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A digital twin framework for the simulation and optimization of production systems

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Abstract

Industry 4.0 has raised the expectations on productivity, automation, and resource efficiency of manufacturing systems. This paper proposes a digital twin framework for the simulation and optimization of production lines and cells that can be used in the design and operation stages. The framework is supported by an architecture that connects manufacturing and machine tool data (digital shadow), the discrete event simulation model and the optimization engine, allowing for a variety of functionalities to plan and manage the production system. A use case is provided to demonstrate this framework, implemented in an automated line for the manufacturing of railway axles.

Keywords: digital twin;discrete-event simulation;monitoring;optimization;servitization

1. Introduction

Industry 4.0 [1] builds upon the advances in Information and Communications Technology (ICT), automation, manufacturing technologies and integration of engineering to develop future manufacturing systems. The implementation of this paradigm intrinsically involves an increased digitalization and complexity of manufacturing systems.

One of the consequences of the implementation process of this paradigm has been the generation of vast amounts of manufacturing data. Data is seen as the new oil of digital manufacturing, where data gathered from the production line and the shopfloor is further used to perform more accurate system modeling, and simulation [2].

At the same time, factories are developing into intelligent environments in which the gap between the real and digital world is shrinking. The Digital Twin concept has a lot to contribute to manufacturing and Industry 4.0 [2]–[4], creating digital counterparts of real processes, products and production systems.

Attention has been paid to the development and implementation of ICT technologies, although it is also recognized that Industry 4.0 will require a business transformation process with implications in operations management [5]. A necessary next step would be to identify new applications and services to provide value to shop managers and technicians, in order to manage better and optimize the performance of production systems and assets. Digital twins should therefore be oriented to these applications.

It is important to mention that the digital twins will also open new opportunities for the providers of these systems, both machine tool builders, original equipment manufacturers (OEMs) and system integrators, in their servitization strategy [6]–[8].

This article focuses on the production digital twin and provides a framework for configuring and implementing digital twins in the design and operation of production systems.

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1.1. Design and operation of production systems

The design of manufacturing and production systems is a complex process [9]. Moreover, production systems are becoming more complex due to the following competitive and context characteristics and trends [10]–[12]: 1) greater variability of product, 2) shorter product life cycles, 3) variable product routing, 4) minimization of the lot size, 5) flexibility in equipment and processes, 6) advanced automation and smart control systems, 7) cyber-physical systems.

Traditional sequential design methods do not adapt well to these new requirements, where the complexity of the systems increase as well as development and commissioning times are becoming shorter. Digital twins have been proposed to enable the interaction of mechanic, electric, software and programmable logic control (PLC) design in the early stage of the development of cyber-physical manufacturing systems [13]. During use stage, the production systems usually undergo modifications in products and configurations that increase the difference between the initial digital model and real production system [14]. Digital twins can fill this gap in the operation of manufacturing systems [3], [12].

At the system level, the design of production systems is a very complex task which involves making multiple trade-offs and decisions. Aware of these complexity, simulation based optimization and discrete event simulation models have been proposed to support in this process [15]–[17].

Moreover, these manufacturing systems also present complexities in the operations management, regarding planning, scheduling, and improvement activities. The production digital twin should therefore support production managers maximizing the performance of their production systems.

This paper proposes a framework for the implementation of Digital Twin at the system level, based on simulation and optimization, to be used for the design and operation of complex manufacturing systems.

1.2. Structure

The remainder of this paper is organized as follows. Section 2 proposes the state-of-the-art, which has been divided in two sub-sections: a) the digital twin concept and b) simulation and optimization of production systems. The 3rd section shows the production digital twin framework, explaining the elements and possible architectures. A demonstration of this framework is explained in Section 4. Finally, conclusions and future work are summarised in Section 5.

