



HAL
open science

Towards a Requirement-driven Digital Twin Architecture

Chukwudi Nwogu, Giovanni Lugaresi, Anastasia Anagnostou, Andrea Matta,
Simon J.E. Taylor

► **To cite this version:**

Chukwudi Nwogu, Giovanni Lugaresi, Anastasia Anagnostou, Andrea Matta, Simon J.E. Taylor.
Towards a Requirement-driven Digital Twin Architecture. *Procedia CIRP*, 2022, 107, pp.758-763.
10.1016/j.procir.2022.05.058 . hal-03880507

HAL Id: hal-03880507

<https://hal.science/hal-03880507v1>

Submitted on 1 Dec 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

55th CIRP Conference on Manufacturing Systems

Towards a Requirement-driven Digital Twin Architecture

Chukwudi Nwogu^a, Giovanni Lugaresi^b, Anastasia Anagnostou^a, Andrea Matta^b, Simon J.E. Taylor^a

^aBrunel University London, Uxbridge, UB8 3PH, UK

^bPolitecnico di Milano, Via La Masa 1, 20156 Milano, ITALY

* Corresponding author. Tel.: +44-189-527-4000 ; fax: +44-189-523-2806. E-mail address: chukwudi.nwogu@brunel.ac.uk

Abstract

The fourth industrial revolution brings new technological innovations and amplifies the importance of some existing technologies such as Artificial Intelligence (AI), Internet of Things (IoT), and Blockchain. The Digital Twin (DT) has emerged as one of the most prominent technologies of this era and has caught the attention of the industry, academia, and governments. However, the realisation of the full potential of DT is challenged by the lack of standard terminologies and practices, amongst others. This is reflected in the state-of-the-art in DT architectures, which indicates that there is no widely accepted DT framework. Literature on DT architecture is dominated by application- and/or technology-specific architectures with components and connectors, that not only vary extensively but are named differently. The use of different terminologies for components could hinder the ability to identify commonality in frameworks and makes it difficult for novices to find guidance. Also, literature does not clarify on the connection between the requirements and the components of a DT architecture. To address these problems, this paper proposes a requirement-driven, technology-agnostic DT architecture that consists of standard components that can be traceable to the definitions, requirements, and mandatory functionalities of DT captured in existing literature. The architecture can be applied to various fields and uses cases, based on their respective needs. The paper aims at providing guidance for developing digital twin architectures for a flexible spectrum of applications.

© 2022 The Authors. Published by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

Peer-review under responsibility of the scientific committee of the 55th CIRP Conference on Manufacturing System.

Keywords: Digital Twin; Industry 4.0; Cyber-physical systems; Internet-of-Things

1. Introduction

Although there are several definitions of Digital Twin (DT) in literature [10, 29, 14, 33], none has been officially endorsed. This study will adopt the definition of DT by van der Valk et al. [36]. The authors note that “*DT is a virtual construct that represents a physical counterpart, integrates several data inputs with the aim of data handling, data storing, and data processing, and provides an automatic, bi-directional data linkage between the virtual world and the physical one. Synchronization is crucial to the Digital Twin to display any changes in the state of the physical object. Additionally, a Digital Twin must comply with data governance rules and must provide interoperability with other systems*”. This definition encapsulates most of the ‘mandatory’ characteristics of DT (such as synchronization, di-directional communication, control, anomaly detection and diagnostic, optimization, etc.).

In a nut shell, a DT acquires data from its real-world entity and manipulates the data to provide services, which have the

potential of improving its real-world counterpart, as well as itself. In order to improve or effectively reflect the behaviour of the physical entity, a DT should have the capability to automate data acquisition [6], and this should be a fundamental element of a DT architecture [35]. However, there is also an emerging case for semi-manual data acquisition, which is a mixture of automatic and manual data acquisitions ([36], especially given that DT must allow for multiple data sources, including offline data sources (e.g. databases, stored data, external data, maintenance logs, etc.). Lack of a generic practical approach for implementing data acquisition has been identified as one of the major challenges of realising DT and a source of cost increase in DT development; this stems from the absence of guidance on the approaches of developing DT architectures [6].

