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Digital twins for manufacturing and logistics systems: is simulation practice ready?

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Abstract

This article provides a theoretical contribution to the state-of-the-art of digital twins for manufacturing and logistics systems. The primary goal of this paper is to draw attention to the gap between the theoretical framework of digital twins in manufacturing and supply chain and their practical implementation from a simulation modeling point of view. Therefore, highlighting the recent innovations in the simulation practice that could provide the basis for digital twins with high levels of data integration, automation, and smart capabilities. This study follows a comparative approach to analyzing theoretical and technical readiness for developing digital twins with high fidelity and computational power. The methodology is based on a benchmarking analysis that aims to identify the current sate of the art from a theoretical and a practical standpoint.

Keywords: Symbiotic Simulation; Big Simulation; Distributed Simulation; Digital Twins; Simulation Tools

1. Introduction

The emerging concept of industry 4.0 implies the extensive utilization of industrial data to solve complex problems related to planning, scheduling, and control of production and logistics requirements. The utilization of industrial data became possible in recent years due to the substantial advancements achieved in the state-of-the-art of several research fields, e.g., Data Analytics, computational intelligence, Artificial Intelligence AI, and operations research. In the industry 4.0 context, these approaches could be significantly leveraged thanks to technologies like the Industrial Internet of things (IIoT), Cyber-Physical Systems (CPS), and cloud computation (Sharif Ullah, 2019). This positive correlation between recent technological advancements and analytical approaches within the industry 4.0 framework made it possible to emerge the Digital Twin (DT) concept of production systems, products, and processes.

The concept of the digital twin was originated in 2002 by Grieves to build a digital informational construct of a physical system. This digital information acts as a "twin" of the embedded information within the physical entity and is linked through its entire life cycle (Kahlen et al., 2016). Therefore, a digital twin is a virtual duplication of a complete or a context-dependent sub-system and consists of the relevant data and models designed for their intended purposes (Shao et al., 2019). In manufacturing systems, digital twins allow manufacturers to create digital models of their production processes and systems using real-time data collected from smart sensors and actuators to perform near-real-time analysis and control.

The concept of DT is often used interchangeably with simulation models (Shao et al., 2019). However, simulation models do not always define digital twins, as simulation models may replicate possible scenarios of the real world, but this does not necessarily imply showing what is happening in real-time. On the other hand, digital twins involve the real-time flow of data with the physical world, enabling them to perform real-time or near-real-time analysis for the modeled physical entity.

Noteworthy, A digital twin is also differentiated from what is referred to as digital shadows, and both are considered as a digital representation of a physical system (digital model). Nevertheless, a Digital Twin involves the bidirectional data flow between the digital model and the physical entity. In contrast, the data transmission of a digital shadow is only unidirectional from the physical world to the digital model (Shao et al., 2019).

However, the implementation of digital twins in the manufacturing and supply chain context is hindered by several technical and conceptual challenges related to the development of simulation models with extensive data exchange capabilities. For instance, the adjustment of stimulation parameters can no longer be straightforward in real-time data acquisition. Indeed, most simulation software are equipped with manual parameter adjustment functionality. However, in the case of real-time data exchange, the simulation parameters' manual adjustment and validation process become impractical. Another major challenge for digital twins' development is limited the computer processing power with respect to the huge amount of data that should be prepared and processed in real-time. Therefore, there is an urgent need for a comprehensive conceptual and technical framework for implementing digital twins based on real-time and continuous simulation instances.

To this end, the objective of this study is to answer two research questions:

- RQ1: Is simulation theory ready for the implementation of digital twins of manufacturing and logistics systems?
- RQ2: Are simulation tools ready for the development of digital twins of manufacturing and logistics systems?

The remainder of this paper is organized as follows; Section 2 discusses the state of the art of digital twins from a manufacturing and supply chain simulation point of view. Section 3 depicts the utilized methodology for the analysis in this paper. Section 4 provides a detailed discussion about the available applications of simulation software to develop digital twins in the industrial context. Section 5 considers the conclusion of this study and suggests future research directions.

2. State of the art

A digital twin represents the physical systems in the digital domain that could be useful for various purposes. In the manufacturing and logistics industry, digital twins guarantee continuous information integration through the entire product/system life cycle and provide an environment for testing, monitoring, planning, and decision making without subjecting to time or physical limitations. Therefore, digital twins can be used to perform real-time monitoring, perform production optimization and control, predict systems behavior, allow predictive maintenance, and realize virtual commissioning. However, digital twins help improve the performance of the industrial value chain by reducing resource downtime, improving the products' quality, ensuring operation safety, and reducing manufacturing cost.