2. State of the art

2.1. Digital Twin

The Digital Twin [3] has received increasing attention from industry and academia. Using the definition provided by Stark [6], "a digital twin is the digital representation of a unique asset (product, machine, service, product-service system), that alters its properties, condition and behavior by means of models, information and data". The elements of the Digital Twin according to [13] are the Digital Master, the Digital Shadow and their linkage. Conceptually, the Digital Master would be related to the Digital Factory, which is based on the software tools and methodologies that allow to design, simulate and optimize products and their production systems [18]. The second major element of the Digital Twin is the Digital Shadow, composed of operational data collected by Industry 4.0 technologies (OPC-UA, Big Data, among others) [19]–[21].

The Digital Twin of the manufacturing system is defined by Kunnath [22] as a data-oriented representation of all elements of the manufacturing equipment system, the material flow system, the value stream system, the operating materials system and the human resource system. This definition includes therefore the main systems that should be modelled in the model.

Regarding the level of integration of the data flows, Kritzinger [23] presents an evolutionary categorization between the Digital Model, the Digital Shadow and the Digital Twins, where they differ in the automation of the data. The Digital Model would be similar to the standard simulation model, where there is no automatic data integration. A step forward in the automation of data integration would be the Digital Shadow, where it further exists an automated one-way data flow between the physical and digital objects. This paper introduces The Digital Shadow as the combination of the elements from physical to digital, a concept that differs from the Digital Shadow defined by [6]. Finally, the Digital Twin would require bi-directional integration between the physical and digital object, and vice versa.

The digital twin of a production plant can be hierarchically classified according to its scope. Qi [20] and Tao [21] divide the digital twin into three different levels: unit level, system level, system of system (SoS) level. The unit level is the smallest unit in the production plant, and it represents the equipment on the field (i.e. sensors, actuators, devices). The system digital twin is composed of multiple unit level digital twins (i.e. production line, shop floor, factory) and the SoS digital twin is composed of multiple system level digital twins (i.e. cross company platform). In the same way, D. Guo et al. [24] proposes a unified digital twin at object level, product level and system level where the digital twin of the assembly process is also detailed.

Machine/process twin data can be used for monitoring [25], [26], health, wear estimation and parameter optimization [27], [28]. Focused on manufacturing systems, the applications of the digital twins mentioned in literature are [12], [23], [29], [30]: production planning and scheduling, maintenance, layout planning, engineering design, process control and traceability.

2.2. Simulation and optimization of production systems

Among different simulation approaches, discrete event simulation (DES) is well suited to modeling manufacturing systems [31]–[33]. Discrete event simulation is a popular technique for modelling and analysis of manufacturing systems [31], [34]–[36], both in design and operation stages, with more detailed applications such as: system design and facility layout, improvement and optimization of production flows [37], production planning and control [38], [39], scheduling, maintenance, performance analysis. A complete and thorough review of these applications is provide in [35].

A more novel approach is the integration of optimization in simulation [15], [16], [36], [40]. Optimization enhances the capabilities of simulation for decision making. Simulation based optimization allows to find the optimal or nearly optimal solution in the case of conflicting objectives. Such conflicts may require real time or near real time response when the system is operational. Thus, symbiotic simulation systems [41], [42] and online simulations [43] have been proposed in the literature to enable real time optimization and decision making over the physical system. This is achieved by linking optimization and decision maker engines to the digital twin model. However, the latter should be continuously synchronized with the real system to make accurate decisions.

Regarding data requirements, one of the problems traditionally reported when using DES is the time and cost invested in collecting input data [44], and the quality of the data [45]. Senington [16] proposes a linked data approach for the automatic extraction of data and information to feed plant simulation models. Precisely, the Digital Twin overcomes these limitations, since it is based on the connection between the real data of the physical system and the digital model, performing this task in an automated way.

3. Production Digital Twin Framework

3.1. Proposed framework

This section details the digital twin framework presented in Fig. 1. On the left side of the framework, the digital twin is shown, whereas on the right side, the real smart factory is depicted. The digital twin has been divided in the digital model and the digital shadow [13], [23], whereas the digital shadow is created through the monitoring of the real plant, with different production elements. In this way, four different quadrants have been represented, and the related connection interfaces between them.

Based on the previous hierarchy proposals, our framework considers a unified multi-level digital twin that describes the machine/process twin at the unit level and the production twin at the system level, with the purpose of optimizing system level performance.

