entering a digital era, thanks to the progress made in data science and virtual technologies. The digital twin (DT) is one of the key concepts associated with this transition to Industry 4.0. Yet, in the literature, the term is differently used in various communities. In addition, the DT implementation in the product development process (PDP) lacks a conceptual ground, which hinders the proper use and wider application of this technology in engineering design and product life cycle management. This paper proposes an interoperability framework for digital twin-driven product design, based on data integration at different stages of the respective life cycles of the product and its digital twin. Such a framework can greatly help companies optimize their PDP.

Keywords Digital twin · Product life cycle · Product development process · Interoperability · Industry 4.0

1 Introduction

In recent years, the product development process (PDP) is becoming more digitalized than ever before. Although data has always been a relevant issue examined by different bodies of knowledge, it is now becoming an important asset in the industrial transformation. Data is gathered from various sources at different stages in a product life cycle.

Taking benefit of the progress made in data science and virtual technologies, the digital twin (DT) approach emerged as a data-based value chain, which is gradually becoming a key research trend in smart engineering. Yet, in the literature, the term

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is used differently from one discipline to another. Moreover, the implementation of DT in the PDP lacks of a conceptual ground, which hinders the proper use and wider application of this technology in engineering design and product life cycle management. Driven by this need, this paper first reviews the concept of DT and its evolution. Then a reference model for digital twin-driven design is presented. On this basis, a framework to design a physical product and its DT by integrating different data from their respective life cycles is proposed. This can guide companies in how to deploy a DT and use the data it provides to support their PDP at different stages. A conclusion and future work are given at the end.

2 The Concept of Digital Twin

In this paper, we consider a DT as a digital model of a product, a system or a process, which includes all the data that can support different phases of the engineering activities. In this section, the several aspects of DT are briefly highlighted, and recent definitions are discussed.

2.1 Concept Definition

The concept of DT was first introduced by NASA in their integrated technology roadmap in 2003 [1]. The DT concept has initially been defined as a simulation model, which is paired with the system of interest in a way to continuously reflect changes happening in that system [1, 2], while in [3–5] it is defined as the set of digital information gathered, aggregated, and analyzed throughout the product life cycle (thus, it exists prior to the product design and after the product end of life). The pairing between the digital twin and the system of interest is based on data collected from the system, including historical data and sensor data.

Beside the modeling purposes, the digital twin concept has also been applied for other purposes, such as verification [5, 6], prediction [1], and analytic activities [7]. From the modeling and simulation perspective, it appears as a disruptive approach [8].

2.2 Concept Application

The concept of DT provides an effective way to learn more about smart manufacturing. Many studies have contributed to promote DT in industrial practice. The current applications of DT in industry are briefly summarized in this section.

Negri et al. [2] defined a DT as a virtual representation of a production system, both being synchronized to each other thanks to data sensed from smart devices.

The DT value chain includes mathematical models, which are used in Industry 4.0 engineering systems for forecasting and real-time optimization of the manufacturing processes.

Schleich et al. [9] explained that product life cycle management (PLM) developers focus on tightly coupling the physical product with its digital model in order to increase the industrial resilience and competiveness. For example, SIEMENS is deploying several Industry 4.0 concepts (including DT) in order to improve productivity and quality in manufacturing, while General Electric concentrates on DT-based predictions and performance evaluation of their products over a life span. TESLA's target is to develop a DT for every produced car, so that a concurrent data transmission between the car operating in the real-world and the plant can be ensured.

As a result of various existing DT definitions and industrial applications, multiple partial understandings of this concept can be found in the literature [8, 10, 11]. We see in data integration a generic way to gain a more general understanding. The next section is devoted to the levels of data integration.

3 DT-Driven Design Process

Empowered by a combination of different Internet of Things (IoT) technologies and interoperability, a DT can mirror the physical twin. It can also predict and address the potential issues. To do so, a range of sensors are imbedded with the physical model. These sensors transfer real-time data about the product and its environment. The data collected is then analyzed. The use of this feed of real-world data by the DT can enhance the data-driven design. Moreover, it can help manufacturers understand how products operate in the field and therefore enable companies to take more informed, market-driven decisions about future generation of products.

Accordingly, a DT can be considered as an enabler for information refinement and integration. By refining a large amount of data, the DT allows gaining useful insights that can guide design activities toward new design options. By integrating several types of data from various sources, the DT allows identifying hidden patterns and facilitating the cross-checking of data and information [11].

Figure 1 shows the DT-driven design process, with a standard data life cycle including data collection, data mining, data integration, data storage, data analysis, and data transmission. Using this life cycle, raw data and real-world data are transformed to valuable information that can be directly investigated by engineers to support their design options. The phases are described below:

Data collection: This is the primary stage. In DT-driven design, the real-time operating data is collected by sensors and integrated by data acquisition tools.

Data integration: Data integration consists in combining data which is located in different sources and providing users with an overall view.