2.1. Difference between a Digital Model, a Digital Shadow, and a Digital Twin

In the discourse of digital twins, it is necessary to differentiate between three categories of digital representations to avoid potential confusion in the literature. (Kritzinger et al., 2018) suggested three categories of possible digital representation of a physical object:

1. *Digital Model*: Is a digital representation of a physical objects that allows only manual augmentation of the relevant data to the model. (e.g., mathematical models, Simulation models).

2. *Digital Shadow*: this digital representation describes the physical objects through one-way automated data flow from the physical space to the digital model, but only allows for manual data flow from the digital model to the physical entity/s.

3. *Digital Twin*: is digital representation that allows automated bidirectional flow from the physical space to the digital model.

To this end, (Shao et al., 2019) proposes a four-dimensional framework for the desired capabilities of digital twins. Namely, connectivity that implies the communication level with the physical system; the visibility that entails the ease of perception for the human user; the Analyzability that indicates how the digital twin can be utilized for decision support; and the Granularity that indicates the level of detail of the digital model. A digital twin can involve different levels of resolution in each capability area based on their goals and design requirements. Therefore, implementing digital manufacturing systems with various levels of capability typically requires implementing different simulation approaches.

2.2. Simulation as a key enabler for Digital twins

The simulation theory has evolved rapidly in the last years due to the increased awareness of its importance in solving several real-world problems, especially as a tool for decision support. In the Manufacturing and supply chain industry Discrete Event Simulations (DES) and Agent-Based simulations (ABS) proved their successful applications for modeling reality with high fidelity. However, the advent of digital twins as an accelerating trend on the manufacturing systems' simulation highlighted the importance of investigating innovative simulation approaches to tackle the demanding features of DT. Therefore, researchers explored the so-called hybrid simulation, which is achieved by fusing two or more traditional simulation approaches (e.g., DES + ABS). Recently, other simulation concepts, such as "Big simulation," were proposed as an advancement of the concept of distributed simulation (Taylor, 2019). Therefore, allowing to process big data input and produce big data output in near to real time.

The concept of "symbiotic Simulation" (Aydt et al., 2008) is recently emerging as an interesting approach to successfully integrating sensorial data with digital twins. This newly emerging simulation-style could be of great use for the future implementation of data-driven digital twins, as it is foreseen to consider the implementation of big data analytics and IoT to produce digital twins with high computational and analytical power. However, both the symbiotic and Big simulations concepts are still in their early stages from theoretical and practical perspectives. The following section discusses them in more detail.

2.2.1 Distributed & Big simulation

Digital twins of manufacturing systems typically require dealing with huge amount of sensory data; this implies a significant burden on the digital twin's development and operation process to ensure a high quality of data from one side and the continuity of the data exchange from the other. Moreover, the requirement of a digital twin to provide near-real-time evaluation and suggestions about the modeled systems implies the need for fast simulation runs regardless of the amount of data used in the application.

Since the 1970s, simulation researchers and practitioners have strived to decrease the run time of simulation models of complex systems. The Parallel Decrease Event Simulation (PDES) community investigated the opportunity of using multiple processors in high-performance computing systems. Eventually, this effort led to the emergence of Distributed simulation as a field with roots in Computer science, mainly Parallel and distributed computing. The main goal of Distributed simulation is to use Parallel and distributed computing techniques and multiple computers to speed up the execution of simulation programs and link together simulation models to ensure reusability. However, the emergence of cloud-based technologies, namely, cloud computation and cloud storage, opened the opportunity for a vast increase in overall computation power. Therefore, this paved the way for the timely execution of complex simulation models with a large number of intertwined factors and initial data.

Taylor et al. (2015) recently introduced the concept of Big simulation as an extension of the concept of cloud-based simulations to describe sets of coupled simulation that deal with Big data input and output in real to near real-time. Therefore, the concept of Big simulation can address the problem of the demanding computation power required to implement digital twins of complex systems, as they allow the processing of Big-data using cloud-based infrastructure and computation techniques. However, as mentioned earlier, the field of Big simulation is still in its infancy and lacks the proper practical guide due to its demanding technical nature.

