Digital Twin for production systems: a literature perspective

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Abstract. Digital Twin is one of the key enabling technologies of the fourth industrial evolution. Alongside with the cyber-physical systems it is expected to widen the perspectives of smart manufacturing development and for production systems in particular. For these systems on-going state monitoring, simulation and prediction of manufacturing operations are crucial to improve the production efficiency and flexibility. Moreover, through the principles of system engineering, Digital Twin establishes interconnection and interoperability between cyber and physical environments allowing a human to act confidently based on accurately analysed data and verified simulation models. In order to design and implement Digital Twin the architecture and main components must be identified.

Keywords: Digital Twin, architecture, cyber-physical systems, smart manufacturing, production systems

1 Introduction

Current trends in industry require quality, cost and maintenance control for products and manufacturing facilities. In the current "Industry 4.0" approach, to use accurately the increasing amount of data from each lifecycle stage it is important to implement and maintain digital thread of the same data from design and manufacturing to sales and services [1]. It is where the concept of Digital Twin (DT) enters the industrial stage [2, 3], especially for production systems. It is used to cover and to test various scenarios on models of physical objects in virtual environments to gain in their quality and related parameters. These models based on accurate real-time data can help to predict behaviour of the physical twin. Moreover, the efficiency of DT can be tracked during the whole system lifecycle.

Nevertheless, the concept of DT for production systems still lacks of maturity, as we can observe in one hand the the variety of use cases and related DT architectures and techniques for implementation and in the other hand the very few examples of implantation success story in industry. **The purpose of this paper is so to review current state-of-art on tools and developments of DT for production systems, discuss existing architectures of DT in this area and propose potential architecture components to develop the DT regarding on its application.**

To achieve this objective, the paper starts with recent developments on the concept from the overview of existing DT applications (Section 2). This is followed by the research development on the DT architectures within smart manufacturing in Section 3,

highlighting how DT will incorporate existing information systems. Section 4 highlights and discusses the emerging scientific issues related to DT.

2 DT paradigm

2.1 DT concept definition and evolution

The evolution of DT definition provided by [2] has gone from asset simulation and virtual replica to an idea of multi-technological environment or platform converging physical object and virtual space [3]. Regardless of its application, DT concept differs from digital model or digital shadow by precision and integration level of the asset virtual representation [4]. Authors define digital model (DM), digital shadow (DS) and digital twin (DT) by the level of automatic data transfer and up-date between physical and virtual counterparts. In DM real part is a source of manual data assignation for its virtual twin. Also, in DM and DS virtual object linked with its physical counterpart by manual data flow, whereas in DT between real object and virtual object data-flow is automated bi-directionally forming the digital thread of different types of data. The static data or past data is not supposed to change after it is collected. Helping to identify assets, static data can include design and manufacturing files, operation and installation manuals, maintenance schedules, warranty information and certificates or any other related information from corporate database management systems. Dynamic or present data – is the constantly changing data from sensors monitoring state of production systems or products also known as industrial Internet of Things and providing assets performance feedback. Industrials also distinguish future data as a machine learning results and possible engineering inputs.

A DT is a high-fidelity representation of the operational dynamics of its physical counterpart, enabled by near real-time synchronization between the cyberspace and physical space [5]. Consequently, DT as a technology has its own accuracy that depends of the precision of data it is built on. For production systems DT is defined from the angle of its implementation purposes [6]. DT should include all the functionalities that the asset can perform in the real world on various tasks that later can be used for simulation and reconfiguration [7]. An up-to-date definition development is tracked in [3] and states that DT is a "set of adaptive models that emulate the behaviour of a physical system in a virtual system getting real time data to update itself along its life cycle. The digital twin replicates the physical system to predict failures and opportunities for changing, to prescribe real time actions for optimizing and/or mitigating unexpected events observing and evaluating the operating profile system". At the same time the [8] refers to the ISO/DIS 23247 series which establish the definition of DT from its reference architecture to integration framework for manufacturing including functional entities attributes and exchange protocols.

Since the beginning of DT introduction numerous attempts are being made to define and specify more accurately the meaning of the concept, yet there is no unique defini-

tion accepted by the scientific community. Clearly, that because DT can be implemented using various technologies and for various purposes, it is possible to determine it on applications. Thereby, [9] try to explain the DT by providing the usage-driven classification.