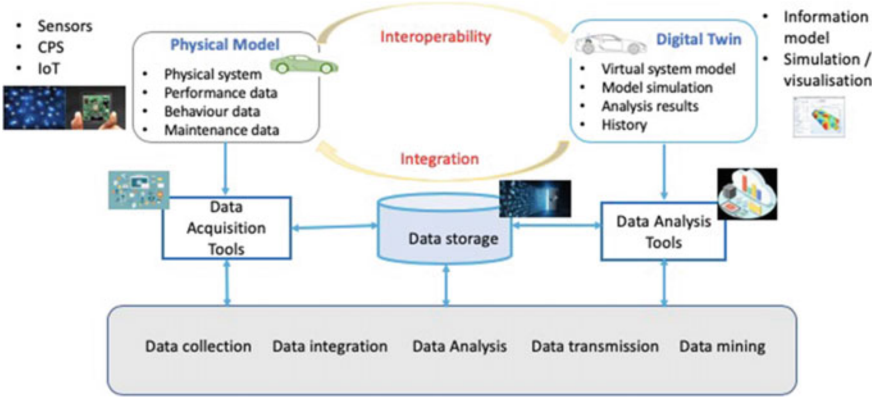

Fig. 1 DT-driven design process (D^3P): from data-driven to data-informed design

Data analysis: Data has always been at the center of decision making. Thus, this phase involves applying advanced data analytics tools to drive insights and find a correlation between the different data collected in order to turn it into information.

Data mining: In DT-driven design, the purpose is to obtain information from the collected data set and transforming it into useful insight. This phase involves different steps such as data preprocessing, data management, physical and digital model inference, complexity consideration, visualization, and online updating [12]. Therefore, the DT-driven design can shift from being a data-driven design to a data-informed design.

Data transmission: Data transmission refers to the process of transferring data between the physical product and its DT and vice versa. The interoperability of these two systems allows them to communicate between each other. The DT-informed design tries to assess the behavior that is behind the data; therefore, the real-time data sent by the physical product is a key input among other assets to build a deeper understanding of what value companies are providing to users.

The DT-driven design uses real-time data and becomes a data-informed design. Therefore, this can allow companies to make decisions which are grounded in reality and based on actual facts which can have a long-term downstream impact on the overall product development process.

4 Interoperability Framework for DT-Driven Design Process

In this paper, we consider a DT as a digital model of a physical asset. The digital model turns into a twin when it is connected to its physical component, system, or product. As shown in Fig. 2, there are three possible scenarios to develop a DT. The

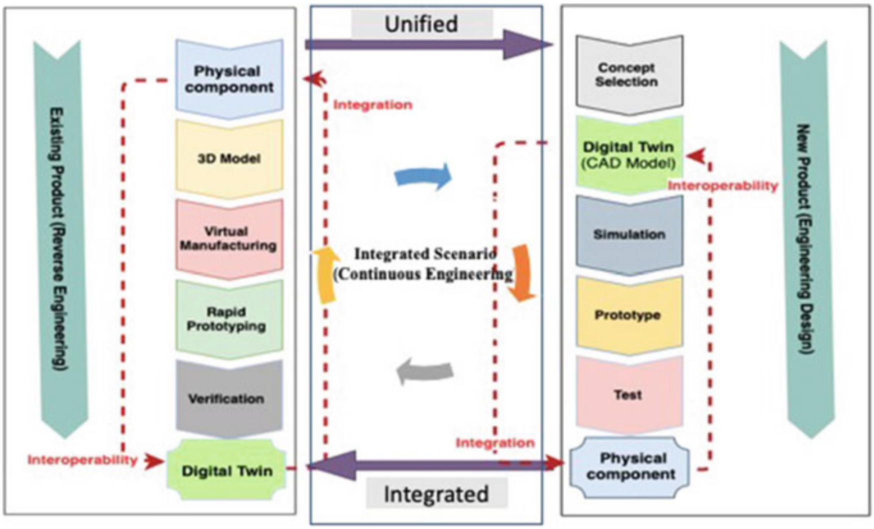

Fig. 2 Interoperability framework for D^3P

different steps are going to be described in this section. However, it should be noticed that, in an industrial context, manufactures may not use the same steps to develop their DT. It is also possible to carry out these steps concurrently.

4.1 First Scenario: A DT of a New Product (DTNP)

- Process the available data to select a concept: The product development in the era of Industry 4.0 relies on companies' ability to handle data. Therefore, the first step is to process the empirical data. As discussed in the previous section (see Fig. 1), data can be collected from different sources. The collected data needs to be analyzed in order to be transformed into significant input that can be used by designers in order to select the right design concept for their product.
- Develop a DT model: At this stage, the commonly used technology in product design is computer-aided design (CAD). Designers develop these models using an existing database which provides different libraries that handle a wide range of production resource data, including bills of materials, layouts, interfaces, and other elements. To enable a holistic product/production view, companies must expand the functionalities of the commercially available software tools, with additional functionalities, i.e., pre-defined agents that contain additional technological information. Accordingly, the DT can easily interoperate with its physical twin at later stages.
- Simulate model/product behavior: The simulation is used to duplicate the key features and the expected behaviors of the physical product in the virtual world.

