Vertically Integrated Digital Twins for Rapid Adaptation of Manufacturing Value Chains

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ABSTRACT

The rapid changes in social, political and economic policies in today's European landscape create an increasingly turbulent and demanding market. In response to disruptive internal and external factors, the manufacturing industry strives to establish integrated, intelligent and digital solutions, targeting sustainable, reconfigurable and resilient systems capable of swiftly ramping up to maximum production capacity, enabling rapid adaptations in product functionality, process technology and production volume. In this context, Digital Twins (DTs) are means to map complex manufacturing systems and process chains for fast and efficient reconfiguration of production lines and entire value chains. This paper proposes a holistic architecture for digital twins spanning various hierarchical levels: *(i)* product level, *(ii)* process level, *(iii)* system level, and *(iv)* system of systems level. The benefits and challenges of the proposed approach are discussed in a real case study from automotive industry.

INTRODUCTION

Traditional manufacturing systems are vulnerable to sudden changes in their local ecosystem and market environment. Co-evolution of products, processes and production systems necessitates a transformation enabled by state-of-the-art technologies in order to remain globally competitive (Tolio et al. 2010). Early implementations of digitally-enhanced systems were oriented towards boosting system's productivity, resource efficiency and mid-term responsiveness (Tolio et al. 2014). However, the adoption of digital technologies in the context of Industry 4.0 to date typically follows a gradual approach. Nowadays, this gradual adaptation falls short to proactively compensate production losses imposed by ever-fluctuating demand and higher customer expectations. Hence, reconfigurable manufacturing systems (RMSs) gain particular attention to cope with these issues. RMSs exploit the advantages of decision-making mechanisms and the set of technologies to design, develop, monitor and control manufacturing systems (Koren et al. 2018). Digital Twins (DTs) are one of the widely adopted tools in RMSs for representing both the physical and logical state of a specific product, process or multi-stage manufacturing system in a digital domain (Boschert and Rosen 2016; Schleich et al. 2017; Wang et al. 2019). DTs are able to elaborate in-line gathered heterogenous planning and process data (Tomiyama et al. 2019), which allows them to explore and evaluate a priori the possible future scenarios and provide the best strategy in decision support framework that optimizes certain production aspects: for instance, final quality (Yemane et al. 2018; Colledani et al. 2018; Ceglarek et al. 2020; Magnanini and Tolio 2021a; Matta and Lugaresi 2021), predictive maintenance (Makris et al. 2019) or production planning (Magnanini et al. 2021b). On the other hand, the factors that are outside the process chain, such as inter-organizational circumstances and external environment dynamics (e.g., raw material shortage, technological advancements), also need to be considered for the consistent mapping of DTs (Hänel et al. 2021a). Indeed, the logistical disruptions and high market variability in demand-driven production (Just-In-Time or Just-In-Sequence) continuously raise significant challenges in delivery strategy and warehousing. Therefore, logistics DTs can be utilized for supply chain networks to early detect changes and

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simulate alternative intralogistics scenarios to respond promptly (Ivanov and Dolgui 2021; Moshood et al. 2021).

Even though these contributions to scientific literature are relevant, they primarily focus on the development and implementation of individual DTs at single level within a manufacturing system or their horizontal collaboration. The term *horizontal collaboration* here refers to the DTs collaborating at the same hierarchical level. On the contrary, to achieve completely sustainable, agile and smart manufacturing, a holistic approach that incorporates both the horizontal and the vertical linking of digital representations in the form of DTs is required. In RMS context, this means deriving the optimal network-level solution by embedding product, process, system and system of systems DTs in an integrated framework to provide a comprehensive reconfiguration strategy.

This paper discusses the vertical integration of several DTs acting at various levels in a unified, human-centred architecture that leverages the benefits of digital technologies to demonstrate a synthetic view of the value chain and feasible reconfiguration options. In fact, the advantage of having a unique and comprehensive model for the performance evaluation and joint parameter adaptation of the manufacturing system, based on data gathered from the operating system and its surroundings, is discussed in particular when tactical, but also strategic decisions are to be considered.

The paper is organised as follows: the proposed framework is presented in Section 2; in Section 3, a real case study is introduced, challenges and solutions are explained; lastly, the conclusions and future research directions are addressed in Section 4.

PROPOSED VERTICAL FRAMEWORK

The developed framework for rapid repurposing, adaptation and ramping-up of production lines and dynamic networks to match new production requirements is provided in Figure 1.

DTs can fulfil divergent functions at each level. A uniform subdivision has not yet been established in the literature, as there are peculiar views on classifying part of a manufacturing system as a self-contained system or an integral part of a larger system. A systematisation into hierarchically arranged system levels is however widespread. While some industrial enterprises use production-specific terms such as equipment, process or plant (Wanasinghe et al. 2020; Cinar et al. 2020), a broader division is given as unit, system and system of systems in (Barth et al. 2020; Tao et al. 2019). In this article, the terms product-level, process-level, system-level and system of systems-level DTs are considered.