Another challenge lays in correlation between DT concept and cyber-physical systems (CPS) [10]. Authors show that the difference between these two concepts lays in their so-called nature: CPS are more akin to a scientific category because they represent a fundamental organization rather than implementation of technologies or applications. To compare with CPS, DT is more an engineering category as it implies various engineering applications such as IoT or sensors. Authors define structural similarity in their hierarchical models on a level of magnitude: unit level, system level, and system of systems (SoS) level. Unit-level of DT relates to a DT of the product, system level of DT is arranged of multiple unit-level DTs, SoS DT is an amalgamation of the various stages of a system life-cycle. Oppositely, [11] affirm that the core of CPS is an embedded system that process information of physical environment. With this in mind DT can contain CPS as a unit that interacts with physical twin connecting to its programmable logic controllers (PLC), sensors and actuators. Cyber-physical production system (CPPS) is an extension of CPS in manufacturing environment as mentioned in [12]. [13] understands DT from opposite point of view that DT is a part of CPPS defining a DT based cyber-physical system. From this angle CPPS seems to be a main component in smart manufacturing paradigm. [14] admit that these two concepts differ in core elements and application but are also related to each other. Clearly, both are polyvalent and there is a direct relationship between them, as well as a reversal of roles on the time axis. The two are engineering categories used by different communities of design and operation domains.

In a scientific paradigm regardless of the DT use-case, [3] propose to answer to the questions where (industrial domain), when (lifecycle stage), why (DT functions or roles) and how (architecture and components) DT will be implemented. Consequently, this methodology could be used for manufacturing domain in addition to existing automation principles, product lifecycle management perspective, model-based system engineering (MBSE) and other approaches.

2.2 DTs in smart manufacturing production systems

In [15] applications for smart manufacturing are selected by the DT precision level and from system engineering point of view. Authors define 3 types of DT applications:

- on equipment level: diagnosis, controlling, and optimizing the running mode of real equipment by interoperability between digital twin models;
- on manufacturing system level: planning and optimizing more accurately the operation of real production line by building and simulating digital twin of the production line; For example, [16] presents the method to optimize existing or planned production lines using a DT and CPS. In addition, [17] provides an example of DT for production line that covers also the designing stage;

- on system of system level: to achieve smart operations, simulation, control, and optimization of product manufacturing in the smart shop floor and smart factory, namely [8], [15], [18].

DT role is not limited by its definition to mirror its physical counterpart. [12] summarize three main functions of DT: prediction – execution of studies ahead of the system run, safety – monitoring and control of the system state in terms of a continuous prediction during the system run and diagnosis – analysis of unpredicted disturbances during the system run. Other purpose is to control it throughout lifecycle as it is mentioned in [4], [6], [19]–[27]. Additionally, some functions result from DT sub-components capabilities, technologies which are used to implement DT into a CPPS. For example, with the help of IIoT to provide real-time data transfer and data acquisition into a cloud-based depository and machine learning algorithms to analyze and detect anomalies, it is possible to implement DT to ensure predictive maintenance for production systems [28]. Earlier [29] defined a continuous production system evaluation and planning using automatic data acquisition. However, the biggest attention is offered to maintenance including evaluation methods and data management. With the augmenting data flows the challenges increase in highly volatile industrial environments. In this case DT serves as an instrument for better decision choice. For instance, [25] classifies various roles of DT for CPPS in the fields of aeronautics, space, robotics, manufacturing and informatics and that can be divided into three main groups by the types of decision to make:

1. On-going state and behaviour analysis "for improved maintenance activity and planning". For example, anomalies, physical deformation, cracks monitoring and product/system reliability modelling;
2. Long-term behaviour analysis and digital mirroring of activity for predictive maintenance, data management through the lifecycle and virtual commissioning;
3. Support for decision making through engineering and statistical analyses in all phases of product/system lifecycle, for example, optimization of system present and future behaviour.

Based on the previous examples it is possible to classify decisions which could be done with the help of DT depending also on company's size. While in small and medium sized enterprises (SME) the focus is on near real-time production control applications [29], big companies progress, for instance, in virtual commissioning and predictive maintenance for production systems [28], [30], [31]. As it is stated in [29], for many SME looking to increase their level of automation for production processes the main interest relate to data acquisition and "working space layouts" optimization.

[8] provide summary of DT for typical applications in manufacturing:

- On-line/off-line analytics digital twins;
- Real-time control digital twins that monitor and control physical twins in real-time;
- Equipment health check digital twins;
- Scheduling and routing digital twins;
- Virtual commissioning digital twins;

- Predictive maintenance digital twins;
- Product digital twins.