There are many types of simulation, like 3D motion simulation or discrete event that can be applied to the virtual model to ensure that the selected design will be able to meet the initial requirements.

- Build a prototype and test: Engineers usually develop prototypes, before a product is released for production. The prototypes help designers to learn more about how the product can be used and how it will operate in a real environment. Once a prototype is developed, it can be equipped with sensors and actuators to test and validate different features of the product before the design is implemented. On the other hand, new technologies can also be used, such as augmented reality. This can enable engineers to interact with the virtual product and test its functions in the simulated environment.
- Develop a physical product and connect it to its DT: When the development of a product is finished and connected to its DT, both become interoperable systems that have the ability to not only share information but to interpret incoming data. As the physical product is equipped with sensors that send back real-time operational data from the physical world, its DT can process this data and make adjustments to the physical product using the appropriate sensor technology and IoT.

Developing a product and its DT can give companies a behavioral outlook at any given point of the life cycle and enable continuous process adjustments.

4.2 Second Scenario: A DT of an Existing Product (DTEP)

Given an existing physical product:

- Do a reverse engineering: The principle is to reverse the engineering process of an existing component, system, or product, in order to develop a digital version. This process has two distinctive phases: The first one lies in collecting and digitalizing data, and the second one consists of creating a 3D model of the object based on the data collected. These data are fed to the step where the DT is created to enhance the interoperability and build a more functional DT.
- Simulation using virtual manufacturing: The concept of virtual manufacturing (VM) is widely used in literature, with a few definitions. VM makes use of virtual reality technologies to integrate diverse manufacturing-related technologies [13]. It provides a representation of the properties and behavior of a given product, using different analysis and simulation methods such as finite element analysis (FEA) and final volume method (FVM). Using this simulation makes possible for companies to optimize key factors which directly affect the product performance such as the final form and reliability in operation.
- Do a rapid prototyping before verification: Rapid prototyping involves different technologies, such as additive manufacturing or selective laser melting, which allow analyzing product functionality based on the physical model of a product.

- Connect the DT to its physical representation: While carrying out the reverse engineering, models are created and data is generated. The connection between the developed DT and its physical representation is enabled by various technologies.

The DT in this scenario can manage and control the data throughout the product life cycle. Accordingly, DT can carry out data collection, data transmission, and data storage from the real world.

4.3 Third Scenario: Integrated Scenario (Continuous Engineering)

The above scenarios are "one dimensional" and can be applicable if a product or a system is designed from scratch. However, nowadays, one of the main challenges is that product design is carried out incrementally and continuous changes are performed. Therefore, the design of the DT should not only focus on the "twining" between the physical and the virtual world but rather integrate the design activity of both.

The idea behind an integrated scenario is to expand and integrate the above scenarios to bring the fundamentals of interoperability and continuous engineering to the concept of DT.

Continuous engineering enabled by the integration of the physical and virtual world will allow engineers to handle the effects of the changes within the ecosystem where the products evolve. Unlike in the traditional V-model for systems engineering where the design is carried out in a sequential number of phases, in continuous engineering, activities are carried out iteratively across the PDP.

On the other hand, interoperability is a key feature in DT-driven design. An important notion in interoperability is the interaction between different systems. In this interaction, data can be federated, unified, or integrated. In the proposed framework, we assume that during the design of the product and its DT, whether this is done concurrently or following the traditional development steps, a number of agents interact by communicating information. This communication implies that one system exchanges and/or uses data of another one. Therefore, the interoperability issues that can arise from the data exchanged between a product and its twin is another challenge that needs to be considered in future work.

At its core, the concept of DT is all about how to increase the efficiency of product development through collaboration and system interoperability, using the operational data and real-time analytics to transform the gathered data into performance knowledge. This knowledge will help engineers to improve their engineering process and performance optimization.

5 Conclusion and Future Work

Modern PDP is not managed anymore by making assumptions about the product performance. Instead, performance-based analysis is used to provide real-world data on product performance from the field. Connecting the physical product to its DT thanks to the available IoT technologies will enable product to send usage data back to the platform and enhance their interoperability. The information gained from the real-world data provides a better understanding of field operations as well as useful insights for new business opportunities.

In this paper, we have proposed an interoperability framework for DT-driven product design. The framework can be seen as a first attempt to introduce a conceptual framework in that perspective, which need to be improved by future work. Thus, our next efforts will concentrate on the following aspects:

- Application of the proposed framework across a PDP to a real-world industrial case. This will help in identifying how the DT concept can concretely shape the PDP.
- DT life cycle management: As for a physical product, where PLM deals with all the data relative to a product across its life cycle, there is a need to consider the digital models and close the gap between product's physical and virtual spaces.

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