The framework distinguishes between the components and functions/applications to perform by the twins, both by the digital shadow and the digital model, at different hierarchy levels. The digital shadow is responsible for the following functions: traceability, current state gathering and model input data estimation, which can be applied to both the system as well as the machine/process level.

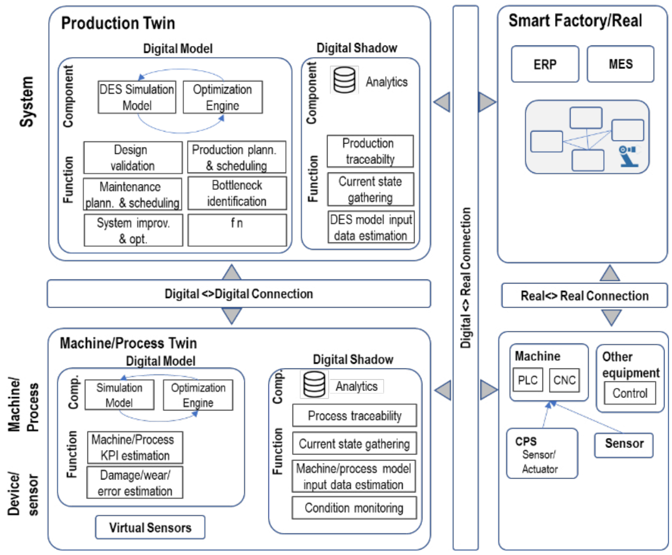

Fig. 1. Production digital twin framework

The envisaged components for building the shadow from the shop-floor Internet of Things (IoT) gateways and cyber-physical systems (CPS) would be data analytics for parameter extraction and repositories for data storage.

On the other hand, the digital models fulfil at the system and machine/process level. System level functionalities are the design validation, production and maintenance planning/scheduling, bottleneck identification, system improvement and system optimization. The main system components are the DES simulation software and the optimization engine. Going down the hierarchy, machine and process components would enhance simulation models with optimization capability, and oriented in a broad sense to the following functionalities: machine/process key performance indicator (KPI) estimation (process time among others) or estimation of damage, wear, or errors (health status, vibrations, or thermal displacements).

During the design stage, OEMs build in an iterative way the production digital model, beginning with more conceptual models. This digital model could be fed with historical data, estimations or synthetic data provided by machine level digital models.

Conceptually, the production digital twin could therefore be updated by gathering data both from the real plant (real->digital connection, through the IoT gateways) or from the lower machine/process level (digital-> digital).

3.2. Proposed architecture

The proposed architecture for the deployment of the framework is shown in Fig. 2. Manufacturing data is gathered directly from the shop floor through an IoT gateway. This data could be related to any piece of equipment, such as machine, handling device or control system. The IoT gateway collects data and sends them to the cloud storage.

The cloud storage is a cloud-based database capable of managing huge amount of data, as well as ordering them according to certain indicators. Moreover, an interoperable mechanism has been integrated to share data through a secured and encrypted API REST.

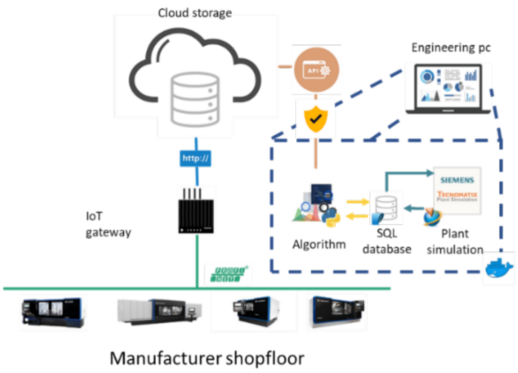

Fig. 2. Proposed architecture

Data stored in the cloud is retrieved by an algorithm built up on the engineering PC. This data is then processed to generate behavioral models of real machines using statistical approaches. Likewise, once the models are built by the algorithm, the results are stored in a local lightweight database (e.g., SQLite). This algorithm is continuously updating the data parameters for process modelling. Based on the monitored data, new product references and flows could be detected.

