Decision Support Based on Digital Twin Simulation: A Case Study

Flávia Pires[1(✉)], Matheus Souza[1], Bilal Ahmad[2], and Paulo Leitão[1]

[1] Research Centre in Digitalization and Intelligent Robotics (CeDRI), Instituto Politécnico de Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal
{fpires,pleitao}@ipb.pt, matheussouza.ipb@gmail.com

[2] University of Warwick, Warwick Manufacturing Group (WMG), Coventry, UK
B.Ahmad@warwick.ac.uk

Abstract. The significance of Digital Twins is considered vital in the reshaping of the manufacturing field with the emergence of the fourth industrial revolution. The potential of applying the Digital Twin technology is being studied extensively as a key enabler of engineering cyber-physical systems. However, it is still in its infancy, and only a few scientific papers are describing its applicability in case studies, prototypes or industrial systems. Bearing this in mind, this paper presents a comprehensive overview of Digital Twins in the manufacturing domain and defines a conceptual architecture that considers simulation capabilities to support the optimisation of production processes. The designed approach is applied to a proof of concept case study that considers a flexible production cell and uses the simulation of the system to dynamically support decision making to optimise the production processes when changes occur in the real production system.

1 Introduction

Industry 4.0 is changing the manufacturing industry landscape, considering the digitisation and the value of data as its foundations. Most of the companies that consider adopting the Industry 4.0 paradigm have to bear in mind the application of, amongst others, Cyber-Physical Systems (CPS), Artificial Intelligence (AI) and Internet of Things (IoT) [5]. In the manufacturing environment, the implementation of CPS comprises the digitisation of systems, merging the real and virtual worlds. This characteristic has provided the opportunity to the Digital Twin to emerge as one of the key enabling technologies.

The concept of the Digital Twin was proposed by M. Grieves in 2002, by defining features as the real space, the virtual space and the connection between them [7]. With the 4th industrial revolution, the rapid evolution of certain technologies, e.g., IoT, simulation, Big Data and Machine Learning allowed to boost this approach, making its application in the manufacturing domain a reality [1,2].

The scientific and industrial world have been directing their attention towards the Digital Twin technology. According to [10], the interest and research about

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Digital Twin technology have not only grown in the academic field but also among industry practitioners. In 2017, a study conducted about the Digital Twin market showed that it is expected to reach $15.66 billion by 2023 [15]. A new study conducted in 2019 showed that the Digital Twin market would reach $35.8 billion by 2025 [16].

Although there has been a growing interest of the scientific community in the Digital Twin, there is still a lack of applications that include the decision support functionality [10,12], mainly using simulation and what-if engines. Bearing this in mind, the main goal of this paper is to reduce the gap that exists in the current research literature related to Digital Twin applications in the manufacturing domain, including decision support capabilities. The main scientific contribution of this paper is the development of a conceptual Digital Twin architecture that considers simulation capabilities to support decision-making and its application in a case study for a proof of concept Digital Twin providing decision support in the manufacturing domain. The presented case study is a flexible production cell with monitoring and decision support obtained the Digital Twin based simulation. The experimental results allowed to verify the applicability of using the Digital Twin to support the production managers in decision-making when a change in conditions occurs.

The rest of the paper is organised as follows. Section 2 presents the Digital Twin concept in the manufacturing sector, and Sect. 3 reviews the decision support approaches based on Digital Twin concept and introduces the proposed system architecture. Section 4 describes the implementation of the Digital Twin simulation architecture to the case study and analyses the achieved results. Finally, Sect. 5 rounds up with the conclusions and points out some future work.

2 Digital Twin in the Manufacturing Domain

The manufacturing domain has evolved since the 1st industrial revolution, with the invention of the steam engine as a new source of energy. Today, the world finds itself in the fourth industrial revolution [3,4].