Similarly, to the definition, there is no unique DT for any application, however it is possible to form multiple DT systems integrating products, processes, production systems. By all these means DT helps a company to sustain in business by maintaining its competitive advantage and serve to interconnect value chain actors supporting win-win relationship in industrial operations during the manufacturing and after-sale services as concluded in [19].

3 DT architectures analysis

Considering the fact that DT is a defining technology for Industry 4.0, its deployment requires a certain level of intelligence of the components, product or production system. Model Based System Engineering (MBSE) defines smart component as an intelligent component with data transfer and acquisition features. Moreover, building a DT requires multi-criterial approach in order to cover all functionalities of physical object. Therefore, the first step in DT deployment is to identify the architecture and its relevant functionalities. To do this, certain criteria are proposed based on the existing use-cases in manufacturing from aforementioned sources (Table 1).

- Physical twin: The type of the physical object for which DT aimed to be created. Due to the fact that some of the selected papers refer to product engineering and manufacturing while the others to production system engineering and manufacturing or their combination, the types of physical twin defined hereafter are: product, process or production system or their combination.
- Approach/Architecture/Framework/Model: DT is often explained from different approaches e.g., model-based system engineering, product engineering or product lifecycle management perspective including specificities of use-cases. For this the DT is understood as a number of components interconnected and interrelated in specific order.
- Features/Functionalities: The relevant abilities or functions that DT possesses in order to ensure its roles fulfilment.
- Deployment strategy/methodology/operating flow/approach: A supposed order of DT deployment or any relevant experience how to realize DT on practice.
- Structure (approach integration/interoperability): Tools or features to ensure the connection between DT functionalities.
- DT Intelligence: A certain level of intelligence related to decision-making, the decision presence and placement in DT architecture or any related DT's characteristic connected to its level of independence from human decisions proclaimed by authors.

Table 1. DT generic criteria

№	Physical Twin	Approach/Architecture/Framework/Model	Features/Functionalities	Deployment strategy/methodology/operating flow/approach	Structure (approach integration/interoperability)	DT Intelligence
[32]	Production system	Modular DT framework/Data-oriented architecture/ industrial IoT platform architecture	Digital module (data part with data processing (including modelling)); connection (data transfer) and DT intelligent module (service module with digital dashboard architecture)	1.Diagnosis of the machine 2.Requirements for the dashboard 3.Defining a template for the dashboard 4.Assuring the existence of necessary resources 5.Implementation, evaluation and improvement	HMI: Modbus TCP/IP, Ethernet protocol	Real-time decision support
[33]	Product	Data-driven architecture, ontology-based data model	Data collection and control, digital modelling and visualisation, simulation”	1.System deployment on a physical object 2.Data capture 3.Model reconfiguration 4.Operating data-based simulation 5.Topology optimization	Arduinio MEGA, STEP, PTC, Creo platform, operational data manually added to the virtual environment	Simulation
[18]	Product, process and production system	MBSE approach/ DT-CPPS framework/ DT model	4 Modules: DT simulation, real-time data processing, manufacturing operations execution and responsive production decision-making. Smart resources; network connectivity; logical mapping; data storage; data computing tool; advanced analytics	1.Information writing on RFID 2.DT model simulation of manufacturing and machine sequencing 3.Verification of current manufacturing statuses with simulated ones 4.The smart product as a result of the smart manufacturing	Logical and cyber-physical mapping OPC-UA	Autonomous

№	Physical Twin	Approach/Architecture/Framework/Model	Features/Functionalities	Deployment strategy/methodology/operating flow/approach	Structure (approach integration/interoperability)	DT Intelligence
[15]	Product, process and production system	MBSE approach/DT-driven product manufacturing system framework	Layers: Physical; Model; Information processing; System (manufacturing service platform system and DT application subsystem).	1.MBD-based design model 2.MBD-based process model 3.Machining model of the product 4.MBD-based quality model 5.Quality inspection model 6.Finished fan blade model 7.MBD-based simulation model	Manufacturing service platform (integration of MES, PLM, ERP…) OPC-UA	Simulation, optimization
[17]	Production line	MBSE approach/ simulation-based solution using data-exchange	Upper-level calculation system and lower-level simulation platform. The control system (J2EE programming architecture) with intelligent multi-objective optimization algorithm on the simulation platform	1.The rapid individualized design based on the predefined reference models and interfaces 2.The distributed simulation of equipment and production line assembly 3.The multi-objective optimization, calculation on schemes and plans	Four-tuple semantic data model (static attributes, motion script, control scheme, and communication interface) OPC-UA, Ethernet Protocol, API, MES	Simulation, optimisation
[34]	Production system (manufacturing cell)	MBSE approach, connection-based architecture	Layers: Physical twin and sensors/actuators; PLC; Local Data Repositories (OPC-UA server, local data base); IoT Gateway (with GUI); Cloud-based databases; Emulations and simulations	-	OPC-UA	Simulation