Finally, a function has been developed to load the parameters stored in the lightweight database into the simulation object. The discrete event simulation input data is updated each time the software starts up.

4. Use case: railway axle production line

This framework has been partially demonstrated through a use case in a production line related to the manufacturing of railway axles. The production line includes the following operations of the axles: identification/marking, manufacturing (turning and grinding) and non-destructive testing (NDT). This line has been developed by a machine tool manufacturer located in the north of Spain, which offers complete and automated solutions. The line is composed of 6 equipment units, entrance conveyor, exit conveyor, a linear gantry and in most of the cases single buffer for each of the machines.

The original installation of the line was commissioned with the following ICT and control elements: Programmable logic control (PLC) and computer numeric control (CNC) for single equipment (machine tools with CNC and PLC, where some other machines are PLC controlled) and a control and monitoring system. This control and monitoring system would be between layer 2 and 3 of the ISA 95 automation pyramid. Machines are connected with the gantry handling equipment. The gantry is upper connected to a server, in which the monitoring and control system, and its supporting database are located.

The line control is located in the gantry, where axle potential movements are decided in response to machine states and priorities.

The line has undergone Industry 4.0 retrofitting, beginning with the installation of machine monitoring gateways to increase current capabilities of the monitoring and control system. In a broader sense, the implementation of the gateways has been the basis for the OEM to maximize the value provided to the customer of the line throughout the whole machine lifecycle. The carried-out activities are listed below, classifying them by activities related to the implementation of the Digital Shadow and the ones related to the Digital Model:

- Implementation of the Digital Shadow
  - Installation of machine gateways to gather CNC/PLC variables.
  - Implementation of a cloud platform for machine level process and state functionalities, which are related but go beyond production functionalities.
  - Business Intelligence (BI) visualization of machine, process, and production data in web format.
  - Implementation of Python based data analytics to estimate indicators based on the cloud variables: estimation of part type process time (distribution per axle reference, mean and standard deviation), estimation of setup times (from reference x to y), estimation of failure indicators.
- Implementation of the Digital Model:
  - Building the DES simulation model in Tecnomatix Plant Simulation.
  - Development of the optimization algorithm in Python, as well as the communication with the simulation engine. The implemented algorithm has been a single-objective genetic algorithm for permutation without repetition to find the best sequence of axles.
  - Implementation of functionalities: production and maintenance planning (2 weeks production execution), sequence optimization based on setup time reduction.

The implementation of the Digital Twin framework has been demonstrated with data transmission from the plant to the model (Digital Shadow concept in Kritzinger [23] classification). At this point, it is not expected that the digital model will automatically change ERP scheduling information as a result of a model simulation.

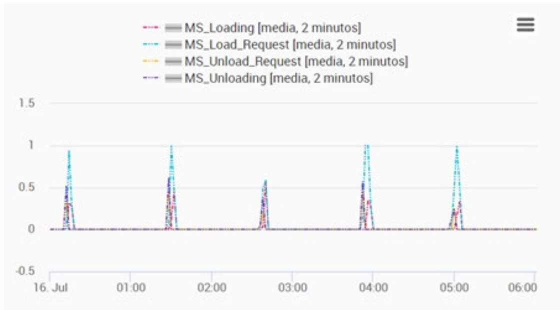

Fig. 3. Monitoring of machine-gantry handling states for process (machining) time estimation over 6 hours of production

Machine level state signals have been visualized and analyzed for the estimation of raw machining time, isolating it from any other time related to the loading and unloading process by the gantry system. This information has also been linked to the axle reference to estimate the average process time by reference type.

As an example, the evolution of these signals over 6 hours is shown in Fig. 3. This figure is one of the visualization objects provided by the BI system, with the possibility to zoom in/out the timescale. Every set of signal peaks involves a sequence of unloading a finished part and loading the next part at a machine. The machining time would be the time between the end of axle loading and the next request for unloading the axle.