Product-level DTs include a product model, which can be based on data-driven, physics-based or hybrid approaches. It contains the material and product design information and correlates Key Quality Characteristics (KQCs) of the constituent components to predict the output product functionality and quality. This information is elaborated in *process-level DTs,* simulating the process behaviour and running an optimisation algorithm to select the optimal process parameters and settings for each associated unit (e.g., the trajectory of a robotic arm) depending on measured KQCs of incoming parts. The increased use of sensors

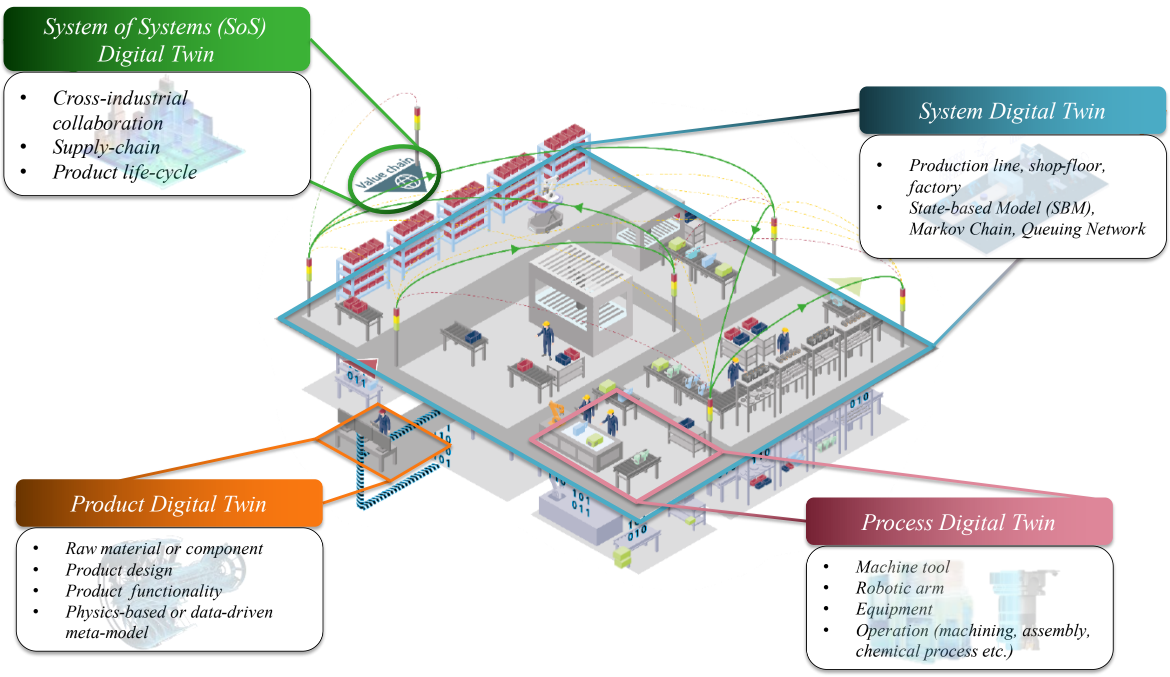

Figure 1. Vertically integrated DTs framework connecting product, process, system and system of systems-level DTs.

and in-line measurement instruments allows the synchronous analysis of simulation models during manufacturing, using empirical data acquired through systematic in-line observations as an input, for downstream adjustment of machine settings for the next operations. Thus, before the actual physical changeover, simulation results in the virtual domain can support the decision-making of the operator, or directly adapt the process parameters, preventing the defect generation or their superimposition into end-of-line waste. In order to increase usability, scalability and interpretability, while reducing the computational burden of these models, proper order reduction and meta-modelling solutions are highly encouraged, simplifying model complexity but capturing the most relevant process dynamics and input parameters - output KQCs correlations. It is extremely critical especially for process-level DTs since they should not interfere with the processing time, turning DTs into system bottlenecks.

System-level DTs, motivated by industrial needs, are innovative manufacturing flow models according to state-based representations of production systems. Thanks to system-level DTs, the production logistics and quality performance of alternative production line configurations and workforce allocations can be evaluated to support inventory and inspection station allocation and properly balance the trade-off between quality and productivity, which leads to an increase in system yield (Y^{system}) defined as the fraction of conforming products produced by the system with respect to the total (E^{eff}/E^{tot}). These models are continuously fed with shop-floor data, in order to provide a high-fidelity, dynamic, virtual representation of the production flow. The user (usually the production planner) can import the DTs of production modules (block-based approach) in the workspace from a catalogue, capturing machine failures, process deviations and disturbances, to select the capabilities and form an initial system layout. For already integrated modules, the available production data is analysed by process intelligence tools to let SBM of the production modules emerge. The SBM for the entire production system is generated starting from the reconfigurable module state models by using a physics-based composition approach. Both long-term and short-term performance measures are predicted under given process chain configurations.