2.1 Digital Twin: The Concept Evolution

The German government launched the Industry 4.0 initiative to drive the digital revolution in the manufacturing industry [5]. According to [5], the manufacturing environment compliant with the Industry 4.0 principles comprises the implementation of CPS, requiring the digitisation of systems and the convergence between the real and digital worlds. Bearing this in mind, the digitisation of the manufacturing environment has been the main focus of both academia and industry in the last few years. In this context, the Digital Twin concept has emerged and received attention in the scientific community as a promising new field of investigation for the digitisation of the manufacturing environment [6].

Grieves proposed the foundations of the Digital Twin technology in 2002. At the time, the concept, called *"Mirrored Spaces Models"*, comprised features as the real space, the virtual space and their connections allowing the flow of data [7]. In 2011, the concept was adopted by the US National Aeronautics and Space Administration (NASA) entering the field of aeronautics to determine the health of aircrafts and predict their structural life [8].

From this point on, the evolution of the concept has grown rapidly covering several sectors, like manufacturing. One of the first authors to bring the concept of Digital Twin to the manufacturing sector was [9], who defined the Digital Twin as a *"the coupled model of the real machine that operates in the cloud platform and simulates the health condition with an integrated knowledge from both data-driven analytical algorithms as well as other available physical knowledge"*. The concept is increasing and *"has evolved into a broader concept that refers to a virtual representation of manufacturing elements such as personnel, products, assets and process definitions, a living model that continuously updates and changes as the physical counterpart changes to represent status, working conditions, product geometries and resource states in a synchronous manner"* [10]. Another recent definition was provided by [6] that defines the Digital Twin as *"a method or tool for modelling and simulating a physical entity's status and behaviour"*, that can *"realise the interconnection and intelligent operation between the physical manufacturing space and virtual space"*.

The growing interest in Digital Twin technology is illustrated in Fig. 1 that presents the evolution in time of the number of scientific papers related to the Digital Twin retrieved from the Scopus database using the search query *TITLE-ABS-KEY ("digital twin" AND "manufacturing").* This analysis shows that the number of scientific publications regarding the use of *Digital Twin* in *Manufacturing* is growing exponentially since 2016. This can be translated to a growing interest from the scientific community and consequent production of knowledge about the Digital Twin technology in the field of the manufacturing sector.

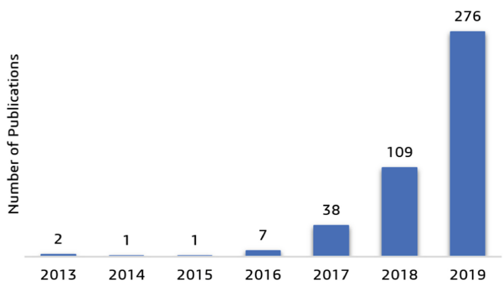

Fig. 1. Evolution of the number of scientific publications in the Scopus database related to Digital Twin (Query *TITLE-ABS-KEY ("digital twin" AND "manufacturing")*) over the years.

2.2 Challenges of Digital Twin

Despite the rapidly growing scientific interest in the Digital Twin technology in the manufacturing domain, there are several challenges to be addressed.

According to [6], the main focus of Digital Twin research in manufacturing tackles two main challenges, namely: 1) lack of standard framework for the physical and virtual worlds to enable real-time interaction between them, and 2) lack of unification in the development of models in various lifecycle phases and domains within the manufacturing environment (e.g., product model for data transmission/sharing).

On the other hand, the study conducted by [10] identified seven key research issues in this field, namely the existence of a pattern architecture for a Digital Twin, the required communication latency between the physical system and its Digital Twin, the data collection mechanisms, the existing standards for Digital Twins, the decision-support functionality of the Digital Twin, the existence of Digital Twin model version for management and, finally, the human role in the Digital Twin applications for the manufacturing domain.

The authors of [11] have concluded that the conducted research in applying Digital Twin in the manufacturing area is still in its infancy, and there is a lack of publications that address end-to-end implementation and integration of Digital Twins in the industrial domain. The existing literature takes into consideration smaller parts and fewer aspects of the Digital Twin (e.g., virtual modelling or monitoring) and uses ad hoc integration methods to connect digital and physical space.

