Digital Twin Framework for Reconfigurable Manufacturing Systems: Challenges and Requirements

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Abstract. Due to the rapid development of new generation information technologies (such as IoT, Big Data analytics, Cyber-Physical Systems, cloud computing and artificial intelligence), Digital twins have become intensively used in smart manufacturing. Despite the fact that their use in industry has attracted the attention of many practitioners and researchers, there is still a need for an integrated and detailed Digital Twin framework for Reconfigurable Manufacturing Systems. To investigate related works, this manuscript reviews the existing Reconfigurable Manufacturing Systems Digital Twin frameworks. It also presents a classification of several studies based on the Digital Twin framework features and properties, the used decision-making tools and techniques as well as on the manufacturing system characteristics. The paper ends with a discussion and future challenges to put forward a structured and an integrated Reconfigurable Manufacturing Systems - Digital Twin framework.

Keywords: Digital Twin (DT), Modular framework, Reconfigurable Manufacturing System (RMS), State of the art, Industry 4.0.

1 Introduction

Recent manufacturing companies are facing, nowadays, an increasing individualization demand in products and high-frequency market changes driven by global competition. To remain competitive, these enterprises must be flexible enough to allow multiple variations of production sequences by adapting changes in the manufacturing system for the production and provision of new customized/individualized products. In this new market environment, traditional manufacturing systems fail to realize customized production with large-scale manufacturing efficiency. Thus, new solutions were proposed in order to overcome the afore-mentioned challenges. For instance, we can mention Reconfigurable Manufacturing System (RMS) introduced by Koren et al. [10]. In RMS, hardware and software components can be added, removed, modified or interchanged to quickly improve production capacity and functionality of manufacturing systems within a part family in response to the sudden changes in demand. This enhancement is possible thanks to the use of RMS comprising reconfigurable machines, reconfigurable controllers as well as methodologies for their systematic design and rapid ramp-up. Such systems combine the advantages of Dedicated Manufacturing Lines (DML) and Flexible Manufacturing Systems (FMS) to cope with fluctuant market demands. On the other hand, the concept of Digital Twin (DT) together with advanced technologies continues to evolve as it expands to achieve intelligent manufacturing. In a reconfigurable environment, characterized by unpredictable changes in demand and flexibility, the DT can be adequately applied to solve problems facing RMS. In fact, DTs are characterized by the seamless integration between the cyber and physical spaces [15], which can help to achieve a flexible decision-making process providing appropriate RMS configuration [2]. Despite the increasing popularity of the DT research and the various frameworks introduced to integrate it in manufacturing environments, few research works considered its incorporation into RMS [20]. Furthermore, the application of a DT framework in manufacturing requires the consideration of different narratives and components, leading to a lack of clearness of the proposed application methods and application frameworks [20]. Therefore, in this paper, we review the existing works on DT, by highlighting the importance of smart manufacturing in identifying the main common narrative about DT frameworks and develop a new DT modular framework for RMS in further study. The remainder of this paper is organized as follows: Section 2 presents the history and definitions of the digital twin. Section 3 describes the used search protocol, while section 4 discusses the recently-developed approaches and frameworks for DT related to manufacturing. Section 5 classifies these approaches. Then the obtained findings are discussed in Section 6. Finally, Section 7 concludes the paper and presents some research issues for future works.

2 Background and definitions

The DT concept can be related to NASA's Apollo project (performed in the late 1960s) in which the vehicle on the ground mirrored the vehicle in space. DT was used for training purposes as well as to simulate solutions for critical situations [14]. Subsequently and in early 2000's, Michael Grieves [7] introduced the concept of DT for product lifecycle management composed of three main parts: physical product in real space, virtual product in virtual space and the two-way connections of data and information, which ties the two spaces together. Later on, Glaessgen and Stargel [5] defined a DT as "an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin." In 2014, Grieves and Vickers [6] defined DT as: 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 picked up from its DT. Hence, the DT concept was expanded from product to the wide manufacturing system [1,16,21]. To summarize, the concept of DT is a high-fidelity virtual representation of a physical system with a seamless and real-time data flow between the two spaces (physical space and virtual space). It reflects a new data-driven vision that combines real time data analytics, optimization and simulation.