To address the aforementioned gap, this paper proposes a requirement-driven DT architecture that consists of standard components that can be traceable to the definitions, requirements, and mandatory functionalities of DT from the existing literature. The rest of the paper is structured as follows: Related literature is presented in Section 2. Section 3 presents the pro-

posed architecture. Discussion on aligning DT requirements to DT architectural components is covered in Section 4. The conclusion and further work follow in Section 5.

2. State of the Art

Developing and using DT would be difficult without standardization or a uniform description. Hence, agreeing on DT components and data analysis techniques is paramount to advancing DT technology [25]. Steindl et al. [32] note that the application of DTs to various domains and at different stages in the lifecycle of real-world entities is testament to lack of clear definition of the capabilities and concepts of DT. The authors argue that this results in case study-driven, varying interpretations of DT and lack of architectural template.

2.1. Existing Architectures

Lee, Bagheri, and Kao [15] develop 5C, a cyber physical system architecture for Industry 4.0-based manufacturing system, provides plug and play smart connection, offers smart analytics for subsystem health, enables DT models for components and machines, support decision-making using cognition, and achieves resilience using self-configuration.

Alam and El Saddik [1] work on a DT architecture called C2PS (cloud-based cyber-physical systems), extends 5C architecture by employing cloud technology in the cyber, cognition and configuration levels. The key contribution of C2PS is that every physical entity is associated with a cloud-hosted cyber entity, such that two entities can establish peer-to-peer (P2P) connections via direct physical connection or via indirect cloud-based DT connections.

A five-layered architecture is proposed by Josifovska et al. [13] as part of the framework for developing DTs of CPS. The framework consists of the Physical Entity, Virtual Entity, Data Management, and Service Platforms.

Borangiu et al. [3] present a four-layered architecture in which every layer on top of the physical system as a DT Layer. The four layers of the architecture are the data acquisition and transmission twin, virtual twins of subprocesses, predictive twins, and decision-making twins.

Souza et al. [31] propose an IIoT-based DT architecture, which consists of Internal Server Layer and IIoT Gateway Layers. The internal server is the computer system that runs the DT and simulations, while the IIoT Gateway is the channel for communication between the DT and its physical twin.

Ghita, Siham, and Hicham [9] develop a three-layered DT architecture, which consists of industrial, application, and communication layers. The industrial layer represents the physical system; the application layer focuses on digital components of the architecture and their features. The communication layer is concerned with the interaction between the DT and the physical system.

Nwogu et al. [23] present a symbiotic simulation system-based architecture for digital twin. The DT Layer of the architecture consists of data acquisition, analytics, scenario manager,

optimisation and symbiotic simulation modules (SSM). The use of SSM and MQTT make the architecture technology-specific.

Redelinghuys et al. [26] study a six-layer architecture for DT that allows for hardware from various vendors to be used in both the physical and digital worlds. According to the authors, the architecture was inspired by Lee, Bagheri, and Kao [15] and consists of the physical twin in Layers 1 and 2. Layer 3 is a vendor-neutral communication medium, which acts as the local data repository for collecting the sensor data from a controller in Layer 2. IoT gateway or data-to-information converter is in Layer 4; while Layers 5 and 6 consist of cloud repository, and emulation and simulation tools, respectively.

In one of the most recent DT architectures, Vrabic et al. [38] offer an intelligent agent-based architecture for resilient digital twin in manufacturing. The architecture employs engineering resilience principles to improve the digital twin's ability to represent its real-world entity. This was achieved by applying the Learning Agent, which enables the restoration of the DT fidelity after a deviation in the performance of the physical system. The Learning Agent consists of Learning, Anomaly Detection, Monitoring and Scenario Generation Mechanisms.

Farsi et al. [7] describe a DT architecture for product life-cycle cost (LCC) estimation, which synchronizes between the physical and digital worlds using an ontology-based approach. The DT architecture is aimed at, supporting the reduction of product cost, and improving product efficiency.

In order to optimize the productivity of Controlled Environment Agriculture (CEA), Chau, Sanchez-Londono, and Barbieri [4] propose a three-layer DT architecture, which consists of the physical asset, the digital twin, and an intelligent layer. The DT architecture was aimed at building a DT that has the capability for bi-directional communication, in which a simulation model is used to optimize productivity. The plan for future work on the architecture includes optimising crop treatment and climate control strategy using the simulation models from the DT.