Fig. 4. Detail of unloading and loading sequence

A detailed view of the unloading and loading sequence is provided in Fig. 4. These variables are directly mapping PLC variables of a certain machine. The sequence begins when both unloading request (MS_Unload_Request) and loading signals (MS_Unloading) turn to 1. Unloading request signal switches to 0 if the gantry is able to perform the task. Once the unloading is complete, the machine launches a load request (MS_Load_Request) and this signal switches to 1. In this case, the gantry is not able to immediately attend the job, since it must finish the previous task, leaving the axle in the required location. However, if the gantry is able to accept the loading job, MS_Loading will switch to 1. The sequence ends when both MS_Load_Request and MS_Loading are set back to 0.

It is worth mentioning the importance of defining the PLC variables in a proper way, certainly considering the control needs, but also taking into account the variables or required signals to define KPIs . These are key elements for building the digital twins. This issue can be well addressed by the OEM machine tool manufacturers, who are responsible for the design and integration of the pieces of equipment (including PLCs and CNCs), following a bottom-up approach that links machine and equipment level data to the upper level of production system towards the digital twin.

The presented Digital Twin framework will allow production managers to simulate, understand and improve the shop performance. Overall performance is aimed to significantly improve based on the simulation of the digital model and the digital shadow, implemented as a web interface that offers system and single equipment information with business intelligence capabilities.

5. Conclusions

This paper starts from the premise that production systems are increasingly complex both in design and operation. Digital and Industry 4.0 technologies are called to improve the management and performance of production systems. DES simulation and Digital Twin literature have been reviewed to clarify concepts and applications to propose the Production Digital Twin framework. The framework has been explained, as well as an architecture for its implementation.

The Digital Twin enhances, and links data based and model-based capabilities in such a way that can open up new servitization opportunities for suppliers (OEMs or system integrators). It is important that these OEMs have a broader perspective when selecting PLC and control signals, not only for control purposes but also for monitoring and building digital twins.

On the other hand, production managers will have more tools to virtually test their facilities, brought to the market in a user-friendly way, and turning in more knowledge-based decision-making approach.

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References

[1] H. Kagermann, W. Wahlster, y J. Helbig, «Recommendations for implementing the strategic initiative Industrie 4.0: Final report of the Industrie 4.0 Working Group», 2013. Accedido: feb. 25, 2016. [En línea]. Disponible en: http://www.acatech.de/fileadmin/user_upload/Baumstruktur_nach_Website/Acatech/root/de/Material_fuer_Sonderseiten/Industrie_4.0/Final_report__Industrie_4.0_accessible.pdf

[2] Z. M. Cinar, A. A. Nuhu, Q. Zeeshan, y O. Korhan, «Digital Twins for Industry 4.0: A Review», en *Industrial Engineering in the Digital Disruption Era*, Cham, 2020, pp. 193-203. doi: 10.1007/978-3-030-42416-9_18.

[3] E. Negri, L. Fumagalli, y M. Macchi, «A Review of the Roles of Digital Twin in CPS-based Production Systems», *Procedia Manufacturing*, vol. 11, pp. 939-948, 2017, doi: 10.1016/j.promfg.2017.07.198.

[4] «Industry 4.0 and the digital twin : Manufacturing meets its match», Deloitte, Deloitte University Press. Accedido: oct. 30, 2020. [En línea]. Disponible en: https://www2.deloitte.com/content/dam/Deloitte/cn/Documents/cip/deloitte-cn-cip-industry-4-0-digital-twin-technology-en-171215.pdf

[5] C. Cimini, R. Pinto, y S. Cavalieri, «The business transformation towards smart manufacturing: a literature overview about reference models and research agenda», *IFAC-PapersOnLine*, vol. 50, n.º 1, pp. 14952-14957, jul. 2017, doi: 10.1016/j.ifacol.2017.08.2548.

[6] P. Legault *et al.*, «Servitization trend in the machine-tools market: comparing value from turnkey and specialized IoT-based analytics solutions using TOPSIS», *Procedia Manufacturing*, vol. 31, pp. 390-397, 2019, doi: 10.1016/j.promfg.2019.03.061.