2.2.2 Symbiotic simulation

From a Simulation theory perspective, one of the closely coupled concepts to digital twins is the concept of symbiotic simulation. This concept primarily emerges from the concept of "co-simulation" in electrical and computer engineering. This concept describes an experiment in which a hardware simulator communicates with software components (Rowson JA, 1994). However, researchers have adopted several terminologies to describe similar applications (i.e., "real-time simulation" and Dynamic Data-Driven Application Systems (DDDAS)) (Fujimoto et al., 2002).

Aydt et al., (2008) propose a generic definition for symbiotic simulation as "a close association between a simulation system and a physical system, which is beneficiation to at least one of them". Onggo, (2019) extended the Adydt by introducing the concept of "symbiotic simulation system (S3)" which refers to a virtual system or digital twin. Moreover, the study proposes a potential architecture for the digital twins as system based on symbiotic simulation. Therefore, the current work bases its premises on the definition of (Onggo, 2019), as it considers the most recent features of the concept of digital twins in the industry.

A Symbiotic simulation model represents the core model of the digital twin that communicates with the data-acquisition components of a physical system at runtime (i.e., smart sensors) and makes response based on the intended design of the digital twin. Unlike non-symbiotic simulation which can initialize the systems' state only at the start of the simulation, symbiotic simulation can re-initialize the state of the system several times during the simulation run. One of the major components of a symbiotic simulations is the Machine learning (ML) component, this component is comprised with ML models that provide automation functionalities for the digital twin based on the data-collected from the physical entity during run-time.

3. Methodology

One of the significant challenges that face the implementation of digital twins in the Manufacturing and Supply chain is the readiness of the existing simulation software to incorporate data synchronization capabilities for their simulation models. This challenge emerges from the lack of off-the-shelf features that allow the immediate integration of industrial data. However, a fundamental goal of this study is to analyze the readiness of the various software for implementing data-driven simulation models for developing digital twins of manufacturing and supply chain. Namely, symbiotic and Big simulation.

To this end, this study analyzes around 50 commercial and open-source simulation software for readiness to developing data-driven simulation models of industrial systems. Therefore, we are looking for ad hoc features that enable the Internet of Things (IoT), cloud computation, and Artificial Intelligence (AI). These software tools are considered for analysis based on the following criteria:

- Popularity: In this article, we consider the software tools that are frequently used for modeling and simulation of Industrial systems. The study emphasizes on the popularity in terms of the number of publications in the Scopus scientific database. However, the popularity factor also considers online practitioners' opinion in websites like (e.g., GitHub, SOURCEFORGE, GetApp, etc.)"
- Discrete Event Simulation (DES) & Agent-Based modeling software (AB): we considered these two paradigms since they are most popular for developing manufacturing and supply chain simulation models.

The different simulation tools are searched in the Scopus database using the searching string **((TITLE-ABS-KEY ("*Simulation tool name*") AND TITLE-ABS-KEY (industr* OR manufacturing OR production OR factory) AND KEY (digital AND twin))),** to identify the different publications that utilize the simulation tools for developing digital twins for Manufacturing systems. Table.1 depicts the number of publications per simulation tool. However, the tools presented in this table are considered for further analysis since the other tools do not have any scientific publications within the analysis scope.

Table 1. Publications per simulation tool in digital twins for manufacturing industry

Simulation tool	Vendor	NO. of Scopus publications
Anylgoic	The Anylogic company	8
Simulink	MathWorks	6
Technomatix Plant SImulaiton	Siemens	1
FlexSim	FlexSim Software Products, Inc	2
Simio	Simio LLC	2
Simpy	Open source	1
Emulate 3D	Rockwell Automation	1

4. Digital twins and simulation software

The second part of this study is dedicated to analyzing the different simulation tools' readiness to develop digital twins for manufacturing and logistics systems. This benchmarking analysis of the simulation tools is based on a literature survey that provides a critical discussion about the past publications that developed digital twin applications in manufacturing and supply chain. To this end, this section provides an overview of the most relevant publications of each simulation software.

Damiani et al. (2018) adopts the terminology of a digital twin to refer to an Anylogic simulation model that aims to optimize a machining cycle for electric motors brake disk. In this study, the authors do not pay a great attention to data integration of the production, this is due to the immaturity of the DT concept at the time of the study. Therefore, the simulation model developed in this study does not consider the production system's real-time data integration. instead, it drives its conclusion based on a priori stochastic assumptions for production parameters. (Ait-Alla et al., 2019) use Anylogic to develop a digital model for a production system to examine the interconnection between the digital twin and physical system for production control purposes. The study examines sensors configuration to ensure synchronization between the physical and digital twin.