3 Decision Support Based on the Digital Twin

The Digital Twin is gaining significant attention in the scientific and industrial community for its versatile embedded functionalities and benefits in the manufacturing sector. A particular aspect is that the Digital Twin can enhance the manufacturing systems ability to use the simulation for decision support using what-if analysis and optimisation techniques in the virtual space.

3.1 Literature Review

The simulation paradigm evolved throughout the years. Initially, around 1960, the simulation was mostly used for individual applications in particular topics, e.g. mechanics. In 1985, simulation started to be used as a standard tool to provide answers to specific problems in specific engineering design domains (e.g. fluid dynamics). Around 2000, the system-level simulation was developed, which allowed for a systematic multi-level and multi-disciplinary approach. Over the last decade, simulation models are considered for use beyond the design phase, i.e. connected to physical assets to enable dynamic optimisation of systems and help in providing decision support [2], giving birth to the concept of Digital Twins (see Fig. 2).

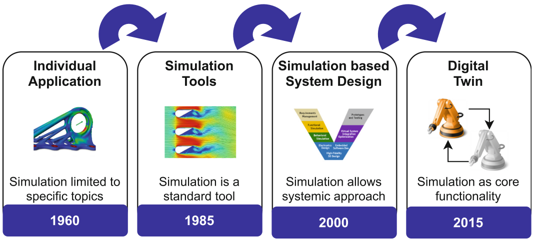

Fig. 2. Evolution of the simulation capabilities (adapted from [2]).

The use of simulation-based Digital Twin for providing decision support is becoming an important area of research. As previously stated, the literature review performed by [10] concluded that most of the reported work about Digital Twin is conceptual and the developed applications are mainly focusing on monitoring and prediction functions. Although most of the applications can be seen as decision-aiding systems, very few of them have included the direct and/or autonomous feedback control system (i.e. Digital Twin control over the physical object). The authors of [13] propose a decision support framework, based on the Digital Twin and using a simulation model, to be applied for the order management process in manufacturing systems. The proposed decision-making process is supported by the collection of data from the physical elements connected to the automatic model generator, which automatically generates a simulation model. In [14], the authors propose a methodology for implementing a Digital Twin for decision support in designing automated flow-shop manufacturing systems (AFMS). The proposed model suggests the use of a hybrid approach, including discrete event models together with system dynamics models, to evaluate the decisions over the AFMS design. By applying the Digital Twin model in a sheet material processing enterprise case study, it was possible to design a new AFMS solution that enabled the reduction of motion waste and decreasing of the unit cost. In [17], the authors make an exploratory study about the benefits that come from using the Digital Twin for decision support asset life-cycle management. The study refers to the literature review of the area and includes two case studies with some details about the decision support provided.

Bearing this in mind, few scientific publications are addressing the application of the Digital Twin concept with decision support functionality. This shows the current need for researching the applicability of decision-making systems and simulation capabilities in the manufacturing area.

3.2 Digital Twin Simulation Architecture

Having this in mind, this paper proposes a general architecture for the Digital Twin decision-support based on simulation capabilities, illustrated in Fig. 3. This architecture is constrained by the following requirements: definition of the physical entity to virtualise (e.g., product, asset, process or factory), modelling the physical entity with a simulation model (e.g., DES model), establishing the connectivity between the physical and virtual through the use of standard industrial network protocols, realizing real-time monitoring of the collected data, using simulation to perform optimisation of the physical entity, and offering decision support to the human operator based on the real-time data and the performed simulations.