3 Methodology

A literature review was conducted to answer our research question:
RQ: What are the future challenges and the main requirements to put forward a structured and integrated RMS-DT modular framework?
To source the related relevant papers, we used the Scopus database with the following keywords: “Digital Twin, framework”, “Digital Twin” and “Reconfigurable Manufacturing System”. We only focused on these keywords to narrow the results to papers that proposed frameworks related to manufacturing (RMS) and to eliminate those related to products. In fact, we did not put any restriction on the type of the manuscript or the year of its publication, but we only considered English papers. We collected 50 papers that were carefully read and analyzed. Besides, we cited some works that have proposed a DT framework for smart manufacturing systems or for RMS. Due to space limitation, only 12 papers were kept for the classification described in Section 5. The selection was based on the complexity of the developed framework and the impact factor of the selected publications.

4 Existing Approaches

The literature presented a number of different narratives about DT [15]. These narratives diverge in terms of features and components that they cover from 3D to 8D frameworks to specified simulation [6, 12, 13, 22]. However, they are often included in each other. In this context, Abid khan et al. [8] built a common narrative about DT by proposing a six-dimensional DT-framework. The DT framework, named spiral DT, presented two new dimensions: spirally and dynamicity. The former refers to a regular enhancement of the physical product and/or the manufacturing system, whereas the latter ensures a consistent and a continuous synchronization of the virtual product with the corresponding physical product. Furthermore, the authors presented a secure and reliable data management blockchain-based solution called twin chain.

One of the key challenges for DTs is data. To provide an efficient and complete data support for the application of workshop DTs, Kong et al. [9] developed a data construction method relying on the functional requirements of manufacturing system analyzed according to the characteristics of the manufacturing data. Authors argued that most existing techniques neglected data preparation. Thus, they included three modules into their framework, namely data representation module, data organization module and data management module.

Moreover, DTs have large applications areas not only to the single robot, product or asset, but also to the full-length manufacturing cell. In this context, Zhang et al. [18] considered an autonomous manufacturing cell as implementation scenario. They proposed a data-driven and knowledge-driven framework for DT Manufacturing Cell (DTMC). This latter, can support autonomous manufacturing by applying an intelligent perceiving, simulating, understanding, predicting, optimizing and controlling strategy thanks to three key enabling technologies used to support this strategy namely: DT model, dynamic knowledge bases and knowledge-based intelligent skills).

Other studies focused on digital assembly as key technology in the design and manufacturing of complex products. For instance, Yi et al. [17] suggested a DT reference model for intelligent planning of assembly process and provided an application framework for DT based assembly. The goal of their work was to improve the assembly quality and efficiency of complex products. The framework comprises three layers: (i) physical space layer for total-elements components of product assembly station, (ii) interaction layer for communication connection and data processing, and (iii) virtual space layer for DT-based assembly application service platform. Other researchers, like Strak et al. [13], used a test environment of smart manufacturing cells to define an 8-dimension DT model. The authors' goal was to investigate the methodological, technological, operative, and business aspects of developing and operating Digital Twins for the ramp-up activities of the smart factory cell. In the same perspective, Francis et al. [4] studied the needs and opportunities to enable data-driven digital twins in the domain of smart manufacturing. They developed a generic data-driven framework incorporating machine learning and process mining techniques as well as continuous model improvement and validation of automated construction of digital twins for smart factories. This work is based on the idea that building digital twins in real-time, based on data collected from IoT devices in smart factories, will allow achieving some purposes such as up-to-date robust models, supporting flexible and reconfigurable factory layouts, integrated ongoing model validation, etc.

On the other hand, some important attributes for nowadays manufacturing systems are flexibility, responsiveness, cost efficiency, reliability, scalability and ability to be easily reconfigurable in order to counter the increasingly mass customization or mass individualization paradigm. In this context, Zhang et al. [19] developed a DT-enabled reconfigurable modelling approach to permit the automatic reconfiguration of the DT-based manufacturing system. Authors proposed a five-dimensional model-driven reconfigurable DT system framework. Besides, by mapping the physical and virtual entities, the latter can derive some of the capabilities and dependencies of the DT. Furthermore, researchers used expandable model structure and optimization algorithms to suggest a reconfigurable strategy. The aim of their study was to fulfill different granularities and targets requirements in terms of reconfigurability. In the same context, Haddou-Benderbal et al. [2] provided a conceptual RMS-DT modular framework as a way to integrate DT into RMS. In fact, the DT framework aims at providing a holistic system visibility and a flexible decision-making process to achieve the needed RMS responsiveness and to improve its performances during its operating phase by continuously collecting real time data from the RMS components. Subsequently, these data can be stored, processed and analyzed by using information analytics as well as simulation and optimization module blocs. Based on the afore-mentioned ideas, DT can quickly provide critical decisions, such as the appropriate RMS configuration, to efficiently cope with sudden changes occurring in market driven by global competition.