Akopov et al. (2021) provide an approach for DT in TV manufacturing systems based on DES and ABM using Anylogic simulation. The study suggests the utilization of genetic algorithms for the optimization of production parameters. However, this article does not say much about the connection between the physical system and the digital twin. Therefore, real-time data synchronization is not handled enough by this article. (Zhang. J et al., 2021) addresses the dynamic resource allocation problem of a flexible production system by proposing a data-driven and cloud-based architecture to build digital twins for the production lines.

Moreover, the work implements this architecture on the cloud using Java, MySQL, and the Anylogic platform. (Singgih, 2021) utilized the concept of digital twins to identify the production factors that significantly affect the system's productivity in a semiconductor fab. The study compares several ML techniques to develop an accurate prediction model for the real-time factors. However, the digital twin is based on a simulation model of Anylogic that acts as a testbed based on the inlet minifab layout. To this end, the study proposes a data collection framework for the production control mechanism. Information about the selected parameters is recorded in real-time with the help of sensors and actuators on the production floor. The collected data is stored as big data, and this data provides a suitable feed for the ML algorithm to predict and evaluate production factors in real-time. (Kassen et al., 2021) offers an in-depth discussion about the concept of digital twins, digital models, and digital shadows. However, this study presents a case study of developing a digital shadow based on the data obtained from ERP. The digital shadow was developed on Anylogic to represent a learning factory at Applied Life Sciences university.

The publication of that includes the utilization of Simulink in the manufacturing industry started in 2019. However, only one paper handles the development of digital twins in the manufacturing and logistics system with a fair representation of the utilized simulation models and a clear description of digital twins as a bidirectional flow of data between the physical and the digital spaces. (Wang, J. et al. 2019) proposes a bidirectional framework between the manufacturing system and the digital space to realize a digital twin of a serial manufacturing system that aims to develop an energy-efficient manufacturing system. The framework conceptualizes three views for the digital twin implementation: the data view, the model view, and the service view. The work adopts the utilization of Max-plus Algebra for implementing an online energy-saving functionality that puts the machines in sleep mode considering the production data of the manufacturing system. A demonstrative example of a simplified automotive production line is used to show the effectiveness of the proposed framework using Simulink as the simulation tool.

Lohtander et al. (2018) suggests a step-by-step approach to develop digital twins of micro-manufacturing units (MMU), this study uses the FlexSim simulation software for building the basic model for the MMU. However, this study is considered relatively old with respect to the evolution of the digital twin concept in the last year. Therefore, the primary motivation of this study is to improve the know-how of students to develop digital twins. It does not detail the implementing methodology and the challenges of developing digital twins for manufacturing systems.

(Sun et al., 2021) conducted a comparative analysis to understand the suitability of Visual Components, Tecnomatix Process Simulate, Emulate 3D, and Flexsim to implement digital twins with the aim for virtual commissioning based on their essential features and connectivity characteristics.

Coelho et al. (2021) The main goal of this paper is developing a simulation model for inbound logistics that acts as digital twin for decision support purposes. However, this recent work addresses the concept of digital twins for logistics and manufacturing systems considering real-time information, flexible and lively operations environments, and autonomous guided vehicles (AGV). The study uses the Simio-based simulation model as the base for the digital twin development. However, the authors highlighted the importance of improving the infrastructures and systems that allow the implementation of cyber physical system in the manufacturing and supply chain industry. Spindler et al. (2021) developed a digital model for a pharmaceutical filling line using a discrete event simulation based on Simio simulation software. Authors aim to the extend the simulation model to complete digital twin of the production line that serves to enhance the production Key performance indicators (KPIs) with the focus on reducing the production lead-time and increasing the overall productivity.

Hofmann & Branding (2019) utilized the open-source python simulation "simpy" library to develop a digital twin for truck dispatching operator assistance to determine optimal displacing policies using simulation-based performance forecasts. The proposed solution couples simply with an-IoT platform for the integration of the real-time data. The digital twin is deployed as a cloud-based service to ensure its effective deployment and scalability. One of the major motivations of this work is to address the challenges associated with the limited interface of commercial simulation tools.

Xia et al. (2019) utilized Technomatix plant simulation software to develop a virtual commissioning environment of an intelligent robot scheduler in manufacturing cells. However, the proposed virtual commissioning system comprises a Virtual cell developed by Siemen's process simulate, a physical cell, and a ML-based scheduler created by Tensorflow.