Mourtzis et al. [20] develop a DT architecture for Fused Decomposition Modelling (FDM), which uses common process data to support engineers in performing online and offline simulation. The idea of the framework is to integrate DT and Augmented Reality (AR) for quality improvement of 3D parts and reduction in human-related error resulting from incorrect machine setup.

2.2. Research Gap

Table 1 matches the reviewed DT architectures to the core functionalities of DT identified in literature. The table shows that none of the architectures completely aligns with the functionalities of DT, probably since most contributions are domain- and use case-specific. Going by the definition of DT adopted by this study, it can be argued that some of the DT architectures may not meet the requirements of fully fledged DTs. Vast majority of the architectures discussed above is use case-driven and varies extensively in terms of their respective components.

Table 1. Features of available DT architectures from the literature.

Reference	Sync.	Bi-Dir. Info	Diagnostic	Control	Predictive/Prescr.	Monitoring	Optimization
[4]	•	•					•
[7]	•						•
[18]			•		•	•	•
[20]						•	•
[38]	•		•		•	•	•
[3]	•	•	•		•	•	•
[9]							
[23]	•	•	•	•	•	•	•
[26]	•		•		•	•	
[32]		•	•	•	•	•	
[13]			•		•	•	•
[31]	•		•	•		•	
[1]	•	•		•			
[15]	•		•		•	•	•

3. Digital Twin Requirements

According to the several studies (e.g., [14, 33, 21]), the requirements of a DT include, in no particular order, synchronization, learning and adaptability, bidirectional information flow, monitoring capability, predictive and prescriptive capabilities, and optimization. In the following, each requirement is described.

3.1. Temporal Synchronization

The Digital Twin needs to reflect the state of the real-world entity at all times. If such alignment is guaranteed, any evaluation that is carried out in real-time can be considered reliable (for instance, the comparison of two production policies).

3.2. Learning and Adaptation

Most physical systems are dynamic and change with a high frequency (e.g., flexible manufacturing systems). Hence, the digital constructs need to be able to adapt to always represent the physical system. We may identify several types of adaptation: (1) adaptation of the model structure, which refers to the logical layout and material flows; those can be either generated or adapted from a previously available model. (2) the tuning of the model level of detail refers to the possibility to exclude from the digital representation the components that do not significantly contribute to estimating the performance of the system, with respect to a particular goal. (3) the adjustment of model parameters to reflect the current conditions.

3.3. Bi-directional Information Flow

In accordance with the definition by Kritzinger et al. [14], a DT can be called as such if information flow is not only from a real-world entity to a digital system, but also vice versa. Accordingly, decisions that are taken within a digital system (e.g., optimization of a production schedule), will be applied

on the corresponding real-world entity, automatically through a control system (e.g., an actuator). Bidirectional communication from the DT to the Physical Twin may not always be to control the Physical Twin; it could result in additional inspection or data collection [37].

3.4. Monitoring Capabilities

Thanks to the real-time information flow from the physical system, a DT can serve the scope to monitor in real-time the condition of its physical twin. For instance, machine tool vibration data can be elaborated and used to produce in real-time a health score of the resource in use.

3.5. Predictive and Prescriptive Capabilities

A DT may include digital models that enable forward-looking analyses. For instance, the real-time state of a manufacturing system can feed a Discrete Event Simulation model, used to estimate the end-of-the-day production performance starting from current conditions and the expected number of orders. By coupling the predictive capabilities with the bi-directional information flow, we may state a DT has also prescriptive capabilities, since it can use the knowledge acquired in forward-looking scenarios to generate actionable commands in the real system.

3.6. Optimization

The possibility to evaluate scenarios that are not yet applied in the real system means a DT is enabled to search for optimal configuration of real system settings. For instance, the scheduling plan may be investigated in search for the one that minimizes the number of resources in use, and consecutively the energy consumption, with the aim to increase the sustainability score of the company.

4. Requirements-driven Architecture

Based on the requirements and characteristics of DT identified in literature and in section 3, this study proposes a requirement-driven DT architecture, as shown in Figure 1. The proposed architecture has three major parts namely: the physical twin; the communication or integration medium; and the digital twin system.

4.1. Physical Twin

The physical twin is the real-world physical or perceived system, for instance, a manufacturing system or an airport process which is dynamically connected with the DT via a communication or integration medium.