In terms of reconfiguration, Leng et al. [11] suggested a novel digital twin-driven approach for rapid reconfiguration of automated manufacturing systems and fast optimizing process. The DT comprises two parts: the semi-physical simulation that maps data of the system and provides input data to the second part, which is optimization. The results of the optimization part are fed back to the semi-physical simulation for verification. The proposed approach could realize rapid alteration of manufacturing system capacity and fast integration of multiple processes into the existing systems, allowing the manufacturers to launch new product orders rapidly. From the perspective of 5-dimension DT model, Cheng et al. [3] introduced a DT enhanced Industrial Internet (DT-II) reference framework towards smart manufacturing. The interplay and relationship between DT and Industrial Internet were first discussed. The sensing/transmission network capability, which is one of the main characteristics of Industrial Internet, urges the implementation of DT, to provide DT with a means of data acquisition and transmission. Conversely, with the capability of high-fidelity virtual modelling and simulation computing/analysis, DT can greatly enhance the simulation computing and analysis of Industrial Internet. The related research and application of DT for product life cycle management were pointed out in Zheng, Yang, & Cheng [20] papers. Zheng et al. [20] presented both a broad sense and a narrow sense definition of the DT concept and characteristics. Based on the mentioned definitions, authors introduced a DT framework for product lifecycle management. This framework includes an information-processing layer with three main function modules, namely data storage, data processing and data mapping.

As we can notice from the literature review and to the best of our knowledge, there is a lack of research works around holistic and unified DT Frameworks that integrate the characteristics of RMS as well as software reconfiguration. In this context, the goal of this paper is to attempt and find the common components that should be used in DT framework, in a later research stage, to establish our future RMS-DT Framework.

5 Classification Analysis

In this section, we classify the existing approaches, as mentioned hereafter in Table 1, based on the **DT-framework features and properties**, the used **decision-making** tools and techniques as well as the **manufacturing system** characteristics. As the literature contains multiple understanding, interpretations and applications of DTs frameworks, we present, in this study, a classification analysis to select the researchers' common points of view about the DT-framework. The main three parts of the DT are the physical part, the digital part and data space. Hence, we classify the existing approaches mentioned earlier relying on the properties of these three parts **as follows:**

a) Features:

- Dimensions (P1): represent the numbers of layers that constitute the DT-framework.
- Human Machine Interface (HMI) (P2): concerns the capability of DT to be set and its ability to transfer data after being processed.
- Virtual Reality/Augmented Reality/Mixed Reality (VR/AR/MR) (P3): to describe the manufacturing system in the virtual and collaborative environment.

b) Physical part and Digital part:

- Physical part: the usage of process model (P4): it shows whether a process model of the physical part was used to implement the simulation model of the virtual part or not.
- Digital part: Model character (P5): the DT model is divided into two categories: static model (S) or dynamic model (D). Model scope (P6) represents either a single entity or a whole system.

- Physical part and Digital part (P7): describe the relationship between the digital part and the physical part that may be directly bound (B) or independent (I).

c) Data space:

- Data input (P8): differentiates between raw data (R) (sensors, RFID (Radio Frequency Identification) or other collection devices) and processed data(P) (by analytic software)
- Processing and transferring data (P9): transfer data from one point (i.e., physical space) to another one (i.e., virtual space).
- Data repository (P10): a data set is isolated to be mined for data reporting and analysis.
- Data driven decision-making (P11): consists in taking organizational decisions based on actual data.
- Data exchange (P12): from information management system (ERP, MES, …)
- Big Data treatment (P13): using cloud, fogs, blockchain (Twinchain), etc.

Soon after, we determined the used:

a) Decision-making tools and techniques: Simulation (P14), Optimization (P15) and Artificial Intelligence (AI) - Machine Learning (ML) (P16).