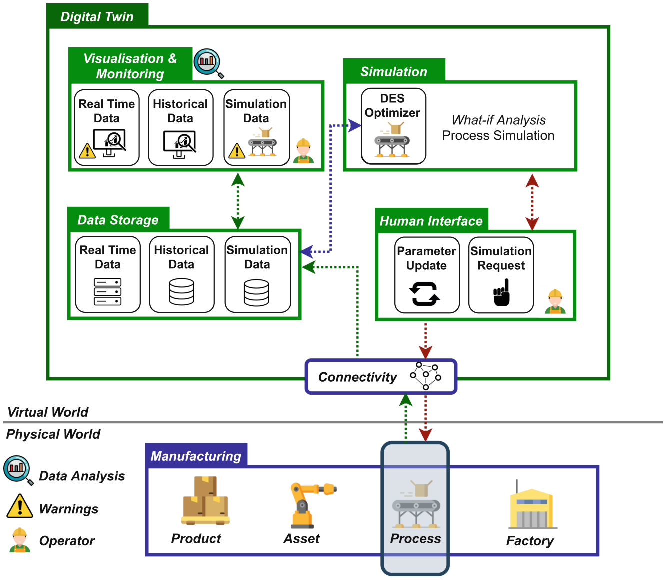

Fig. 3. General architecture for the decision support based on Digital Twin simulation.

The proposed Digital Twin architecture consists of five main modules:

1. **Connectivity Module:** allows the communication between the physical and virtual world through the use of industrial network protocols (e.g., OPC-UA and Modbus TCP/IP), supporting the collection of information/data from shop-floor devices (e.g., robots IoT devices, PLCs and sensors). The collected data is transformed into contextual and readable formats. This module also allows sending commands and deploying new operating configurations, after validation by the user.
2. **Data Storage Module:** designed to store the real-time and historical data from the shop-floor machines/devices, as well as the simulation knowledge created during the execution of various simulation scenarios by the Simulation module. The data stored in this module can be accessed by the other modules using standard interfaces.
3. **Visualisation and Monitoring Module:** responsible for monitoring and visualising the real-time status of the production system, as well as the historical data and future trends based on the results from the simulation scenarios.

This module provides monitoring functions by performing, in the background, data analysis of the retrieved data (e.g., real-time data, historical data and simulation data) from the Data Storage module and displaying the warnings related to the detection of performance degradation and condition change (including machine learning techniques and control rules).

4. **Simulation Module:** comprehends two stages, namely the building of the virtual system model and the performance of discrete event simulation (DES) following the requirements of what-if analysis. The DES optimiser will perform different simulation scenarios allowing the system to find the optimal result for the physical system in the proposed conditions and requirements.
5. **Human Interface Module:** In this module, the human operator, based on the knowledge and information presented to him by the Visualisation and Monitoring module, can request the performance of new simulation scenarios to the Simulation module. The real-time data can be used as a trigger for the human operator to request the simulation of the virtual model or even to feed the simulated model. If the operator verifies that the results are optimising the system according to the imposed requirements, they can be applied as new parameters to the shop-floor devices. The Connectivity module will transform this new information into readable formats for the shop-floor devices.

The proposed Digital Twin architecture aims to overcome some of the identified gaps in the literature and addresses some key issues, for example, the inclusion of the human operator in the Digital Twin applications, the application of a feedback control option based on the decision support provided by the Digital Twin and the conjugation of the Digital Twin with the decision support functionality. This leads to a better decision-making since it includes the ability to test the real system through the application of what-if scenarios, verifying what will be the impact and what will be the most profitable operational strategy to be followed.

4 Flexible Production Cell Case Study

This section presents the implementation and results of the proposed architecture into a case study related to a flexible production cell.

4.1 Description of the Case Study

The case study considered in this work comprises a Fischertechniks flexible production cell that is producing different parts, as illustrated in Fig. 4. This figure also illustrates the virtual system model developed using the FlexSim software.