4.2. Communication or Integration Medium

The communication or integration medium of a DT is typically implemented using communication protocols with the capability of providing a bi-directional communication between the Physical Twin and DT. Bi-directional data flow distinguishes a DT from other digital forms such as digital model, digital shadow, etc. (Kritzinger et al. [14]). The DT requirements determine the type of devices used, and hence the communication strategy and protocols that apply. Such protocols vary extensively and are not the focus of this paper.

4.3. Digital Twin System

The DT system consists of the Data Acquisition Module, Data Analytics Module, Database Module, Simulation Module, Scenario Manager, Optimisation Module, and Controls Module.

4.3.1. Data Acquisition Module

To improve the real-world entity it is representing or effectively reflect its behavior, a DT should have the capability to automate data acquisition [6]. Hence, the Data Acquisition Module is one of the most crucial components of a DT [35]. The data exchange can be volatile (e.g., real-time sensors transmitting the parts location, start and stop timestamps in a manufacturing facility, movement of passenger in an airport, etc.) or non-volatile data capturing (e.g., list of manufacturing equipment, list of airlines or number/location of check-in desks) [5]. The data requirements of the DT drive the implementation of the Data Acquisition Module, which can be implemented as a web service, web application [27, 22] or mobile application [24].

4.3.2. Data Analytics Module

Data Analytics Module is the engine of the DT, which applies various analytics techniques to provide the mechanism to manage, fuse and process the vastly heterogeneous data acquired by the DT System. Analytics techniques such as streaming process, time-series-based, batch-oriented, and security analytics processing, etc., offer feedback mechanisms for decision-making and control of the Physical Twin, as well as

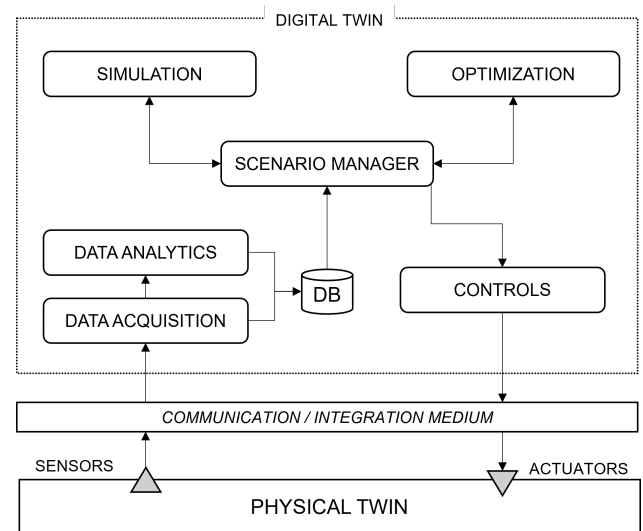


Fig. 1. Exemplary DT architecture.

provide results that become input to simulation and visualisation [5]. Also, simulation outputs can be analysed using data analytics techniques. For example, Johnstone et al. [12] used clustering techniques to analyse simulation event log to identify factors that influence the handling time in an airport baggage handling system. Data Analytics Module processes both historic and real-time data to predict future outcomes using predictive analytics techniques [8, 5].

4.3.3. Database Module (DB)

The Database Module encompasses the internal repository or any form of data storage mechanism that houses the data model of DT. The DB can be cloud-based and this offers benefits such as accessibility, scalability, processing power and efficiency in data transfer [30, 1, 11]. Local-based DM may be used for the security of sensitive data, but a hybrid approach consisting of a combination of local and offsite DM (e.g., cloud, Edge, Fog, Mainframe) may be employed in practice [37]. For instance for use cases involving safety critical or personal sensitive data, the data can be pre-processed by an Edge Computing-based system to stripe the sensitive data before loading it to the cloud system; this also provides resilience in terms of Cloud System performance issue or failure.

4.3.4. Scenario Manager

The Scenario Manager carries out what-if analyses based on the outcome of data analytics and/or simulation experimentation. Scenario manager can control the running of simulation experimentation in order to meet the objective of the experimentation [24]. For instance, by monitoring the production performance over a certain amount of time, the scenario manager module may decide to launch forward looking simulation models to evaluate the performance of different policies under the current set of parameters.