The discussion delivered by this part of the study is summarized in table 2, which includes the relevant publications sorted by simulation software, application area, addressed research gab, and the type of application.

5. Conclusion

This contribution aims to raise the discussion about the practical implantation of digital twins for industrial systems from a simulation point of view. The paper discusses the recent state-of-the-art simulation, which is foreseen to address the extensive data exchange requirements digital twins of manufacturing and supply chain systems. Therefore, a brief discussion about the Symbiotic and Big simulations is provided. These two newly emerging concepts are useful for integrating industrial data into a simulation model, allowing for extending simulation models with machine learning and artificial intelligence capabilities. Particularly, Big simulation, as an extension of the concept of Distributed simulation, can allow the deployment of Big Data Analytics with the help of cloud-based technologies. On the other hand, Symbiotic simulations allow real-time manipulation of simulation parameters during run-time based on real-time data acquisition, which enables near-real-time analysis and optimization of the industrial key performance indicators (KPIs). To this end, the future development of digital twins should incorporate these two concepts to ensure the effective utilization of industrial data.

Table 2. Analysis of the past digital twin publications per Simulation tool.

Simulation tool	reference	Application scope	Paper type	Addressed gab
	(Damiani et al. 2018)	Production Optimization	Conference paper	Optimization of machining cycle of a motors brake disk
	(Ait-Alla et al., 2019)	Production control	Conference paper	Investigates sensors configuration to ensure synchronization between the physical and digital twin
	Akopov et al., (2021)	Production optimization	Journal Paper	The utilization a genetic algorithm simulation-based optimization for production systems.
Anylogic	(Zhang. J et al., 2021)	Resource allocation	Conference paper	Proposition of cloud-based architecture to build digital twins for the production lines
	(Singgih, 2021)	Production bottleneck identification	Journal paper	The study proposes a data collection framework for the production control mechanism
	(Kassen et al., 2021)	Production optimizing	Journal paper	presents a case study of developing a digital shadow based on the data obtained from ERP as the first step for the full development of digital twins
Simulink	(Wang, J. et al 2019)	Energy optimization	Journal paper	a proposal for a framework of a bidirectional digital-twin-based energy-efficient manufacturing system.
Flexim, Emulate 3D, Technomatix Plant SImulaiton	(Sun et al., 2021)	Virtual commissioning	Journal paper	Comparing different commercial software for suitability to implement digital twins for virtual commissioning
Flexim	(Lohtander et al., 2018)	Education	Conference paper	Revealing a step-by-step approach for developing digital twins for manufacturing systems
Simio	(Coelho et al., 2021)	Inbound logistics	Journal paper	Developing a decision support Digital twin for inbound logistics
	(Spindler et al., 2021)	Production optimization / Risk management	Journal paper	Development of a simulation model as the basis for a potential development of a digital twin for a pharmaceutical

				filling line.
Simpy	(Hofmann & Branding, 2019)	Ports operations	Conference paper	Optimization of port dispatching operations using the concept digital twin for dispatching assistance.
Technomatix Plant SImulaiton	(Xia et al., 2019)	Virtual commissioning	Conference paper	Training intelligent robot in a virtual environment.

This study investigates the readiness of the various simulation software to adopt the concepts of symbiotic and Big simulation based on a literature analysis for the most popular commercial and open-source simulation software. This analysis serves as technical benchmarking analysis for this simulation software so that the applications of the digital twins in the literature repository of simulation tools can give a good insight about the technological readiness of these software to effectively implement the concept of digital twins in the industrial context.

To the end of the authors' knowledge, no publications have comprehensively implanted the concepts Symbiotic and Big simulations. However, several studies provide a proposition of their implementation, which is considered plausible as a contribution to the state of the art. Similar studies provides an approximate conceptualization of digital twins in industrial processes. However, industrial information and data integration still persists in developing state of accurate digital twin models. However, there are various research trends for digital twins from a simulation modeling perspective. For instance, production optimization, production control, and virtual commissioning are considered leading trends as prospective applications for digital twins in manufacturing and supply chain development. Moreover, the Anylogic multipurpose simulation software is considered the most used simulation software for developing digital twins.
One of the major limitations of this study is that it considers only the applications of industrial digital twins in the scientific literature, while some more mature commercial applications of digital twins might exist in terms of data acquaint and integration. Therefore, a more comprehensive study in this arena should complement the investigation effort of this study.

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