The flexible production cell consists of five assembly stations, two punching stations (1–2), two indexing stations (3–4), and one pneumatic processing centre (5). All of the stations have their conveyor belts, a set of light sensors and RFID (Radio-Frequency IDentification) readers. The stations are controlled by a programmable logic controller (PLC), in this case, the Schneider Modicon

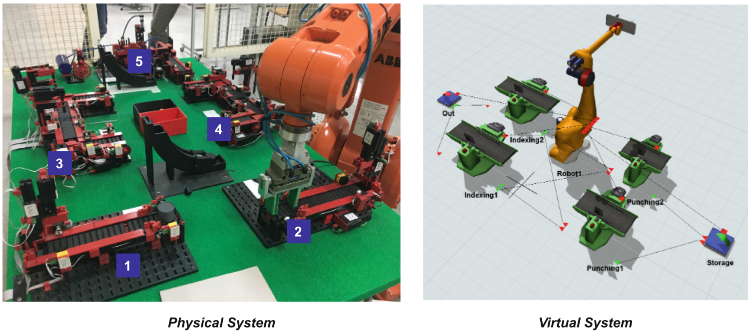

Fig. 4. Case study flexible production cell (physical system and virtual model).

M340. Parts are moved between the stations according to their process plans through the use of an IRB 1400 ABB robot. Additionally, the parts are fed to the stations through an input conveyor and leave the system through an output conveyor.

For this case study, the process plan for a typical part includes the following steps: the robot picks a piece from the input conveyor and feeds it to the punching station; after the punching operation is concluded, the robot transfers the part to one of the indexing stations; and finally, after the conclusion of the indexing operation, the robot transfers the part to the output conveyor.

The developed Digital Twin for this production cell can monitor the performance of the physical system in real-time. When a condition change is detected, the Digital Twin performs a simulation of different scenarios for the virtual system model aiming to define the best strategy that improves the system performance.

4.2 Implementation of the Digital Twin

The implementation of the Digital Twin for the flexible production cell uses the architecture previously defined. Figure 5 represents the technological implementation for the case study.

As shown in Fig. 5, this technological architecture is divided into two domains: the physical and the virtual one. The physical system and the operator are the sources of information for the Digital Twin, and the virtual model and the visualisation and monitoring dashboard are the main components in the virtual domain. Physical-virtual connectivity is achieved through the Modbus TCP/IP industrial communication protocol, which allows collecting data from the PLC used to control the production cell workstations. The data was collected through the use of the KEPServer software, which supports several types of communication protocols, such as Modbus TCP/IP, MQTT (Message Queuing Telemetry Transport) protocol and OPC DA (OPC Data Access). In this work, the communication with the DES model was performed using the OPC

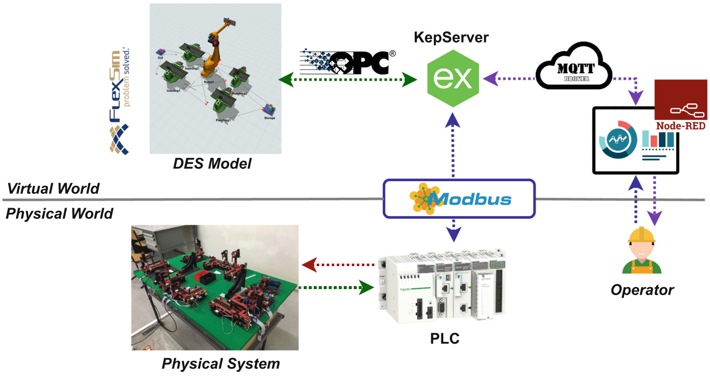

Fig. 5. Technological architecture for the case study flexible production cell.

DA, and the MQTT protocol realised the communication with the developed visualisation and monitoring dashboard.

The DES model representing the digital copy of the production cell was developed using the FlexSim simulation software (see the right side of Fig. 4). This virtual model is fed with the real-time data collected from the physical system through Modbus and OPC DA, being possible to be simulated according to different scenarios devised by the user.

The dashboard for monitoring and visualisation was developed by using NodeRED which allows the operator to visualise the actual operating parameters from the physical system and to receive the warnings on performance degradation or condition change as well as the simulation results. The user can also configure different scenarios to be simulated by the DES, e.g., modifying the availability of machines, processing time, production line configuration and production demand.

4.3 Experimental Results

The flexible production cell was tested in a configuration that contains an input conveyor, a punching station, an indexing station, an output conveyor and the robot, having a maximum capacity of 523 parts per shift. In this situation, the resource utilisation of the punching station, the indexing station and the robot are 56.4%, 56.3% and 87.2% respectively.