4.3.5. Simulation Module

Depending on the requirements of a DT, the simulation module can be implemented using either discrete event, agent-based, system dynamics (continuous simulation), or hybrid simulation [28]. Based on the author's definition, discrete event simulation will be suitable where the use case is about measuring the number of parts produced in a manufacturing system or the number of baggage/passenger processed through an airport baggage handling system; and agent-based simulation will be used for simulating passenger movement around an airport terminal.

As discussed in the Data Analytics Section, input to or output from simulation can support data analytics and/or predictive analytics. The use of simulation models in DT implementation provides additional advantage when its updated parameters reflect the behaviour of an instance of the Physical Twin, and this makes these simulation models useful for offering additional insights to support decision-making, predicting anomalies or future failures [37]. This is especially true for symbiotic simulation models (SSM) because of their ability to interact with physical systems using near real-time or real-time data [2]. SSM differs from non-SSM with its ability to read data at runtime and response according to the current state of the physical system it is representing [24]. Nwogu et al [23] apply SSM to a DT architecture and suggest that SSM has the mechanisms; to detect anomaly in the DT; validate the models in order to identify the most accurate representation of; forecast the behaviour of; and control; the physical system.

4.3.6. Optimisation Module

DT-based optimisation system offers a rapid identification of optimal solutions [17]. These authors propose DT-driven joint optimisation solution to optimise the utilisation and efficiency of a warehouse product service system (PSS).

With the ability of a DT to fuse disparate data and synchronise with a real-world entity, its Optimisation Module can optimise a system along its entire lifecycle, which includes its design, development, operate and retire stages [16]. Depending on the requirements of a DT, the Optimisation Module, in collaboration with the Scenario Manager, may use the output of other DT components (e.g. Data Analytics, Simulation, etc.) to improve the performance of its real-world counterpart. This may result in automated control via an actuator or manual control, of the Physical Twin, in which its parameters are modified based on the outcome of optimisation [24]. According to the authors, optimisation methods can be combined with simulation methods in hybrid approach known as optimisation-via-simulation or simulation optimisation model. An Optimization Module can be called to use algorithms (e.g., gradient-based, greedy) to search for the optimal configuration of the system.

4.3.7. Control Module

Once the simulation-optimization cycles are concluded, the scenario manager can collect results and convert them into a set of instructions for the physical system. This set of instructions is analysed by the Control Module, to verify if the action is still applicable to the real-world system and feasible within the rest

Table 2. Connection between the DT requirements and the components of the proposed architecture.

Requirements	Components
<i>Temporal Synchronization</i>	Scenario Manager; Database Module
<i>Learning</i>	Simulation Module; Database Module
<i>Bi-directional Information Flow</i>	Sensors; Integration Module (Controllers); Actuators
<i>Monitoring Capabilities</i>	Data Acquisition Module; Data Analytics Module
<i>Predictive/Prescriptive Capabilities</i>	Data Acquisition Module; Data Analytics Module; Database Module; Simulation Module
<i>Optimization</i>	Optimization Engine; Scenario Manager; Simulation Module

of the production epoch, in case of a manufacturing system. Once verified, the controls are passed to the actuators, which controls the Physical Twin automatically; this is made possible by bidirectional communication between the Physical Twin and DT [36], and differentiates a DT from other digital forms [14]. Controls from DT to Physical Twin can be exerted manually by a decision-maker or user, who accesses the output of the Scenario Manager via a human-machine interface [36]. Tao et al. [34] and Ma et al. [19] study the manual control of Physical Twin. The requirement of a DT will determine if its implementation includes automated control, manual or both.

5. Conclusions and Further Developments

Several papers propose the application of digital twins for the improvement of real-time decision processes. In this work, a connection is made between the requirements and the components of a digital twin architecture for a wide spectrum of applications, especially on the ability to integrate, and communicate between, the Physical and Digital Twins.

Quintessentially, a DT acquires data from its real-world counterpart and provides services with the processed version of the data. Several challenges hinder DT to seamlessly achieve this, especially the ability to integrate, and communicate between, the Physical and Digital Twins. This challenge is exacerbated by the heterogeneity of the data and data sources, as well as the sheer volume of data and its mode and frequency of exchange that are adequate to synchronise the Physical and Digital Twins. The ability of the DT to synchronise with, and automatically control, the Physical Twin hinges on the Communication/ Integration Medium.