[7] M. A. Khan, S. West, y T. Wuest, «Midlife upgrade of capital equipment: A servitization-enabled, value-adding alternative to traditional equipment replacement strategies», *CIRP Journal of Manufacturing Science and Technology*, vol. 29, pp. 232-244, may 2020, doi: 10.1016/j.cirpj.2019.09.001.

[8] M. Zambetti, M. A. Khan, R. Pinto, y T. Wuest, «Enabling servitization by retrofitting legacy equipment for Industry 4.0 applications: benefits and barriers for OEMs», *Procedia Manufacturing*, vol. 48, pp. 1047-1053, ene. 2020, doi: 10.1016/j.promfg.2020.05.144.

[9] M. E. A. El Abdellaoui, F. Grimaud, P. Gianessi, y X. Delorme, «Integrated Decision Process to Design Manufacturing Systems towards Industry 4.0», *IFAC-PapersOnLine*, vol. 52, n.º 13, pp. 1373-1378, ene. 2019, doi: 10.1016/j.ifacol.2019.11.390.

[10] W. ElMaraghy, H. ElMaraghy, T. Tomiyama, y L. Monostori, «Complexity in engineering design and manufacturing», *CIRP Annals*, vol. 61, n.º 2, pp. 793-814, 2012, doi: 10.1016/j.cirp.2012.05.001.

[11] T. Stock y G. Seliger, «Opportunities of Sustainable Manufacturing in Industry 4.0», *Procedia CIRP*, vol. 40, pp. 536-541, ene. 2016, doi: 10.1016/j.procir.2016.01.129.

[12] R. Rosen, G. von Wichert, G. Lo, y K. D. Bettenhausen, «About The Importance of Autonomy and Digital Twins for the Future of Manufacturing», *IFAC-PapersOnLine*, vol. 48, n.º 3, pp. 567-572, ene. 2015, doi: 10.1016/j.ifacol.2015.06.141.

[13] R. Stark, S. Kind, y S. Neumeyer, «Innovations in digital modelling for next generation manufacturing system design», *CIRP Annals*, vol. 66, n.º 1, pp. 169-172, 2017, doi: 10.1016/j.cirp.2017.04.045.

[14] F. Biesinger, D. Meike, B. Kraß, y M. Weyrich, «A digital twin for production planning based on cyber-physical systems: A Case Study for a Cyber-Physical System-Based Creation of a Digital Twin», *Procedia CIRP*, vol. 79, pp. 355-360, ene. 2019, doi: 10.1016/j.procir.2019.02.087.

[15] A. H. C. Ng, S. Bandaru, y M. Frantzén, «Innovative Design and Analysis of Production Systems by Multi-objective Optimization and Data Mining», *Procedia CIRP*, vol. 50, n.º Supplement C, pp. 665-671, ene. 2016, doi: 10.1016/j.procir.2016.04.159.

[16] E. R. Zuniga, M. U. Moris, A. Syberfeldt, M. Fathi, y J. C. Rubio-Romero, «A Simulation-Based Optimization Methodology for Facility Layout Design in Manufacturing», *IEEE Access*, vol. 8, pp. 163818-163828, 2020, doi: 10.1109/ACCESS.2020.3021753.

[17] I. Ricondo, A. Uriarte, y A. Kortabarria, «Discrete event simulation procedure to build the production digital twin of highly automated and complex production systems», *DYNAII*, vol. 95, n.º 1, pp. 478-481, 2020, doi: 10.6036/9394.

[18] G. Chryssolouris, D. Mavrikios, N. Papakostas, D. Mourtzis, G. Michalos, y K. Georgoulias, «Digital manufacturing: history, perspectives, and outlook», *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 223, n.º 5, pp. 451-462, may 2009, doi: 10.1243/09544054JEM1241.

[19] J. Lee, H.-A. Kao, y S. Yang, «Service Innovation and Smart Analytics for Industry 4.0 and Big Data Environment», *Procedia CIRP*, vol. 16, pp. 3-8, 2014, doi: 10.1016/j.procir.2014.02.001.