During the production system operation, the Digital Twin is collecting the real-time data that is displayed on the visualisation and monitoring dashboard. The monitoring mechanisms are running in parallel aiming to detect abnormalities, condition changes or performance degradation. To simulate a production demand change scenario, the system is fed with a new demand of 580 parts per shift, which generates production demand change warning on the dashboard. Since it is impossible to reach this demand with the current production configuration, the production manager should take decisions on how to increase the production capacity efficiently to meet the new production demand.

Using the implemented Digital Twin, and particularly the available simulation capabilities, the production manager can simulate different scenarios involving distinct configurations and variations, and then analyse the results from each simulated scenario and decide the best action plan to meet the increase in the production demand. Note that this what-if simulation is performed in the background, i.e. not impacting the current operation of the production system.

In this case, the strategic manager considers four different alternatives to solve the problem by considering the following four scenarios:

- **Scenario 1**: addition of one punching station the current configuration.
- **Scenario 2**: addition of one punching station and one indexing station to the current configuration.
- **Scenario 3**: addition of one indexing station to the current configuration.
- **Scenario 4**: increase the speed of the robot, maintaining the current configuration.

The results for the simulation of these four scenarios are listed in Table 1, assessing different key performance indicators (KPIs), e.g., throughput per shift, throughput per hour, mean resource utilisation and profit margin.

Table 1. Achieved results for the four simulated testing scenarios.

	Throughput	Throughput per hour	Mean resource utilisation (%)			Profit (euro)
			Punching	Indexing	Robot	
Current	523	65,4	56,4	56,3	87,2	2571,2
Scenario 1	523	65,4	78,1	56,3	87,3	2555,2
Scenario 2	598	74,8	58,3	58,2	100,0	2910,0
Scenario 3	523	65,4	56,4	28,2	87,2	2551,2
Scenario 4	612	76,5	61,7	61,6	76,6	3016,0

Table 1 also includes the expected profit for each scenario, that is calculated in a simplified manner using the Eq. 1. The calculation of this parameter is based on revenues (calculated by multiplying the number of parts produced per hour by the part value and the production time) and expenses (calculated through the sum of the multiplication between the cost per hour of the machine i and the production time).

$$Profit = N_{Parts} \times Part_{Value} \times Prod_{Time} - \sum_{i=1}^{n} C_i \times Prod_{Time} \quad (1)$$

The achieved results show that from the four simulated scenarios, only Scenarios 2 and 4 can attain the desired production demand. In fact, in Scenario 2, the production capacity is increased but not doubled since the robot manipulator becomes the bottleneck (utilisation of 100%). In Scenario 4, the capability of the robot to perform more operations per time unit leads to an increase in the throughput. On the other hand, for Scenario 1, although a punching station was added, the single indexing station in the system becomes a bottleneck, maintaining the productivity capacity equal to the current production configuration. The same is happening to Scenario 3, where the existing punching station becomes the bottleneck.

Having two scenarios that address the initial requirements, the production manager needs to decide which alternative is better. For this purpose, the profit parameter can be analysed to take the decision. In this case, Scenario 4 is the one that fulfils the requirements and presents the highest profit, since there is no need to add new stations to the current configuration. Based on the achieved results, the manager can make a justified and applicable decision about which would be the most profitable configuration to face the increase in production demand.

5 Conclusions and Future Work

The emergence of Digital Twin technology in the manufacturing domain has shifted the attention of the scientific community. The research in this field is still in its infancy. The existing scientific articles are predominantly theoretical and conceptual, lacking practical demonstrations of the application of the technology. This paper provides a conceptual Digital Twin architecture for enabling decision support based on simulation capabilities and illustrates its applicability in a production cell case study as a proof of concept.

The development of the architecture for the proposed case study used various technologies, namely Modbus, MQTT and OPC DA protocols to implement the connectivity module, the Node-RED to implement the visualisation and monitoring module, and the FlexSim software tool for the simulation module. With the implementation of this Digital Twin, the user can assess the real-time monitoring of the physical system, as well as simulate different scenario configurations aiming to optimise the production processes.