The development of a digital twin remains dependent on the requirements of its intended applications. In each application, several choices are complex, for instance, the choice of communication standards or the level of integration with the existing information systems, data management system, amongst others. Future works shall address some of these issues.

References

- [1] Alam, K.M., El Saddik, A., 2017. C2ps: A digital twin architecture reference model for the cloud-based cyber-physical systems. *IEEE access* 5, 2050–2062.
- [2] Aydt, H., Turner, S.J., Cai, W., Low, M.Y.H., 2008. Symbiotic simulation systems: An extended definition motivated by symbiosis in biology, in: 2008 22nd Workshop on Principles of Advanced and Distributed Simulation, IEEE. pp. 109–116.
- [3] Borangiu, T., Oltean, E., Răileanu, S., Anton, F., Anton, S., Iacob, I., 2019. Embedded digital twin for arti-type control of semi-continuous production processes, in: International Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing, Springer. pp. 113–133.
- [4] Chau, J.D., Sanchez-Londono, D., Barbieri, G., 2021. A digital twin architecture to optimize productivity within controlled environment agriculture. *Applied Sciences* 11, 8875.
- [5] Damjanovic-Behrendt, V., Behrendt, W., 2019. An open source approach to the design and implementation of digital twins for smart manufacturing. *International Journal of Computer Integrated Manufacturing* 32, 366–384.
- [6] Dittmann, S., Zhang, P., Glodde, A., Dietrich, F., 2021. Towards a scalable implementation of digital twins—a generic method to acquire shopfloor data. *Procedia CIRP* 96, 157–162.
- [7] Farsi, M., Ariansyah, D., Erkoyuncu, J.A., Harrison, A., 2021. A digital twin architecture for effective product lifecycle cost estimation. *Procedia CIRP* 100, 506–511.
- [8] Gandomi, A., Haider, M., 2015. Beyond the hype: Big data concepts, methods, and analytics. *International journal of information management* 35, 137–144.
- [9] Ghita, M., Siham, B., Hicham, M., 2020. Digital twins development architectures and deployment technologies: Moroccan use case. *International Journal of Advanced Computer Science and Applications (IJACSA)* 11.
- [10] Glaessgen, E., Stargel, D., 2012. The digital twin paradigm for future nasa and us air force vehicles, in: 53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference 14th AIAA, p. 1818.
- [11] Hu, L., Nguyen, N.T., Tao, W., Leu, M.C., Liu, X.F., Shahriar, M.R., Al Sunny, S.N., 2018. Modeling of cloud-based digital twins for smart manufacturing with mt connect. *Procedia manufacturing* 26, 1193–1203.
- [12] Johnstone, M., Le, V.T., Zhang, J., Gunn, B., Nahavandi, S., Creighton, D., 2015. A dynamic time warped clustering technique for discrete event simulation-based system analysis. *Expert Systems with Applications* 42, 8078–8085.
- [13] Josifovska, K., Yigitbas, E., Engels, G., 2019. Reference framework for digital twins within cyber-physical systems, in: 2019 IEEE/ACM 5th International Workshop on Software Engineering for Smart Cyber-Physical Systems (SEsCPS), IEEE. pp. 25–31.
- [14] Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W., 2018. Digital twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine* 51, 1016–1022.
- [15] Lee, J., Bagheri, B., Kao, H.A., 2015. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing letters* 3, 18–23.
- [16] Leng, J., Jiang, P., 2019. Dynamic scheduling in rfid-driven discrete manufacturing system by using multi-layer network metrics as heuristic information. *Journal of Intelligent Manufacturing* 30, 979–994.
- [17] Leng, J., Zhou, M., Xiao, Y., Zhang, H., Liu, Q., Shen, W., Su, Q., Li, L., 2021. Digital twins-based remote semi-physical commissioning of flow-type smart manufacturing systems. *Journal of Cleaner Production* 306, 127278.