[20] Q. Qi, F. Tao, Y. Zuo, y D. Zhao, «Digital Twin Service towards Smart Manufacturing», *Procedia CIRP*, vol. 72, pp. 237-242, 2018, doi: 10.1016/j.procir.2018.03.103.

[21] F. Tao, Q. Qi, L. Wang, y A. Y. C. Nee, «Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison», *Engineering*, vol. 5, n.º 4, pp. 653-661, ago. 2019, doi: 10.1016/j.eng.2019.01.014.

[22] M. Kunath y H. Winkler, «Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process», *Procedia CIRP*, vol. 72, pp. 225-231, ene. 2018, doi: 10.1016/j.procir.2018.03.192.

[23] W. Kritzinger, M. Karner, G. Traar, J. Henjes, y W. Sihn, «Digital Twin in manufacturing: A categorical literature review and classification», *IFAC-PapersOnLine*, vol. 51, n.º 11, pp. 1016-1022, 2018, doi: 10.1016/j.ifacol.2018.08.474.

[24] D. Guo, R. Y. Zhong, P. Lin, Z. Lyu, Y. Rong, y G. Q. Huang, «Digital twin-enabled Graduation Intelligent Manufacturing System for fixed-position assembly islands», *Robotics and Computer-Integrated Manufacturing*, vol. 63, p. 101917, jun. 2020, doi: 10.1016/j.rcim.2019.101917.

[25] T. Fuertjes, C. Mozzati, F. Peysson, A. Alzaga, y M. Armendia, «Data Monitoring and Management for Machine Tools», en *Twin-Control: A Digital Twin Approach to Improve Machine Tools Lifecycle*, M. Armendia, M. Ghassempouri, E. Ozturk, y F. Peysson, Eds. Cham: Springer International Publishing, 2019, pp. 125-136. doi: 10.1007/978-3-030-02203-7_7.

[26] X. Beudaert, J. Argandoña, J. Loc'h, I. Bediaga, y J. Munoa, «Monitoring and analytics platform for machine tools», San Sebastian, Spain, abr. 2018. Accedido: dic. 15, 2020. [En línea]. Disponible en: https://hal.archives-ouvertes.fr/hal-01901110

[27] Y. Cai, B. Starly, P. Cohen, y Y.-S. Lee, «Sensor Data and Information Fusion to Construct Digital-twins Virtual Machine Tools for Cyber-physical Manufacturing», *Procedia Manufacturing*, vol. 10, pp. 1031-1042, ene. 2017, doi: 10.1016/j.promfg.2017.07.094.

[28] K. Kannan, N. Arunachalam, A. Chawla, y S. Natarajan, «Multi-Sensor Data Analytics for Grinding Wheel Redress Life Estimation- An Approach towards Industry 4.0», *Procedia Manufacturing*, vol. 26, pp. 1230-1241, 2018, doi: 10.1016/j.promfg.2018.07.160.

[29] T. H.-J. Uhlemann, C. Lehmann, y R. Steinhilper, «The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0», *Procedia CIRP*, vol. 61, pp. 335-340, 2017, doi: 10.1016/j.procir.2016.11.152.

[30] «ISO/DIS 23247-1(en), Automation systems and integration — Digital Twin framework for manufacturing — Part 1: Overview and general principles». https://www.iso.org/obp/ui/#iso:std:iso:23247:-1:dis:ed-1:v1:en (accedido oct. 26, 2020).

[31] M. Jahangirian, T. Eldabi, A. Naseer, L. K. Stergioulas, y T. Young, «Simulation in manufacturing and business: A review», *European Journal of Operational Research*, vol. 203, n.º 1, pp. 1-13, may 2010, doi: 10.1016/j.ejor.2009.06.004.

[32] D. Mourtzis, M. Doukas, y D. Bernidaki, «Simulation in Manufacturing: Review and Challenges», *Procedia CIRP*, vol. 25, pp. 213-229, 2014, doi: 10.1016/j.procir.2014.10.032.