№	Physical Twin	Approach/Architecture/Framework/Model	Features/Functionalities	Deployment strategy/methodology/operating flow/approach	Structure (approach integration/interoperability)	DT Intelligence
[8]	Observable Manufacturing Element (OME)	DT reference model	Data Collection and Device Control Entity; Operation and Management Sub-Entity, Application and Service Sub-Entity, and Resource Access and Interchange Sub-Entity for digitally representing and maintaining OME; User Entity (human, MES, ERP or other DT)	Selection of standards and technologies for each layer	MTConnect, STEP, and Core Manufacturing Simulation Data (CMSD)	-
[35]	Production system	RAMI 4.0/ISA-95	Layers: Asset (Physical world); Integration; Communication (data standards); Informational; Functional; Business	-	OPC-UA, MES, ERP	Real-time decision support
[36]	Product, process, system or factory	MBSE approach, simulation-based architecture	Connectivity Module; Data Storage Module; Visualisation and Monitoring Module; Simulation Module; Human Interface Module	1.Modbus, MQTT and OPC DA protocols; 2.Node-RED; 3.FlexSim software tool	Modbus, MQTT and OPC DA	Real-time decision support
[37]	Production system	MBSE approach/automation framework	Physical Layer; CPS; Modelling; Discrete event simulation		OPC-UA	Real-time decision support
[38]	Product,	MBSE approach/de-	Resource layer, data/model integration	Implementation mechanism in product lifecycle level;	Cloud service bus	Real-time decision support, prediction

	process, production system	sign engineering approach/automation framework/II reference framework	layer, ontology of interoperability layer, business logic layer and presentation layer	Implementation mechanism at intra-enterprise level		
[39]	Production system, factory	Holonic architecture ARTI	Decision making technologies; Situation-specific decision making	-	Syntactic (data formats, interaction protocols) and semantic (understanding of the data) interoperability	Real-time Decision support and autonomous DT

From the previous examples the structure and main components of the DT architecture for production system are identified. Firstly, the MBSE approach alongside with automation framework is appropriate to build the DT using multilayered DT model. This DT model should contain the following layers forming DT functionalities: physical (asset/physical twin including IIoT); communication (standardized data acquisition and control); information (data storage, management and analytics); configuration (physical asset models and representations); simulation (emulations and simulations, intelligent multi-objective algorithms); advanced analytics and data computing tools (simulation feedback and decision support). Secondly, to implement DT on the physical environment, the standards and technologies for each layer must be identified [40]. The series of standards ISO/DIS 23247 establish the following steps:

1. Data collection and processing;
2. Interface development for control and translating commands;
3. Data communication and control command communication
4. Digital representations of the OME (selection, development and integration of functional entities)
5. Communication between user and DT (MES, CAD, ERP etc).

However, the DT design process could be started with the definition of purposes and scenarios to be simulated and verified and therefore could be reversed. This can be assured by the interoperable models and technologies allowing bi-directional integration between layers with the help of, for example, Modbus TCP/IP, Ethernet protocol, OPC-UA or MES. Finally, the level of intelligence depends on the analytic tools and therefore include not only simulation and optimization capabilities but also the real-time decision support and predictions.

4 Conclusion

There is a lack of understanding of the implementation of DT concept and its real benefits for manufacturing systems. For now, the main idea of DT concept is to join all needed technologies from different automation layers and on different lifecycle stages to maintain digital thread based on real-time reliable data and provide a constant support for human. This study shows that DT could be built using various approaches and technologies from different industrial domains, however distinguished by specific underlying principles, functionalities and related features. Regarding the content, comparison and their complexity, this work is the first comprehensive step to define the DT concept and its architecture for production systems. As a perspective, an architecture of DT will be proposed to tackle all the aforementioned components for a smart manufacturing systems, with a modular perspective to ensure a practical implementation.

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