As future work, the case study will be further developed by integrating more workstations, smart AGVs and robot manipulators, and also by integrating the control functionality. The described Digital Twin architecture will also be further developed by considering the possibility to introduce the human operator trust in the Digital Twin decision-making cycle.

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References

1. BC Group: Embracing Industry 4.0 and Rediscovering Growth. https://www.bcg.com/capabilities/operations/embracing-industry-4.0-rediscovering-growth.aspx. Accessed 09 Nov 2018
2. Rodič, B.: Industry 4.0 and the new simulation modelling paradigm. J. Manag. Inf. Syst. Hum. Resour. **50**(3), 193–207 (2017)
3. Bloem, J., van Doorn, M., Duivestein, S., Excoffier, D., Maas, R., van Ommeren, E.: The Fourth Industrial Revolution Things to Tighten the Link Between IT and OT (2014)
4. Da Xu, L., Xu, E.L., Li, L.: Industry 4.0: state of the art and future trends. Int. J. Prod. Res. **56**(8), 2941–2962 (2018)
5. Kagermann, H., Wahlster, W., Helbig, J.: Recommendations for implementing the strategic initiative INDUSTRIE 4.0. Final report, Industrie 4.0 WG, no. April, p. 82 (2013)
6. Bao, J., Guo, D., Li, J., Zhang, J.: The modelling and operations for the digital twin in the context of manufacturing. Enterp. Inf. Syst. **13**(4), 534–556 (2019)
7. Grieves, M., Vickers, J.: Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems. In: Transdisciplinary Perspectives on System Complexity: New Findings and Approach, no. August, pp. 85–113 (2017)
8. Glaessgen, E.H., Stargel, D.S.: The digital twin paradigm for future NASA and U.S. air force vehicles. In: 53rd Structures, Structural Dynamics, and Materials Conference, pp. 1–14 (2012)
9. Lee, J., Lapira, E., Yang, S., Kao, H.: Predictive manufacturing system - trends of next-generation production systems. Soc. Manuf. Eng. **1**, 38–41 (2013)
10. Lu, Y., Liu, C., Wang, K.I., Huang, H., Xu, X.: Digital Twin-driven smart manufacturing: connotation, reference model, applications and research issues. Robot. Comput. Integr. Manuf. **61**, 101837 (2020)
11. Fuller, A., Fan, Z., Day, C., Barlow, C.: Digital twin: enabling technology, challenges and open research. IEEE Access **8**, 108952–108971 (2020)
12. Pires, F., Melo, V., Almeida, J., Leitão, P.: Digital twin experiments focusing virtualisation, connectivity and real-time monitoring. In: Proceedings of the 3rd IEEE International Conference on Industrial Cyber-Physical Systems (ICPS 2020), pp. 309–314 (2020)
13. Kunath, M., Winkler, H.: Integrating the digital twin the manufacturing system into a decision support system for improving the order management process. In: 51st CIRP Conference on Manufacturing Systems, vol. 72, pp. 225–231 (2018)
14. Liu, Q., Zhang, H., Leng, J., Chen, X.: Digital twin-driven rapid individualised designing of automated flow-shop manufacturing system. Int. J. Prod. Res. **7543**, 1–17 (2019)
15. Rohan: Digital Twin Market Worth 15.66 Billion USD by 2023. MarketsandMarkets (2017). https://www.prnewswire.com/in/news-releases/digital-twin-market-worth-1566-billion-usd-by-2023-642374603.html. Accessed 30 Apr 2020
16. Singh, S.: Digital Twin Market worth $35.8 billion by 2025 (2019). https://www.marketsandmarkets.com/PressReleases/digital-twin.asp. Accessed 30 Apr 2020
17. Macchi, M., et al.: Exploring the of digital twin for asset lifecycle management. IFAC-PapersOnLine **51**(11), 790–795 (2018)