[33] D. Mourtzis, «Simulation in the design and operation of manufacturing systems: state of the art and new trends», *International Journal of Production Research*, vol. 58, n.º 7, pp. 1927-1949, abr. 2020, doi: 10.1080/00207543.2019.1636321.

[34] S. Boyang, H. Windo, T. Ashutosh, y E. Shane, «Integrating Optimisation with Simulation for Flexible Manufacturing System», *Advances in Transdisciplinary Engineering*, pp. 175-180, 2016, doi: 10.3233/978-1-61499-668-2-175.

[35] A. Negahban y J. S. Smith, «Simulation for manufacturing system design and operation: Literature review and analysis», *Journal of Manufacturing Systems*, vol. 33, n.º 2, pp. 241-261, abr. 2014, doi: 10.1016/j.jmsy.2013.12.007.

[36] S. Lidberg, T. Aslam, L. Pehrsson, y A. H. C. Ng, «Optimizing real-world factory flows using aggregated discrete event simulation modelling», *Flexible Services and Manufacturing Journal*, jul. 2019, doi: 10.1007/s10696-019-09362-7.

[37] A. Goienetxea, A. H. C. Ng, E. R. Ruiz, y M. U. Moris, «Improving the material flow of a manufacturing company via lean, simulation and optimization», en *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Singapore, dic. 2017, pp. 1245-1250. doi: 10.1109/IEEM.2017.8290092.

[38] B. Kádár, A. Lengyel, L. Monostori, Y. Suginishi, A. Pfeiffer, y Y. Nonaka, «Enhanced control of complex production structures by tight coupling of the digital and the physical worlds», *CIRP Annals - Manufacturing Technology*, vol. 59, n.º 1, pp. 437-440, 2010, doi: 10.1016/j.cirp.2010.03.123.

[39] D. Gyulai, A. Pfeiffer, B. Kádár, y L. Monostori, «Simulation-based Production Planning and Execution Control for Reconfigurable Assembly Cells», *Procedia CIRP*, vol. 57, pp. 445-450, ene. 2016, doi: 10.1016/j.procir.2016.11.077.

[40] S. E. H. Petroodi, A. B. D. Eynaud, N. Klement, y R. Tavakkoli-Moghaddam, «Simulation-based optimization approach with scenario-based product sequence in a reconfigurable manufacturing system (RMS): A case study», *IFAC-PapersOnLine*, vol. 52, n.º 13, pp. 2638-2643, ene. 2019, doi: 10.1016/j.ifacol.2019.11.605.

[41] B. S. Onggo, N. Mustafee, A. Smart, A. A. Juan, y O. Molloy, «Symbiotic simulation systems: hybrid systems model meets big data analytics», en *2018 Winter Simulation Conference (WSC)*, Gothenburg, Sweden, dic. 2018, pp. 1358-1369. doi: 10.1109/WSC.2018.8632407.

[42] E. L. Silva Teixeira, B. Tjahjono, S. C. A. Alfaro, y R. Wilding, «Extending the decision-making capabilities in remanufacturing service contracts by using symbiotic simulation», *Computers in Industry*, vol. 111, pp. 26-40, oct. 2019, doi: 10.1016/j.compind.2019.06.005.

[43] J. Leng *et al.*, «Digital twin-driven rapid reconfiguration of the automated manufacturing system via an open architecture model», *Robotics and Computer-Integrated Manufacturing*, vol. 63, p. 101895, jun. 2020, doi: 10.1016/j.rcim.2019.101895.

[44] P. Barlas y C. Heavey, «Automation of input data to discrete event simulation for manufacturing: A review», *Int. J. Model. Simul. Sci. Comput.*, vol. 07, n.º 01, p. 1630001, mar. 2016, doi: 10.1142/S1793962316300016.

[45] J. Bokrantz, A. Skoogh, D. Lämkull, A. Hanna, y T. Perera, «Data quality problems in discrete event simulation of manufacturing operations», *SIMULATION*, vol. 94, n.º 11, pp. 1009-1025, nov. 2018, doi: 10.1177/0037549717742954.