- [18] Liu, M., Fang, S., Dong, H., Xu, C., 2021. Review of digital twin about concepts, technologies, and industrial applications. *Journal of Manufacturing Systems* 58, 346–361.
- [19] Ma, X., Tao, F., Zhang, M., Wang, T., Zuo, Y., 2019. Digital twin enhanced human-machine interaction in product lifecycle. *Procedia Cirp* 83, 789–793.
- [20] Mourtzis, D., Toghias, T., Angelopoulos, J., Stavropoulos, P., 2021. A digital twin architecture for monitoring and optimization of fused deposition modeling processes. *Procedia CIRP* 103, 97–102.
- [21] Moyne, J., Qamsane, Y., Balta, E.C., Kovalenko, I., Faris, J., Barton, K., Tilbury, D.M., 2020. A requirements driven digital twin framework: Specification and opportunities. *IEEE Access* 8, 107781–107801.
- [22] Mustafee, N., Powell, J., Harper, A., 2018. Right hospital-right time: A business analytics framework for analysing urgent care/a&e wait time data, in: Proceedings of the 2018 Simulation Workshop, The Operational Research Society. pp. 105–115.
- [23] Nwogu, C., Taylor, S.J.E., Anagnostou, A., 2020. Towards a generic architecture for symbiotic simulation system-based digital twin. *Winter Simulation Conference Proceedings*.
- [24] Onggo, B.S., Juan, A.A., Mustafee, N., Smart, A., Molloy, O., 2018. Symbiotic simulation system: Hybrid systems model meets big data analytics, in: Proceedings - Winter Simulation Conference, Institute of Electrical and Electronics Engineers Inc.. pp. 1358–1369. doi:10.1109/WSC.2018.8632407.
- [25] Qi, Q., Tao, F., Zuo, Y., Zhao, D., 2018. Digital twin service towards smart manufacturing. *Procedia Cirp* 72, 237–242.
- [26] Redelinghuys, A., Basson, A.H., Kruger, K., 2020. A six-layer architecture for the digital twin: a manufacturing case study implementation. *Journal of Intelligent Manufacturing* 31, 1383–1402.
- [27] Rhodes-Leader, L., Onggo, B.S.S., Worthington, D.J., Nelson, B.L., 2018. Airline disruption recovery using symbiotic simulation and multi-fidelity modelling.
- [28] Robinson, S., 2014. *Simulation: the practice of model development and use*. Bloomsbury Publishing.
- [29] Rosen, R., Von Wichert, G., Lo, G., Bettenhausen, K.D., 2015. About the importance of autonomy and digital twins for the future of manufacturing. *IFAC-PapersOnLine* 48, 567–572.
- [30] Shafto, M., Conroy, M., Doyle, R., Glaessgen, E., Kemp, C., LeMoigne, J., Wang, L., 2012. Modeling, simulation, information technology & processing roadmap. *National Aeronautics and Space Administration* 32, 1–38.
- [31] Souza, V., Cruz, R., Silva, W., Lins, S., Lucena, V., 2019. A digital twin architecture based on the industrial internet of things technologies, in: 2019 IEEE International Conference on Consumer Electronics (ICCE), IEEE. pp. 1–2.
- [32] Steindl, G., Stagl, M., Kasper, L., Kastner, W., Hofmann, R., 2020. Generic digital twin architecture for industrial energy systems. *Applied Sciences* 10, 8903.
- [33] Tao, F., Qi, Q., Liu, A., Kusiak, A., 2018. Data-driven smart manufacturing. *Journal of Manufacturing Systems* 48, 157–169.
- [34] Tao, F., Sui, F., Liu, A., Qi, Q., Zhang, M., Song, B., Guo, Z., Lu, S.C.Y., Nee, A.Y., 2019. Digital twin-driven product design framework. *International Journal of Production Research* 57, 3935–3953.
- [35] Uhlemann, T.H.J., Schock, C., Lehmann, C., Freiburger, S., Steinhilper, R., 2017. The digital twin: demonstrating the potential of real time data acquisition in production systems. *Procedia Manufacturing* 9, 113–120.
- [36] van der Valk, H., Haße, H., Möller, F., Otto, B., 2021. Archetypes of digital twins. *Business & Information Systems Engineering*, 1–17.
- [37] VanDerHorn, E., Mahadevan, S., 2021. Digital twin: Generalization, characterization and implementation. *Decision Support Systems*, 113524.
- [38] Vrabčič, R., Erkoyuncu, J., Farsi, M., Ariansyah, D., 2021. An intelligent agent-based architecture for resilient digital twins in manufacturing. *CIRP annals* 70, 349–352.