References	Features			Physical Part / Digital Part				Data Space						Decision making			Manufacturing System			
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
[Li et al, 2020]	5			*	D	S	B	R	*	*	*		*	*				*		
[Khan et al,2020]	6			*	D	E	I	R	*	*			*	*						
[Zhang et al,2020]	5	*		*	D	S	I	R/P	*	*		*	*	*						
[Yi et al,2020]	5	*	*	*	D	S	I	R/P	*	*	*	*	*	*		*				
[Kong et al,2020]	3			*	D	S	B	R	*	*	*		*	*						
[Stark et al, 2019]	8	*	*	*	D	S	I	R/P	*	*	*		*	*		*				
[Jiewu et al, 2020]				*	D	S	I	R	*	*			*	*			*		*	
[Zhang et al, 2019]	4	*	*	*	D	S	I	R/P	*	*	*	*	*	*		*	*			
[Francis et al,2021]	3	*		*	D	S	I	R	*	*	*		*	*	*		*			
[Benderbal et al,2020]	3			*	D	S	I	R/P	*	*	*		*	*	*		*			
[Cheng et al, 2020]	5			*	D	S	I	R/P	*	*	*	*	*	*			*			
[Zheng et al, 2019]	3			*	D	S	I	R/P	*	*	*		*	*	*					

Table 1. Classification analysis

At last, we focused on the:

b) Manufacturing System characteristics: cited the applied approaches: Reconfigurability/changeability (P17), Sustainability (P18), Modularity (P19) and Scalability (P20).

6 Discussion

Table 1 demonstrates the differences between the DT frameworks presented in literature and illustrate the main features, proprieties and technologies required to propose modular RMS-DT framework. The goal of reference frameworks, is to help at different levels, identifying the development requirements and constraints. This identification is possible by matching the user's requirements with the application of enabling technologies evaluation methodologies. We can conclude, from the literature that:

- At least, **5-dimension frameworks** should be adopted to cover all the required properties and integrate all the advancing techniques and enabling technologies that can facilitate the functioning of the manufacturing system.
- The majority of the DT frameworks contain a **bi-directional data link** between the digital part and the physical one. Furthermore, all papers described a DT **employed to process and transfer data, while** only few of publications dealt with the role of DT in **storing** them. Therefore, a **data repository** can be incorporated, allowing the manufacturing companies to create their own knowledge base. It is clear that the basis of DT integration is Data and information incorporation, which represents an important challenge for manufacturers [23]. It is used/adapted by DT users according to their requirements even if was initially it developed for such requirement. Consequently, to face this challenge, DTs must be designed from the outset for such eventuality. The RMS-DT framework must deal with several aspects of the different production lines that usually represent complex and heterogeneous areas. Hence, a modular aspect should be considered for such additional purposes. Furthermore, the conceptual elements of most DT should be physically bound to their counterparts to ensure a bidirectional communication between all the DT parts.
- **Information management system**, such as Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP), can help a corporation become more self-aware by linking business areas, a single source of information, and accurate, real-time data reporting.
- **Human-machine interface** should be used to ensure the best interaction between the physical part and virtual part of the D T. This interface is usually used is to attain an intelligent and data-driven decision-making within the smart manufacturing environment.
- **Sustainability** and sustainable manufacturing are becoming very crucial issues in new manufacturing environment. However, few works considered sustainable development and performance evaluation as parts of their established DT frameworks. Hence, Digital Twin-driven sustainable manufacturing should be critically analyzed.

- The ultimate goal of RMS and changeable manufacturing system is to ensure responsiveness with a customized flexibility. Hence, there is a need to consider the **coupling** of the manufacturing systems **flexibility** with **scalability** and **modularity**. This coupling must be also taken into account in RMS-DT frameworks.
- **The reconfiguration of the software part of the RMS** in "plug & play" manner is still relatively an emerging idea. However, it represents the path to be followed in order to produce high-quality product and to meet the market requirements.

Each paper focused on developing a different DT. Thus, the research challenge is to form a structured and an integrated RMS-DT framework that assesses the sustainability performance of the whole manufacturing system and ensures the reconfiguration of both the hardware part and software part to provide a flexible decision-making process.

7 Conclusion and further works

With the increasing individualization demands in product and mass customization, Reconfigurable Manufacturing System has become more and more important. RMS with DT has the functions of intelligent sensing, simulation, which makes the production more efficient, and more intelligent. In this paper, a review for the existing DT frameworks defined in literature was presented. After that, a classification analysis was performed to extract the most common narrative between them. For future research perspectives, a DT modular framework for RMS will be introduced. The concept of sustainability of our RMS-DT framework was integrated to account for the crucial and urgent need for more sustainable manufacturing. Additionally, the integration of AI in RMS-DT framework can improve Digital Twins performance by applying machine learning (ML) for prescriptive analytics in production, which will facilitates flexible and robust decision making in the design stage as well as in the real time operation stages. Finally, an interesting direction of work is to study how other RMS characteristics can be integrated using this RMS-DT framework describe this model general use to meet the needs of the Industry 4.0.

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