It is important to note that, during the reconfiguration of a manufacturing system, the intralogistics and supply chains need to be analysed as well. With the help of previously gained knowledge, early prediction of the impact of changes, for instance in shipping traffic, becomes available as a result of logistics DTs that continuously evaluate the supply chain on the level of *system of systems*. At this point, system-level DT and logistics DT can be unified in a multi-objective optimisation workflow to simulate the alternative value chains to generate KPIs (e.g. lead time, robustness, costs) and make them accessible for an interactive decision tool to choose the final reconfigured process chain based on a situation-adapted mix of KPIs. Here, each value chain is generated by exploring and combining feasible parameters of the two DTs that perform the accurate analysis of the individual value chains and related KPIs. Additionally, the alternative value chain generation and analysis allow the expansion of feasible solution space of supply chain and manufacturing process reconfiguration scenarios. The integrated formulation of the value chain, linking the product to process decisions in a factory to logistics process decisions in cross-sectorial business environment and vice versa, enables to derive the optimum network-level solution. The sequential approach, where the optimal logistics reconfigurations determine the manufacturing process decisions or vice versa, leads to suboptimal solutions. The iterative two-way communication of these two DTs inside a unique framework is a missing aspect in most of current tools and is the key to deriving global optimal reconfiguration solutions.

As explained, the proposed framework is based on the coupling and intertwining of four pillars, each of them exchanging data and information collected from their respective levels through PLC, MES, PLM or ERP. The acquisition and management of such unsynchronized, heterogenous, multi-resolution and multi-scale data about:

i) Material/product, gathered by inspection technologies, both contact and non-contact, in-line and off-line,
ii) Process, gathered by in-process sensors,
iii) Machine state, gathered by production monitoring system,
iv) Product flow, gathered by part tracking solutions,
v) Codified feedback, gathered operators,
vi) Market, gathered from external data lakes,

pass semantic tagging, processing and integration steps in data management layer (Magnanini et al. 2020). This allows to achieve the observability of product, process and resource states. Hereby, certain data gathering and cybersecurity protocols need to be established for safe and secure upscaling of the framework. In this sense, one solution could be European activities such as GAIA-X (Seidel et al. 2022), which can, for example, realise trustworthy handling of data and its use at all levels of the value chain, especially in the area of high-tech applications (Hänel et al. 2021b).

The output of this framework is composed of a set of management decisions or control actions for dynamically driving the manufacturing value chain to the achievement of production efficiency and quality targets, with a continuous improvement loop, suitable for fast-changing, difficult-to-predict production and performance requirements.

Lastly, the main challenges posed by the necessary seamless integration of DT technology into the manufacturing system and the cognitive loads on the operating personnel are taken into account with the help of a human-centred approach (Longo et al. 2022). This approach depends on the basis of experience and technical competencies of the employee. Firstly, the interaction and awareness with digital technologies are driven, particularly for skilled workers, using upskilling based on education levels and needs. This includes, for example, the application of Augmented Reality (AR) and Virtual Reality (VR) at product or process level. Furthermore, the application of sensor-equipped tools, for instance in fields involving highly manual work, enable process recording and down skilling process evaluation. On the other hand, KPI-based metrics can be made available to the user, i.e., decision-makers. To facilitate user interaction, a set of simplified GUIs and HMIs can be designed and developed to support production and quality planning managers as well as shop-floor operators, to quickly adapt production targets and line management strategies to the specific changing demand levels and features. In addition to that, a broad database enables the user to make predictions, which are particularly suitable for the system and system of systems level to make optimal decisions based on the observed situation. Hence, the human can actively participate in each manufacturing step and collaborate with developed DTs, putting into work also their knowledge to comprehensively compensate for the drastic changes implied by fluctuating market requirements.

REAL CASE STUDY FROM AUTOMOTIVE INDUSTRY

The challenges, benefits and preliminary implementation steps of the proposed architecture in previous section are elaborated under this section in a demonstrator from car body parts.

Car body parts – Fontana Group

Fontana Group is a leading Italian producer of luxury and sports car body parts. The process chain of Fontana includes manufacturing of dies, stamping of body panels, production of outer and inner body parts, assembling of complete body-in-white and sub-assembly of closures and fixed components, as shown in Figure 2.

The expanding use of secondary and "green" aluminium, to answer the volatile market dynamics in terms of raw material availability, elevates the number of scraps in automotive industry since these alloys have variable mechanical properties that affect the final quality. Thus, it becomes very crucial to predict the forming behaviour before the defects accumulate and result in non-conforming products. Moreover, due to:

i) The growing demand and customization for member of car models call for increasing number of production cells since each cell is customized for individual parts, not capable of being used for families (similar models derived from single versions) because the equipment is not modular and automated. Eventually, the space occupied for production operations and logistics management rises day by day, in addition to long cycle times caused by handling.

ii) Increasing the grade of automation and quality standard requirements force greater investments, but manual production with low investments and high quality guaranteed by automation with high investments must be correctly balanced to achieve the desired quality in the scheduled time.

iii) Short notice to produce, shorter time to market requests smaller batches and rapid reconfiguration. For this purpose, the production cells suitable for several types of pieces, instead of one-to-one matching, are preferred for a conversion in the event of a product change, rather than dismissing the cells

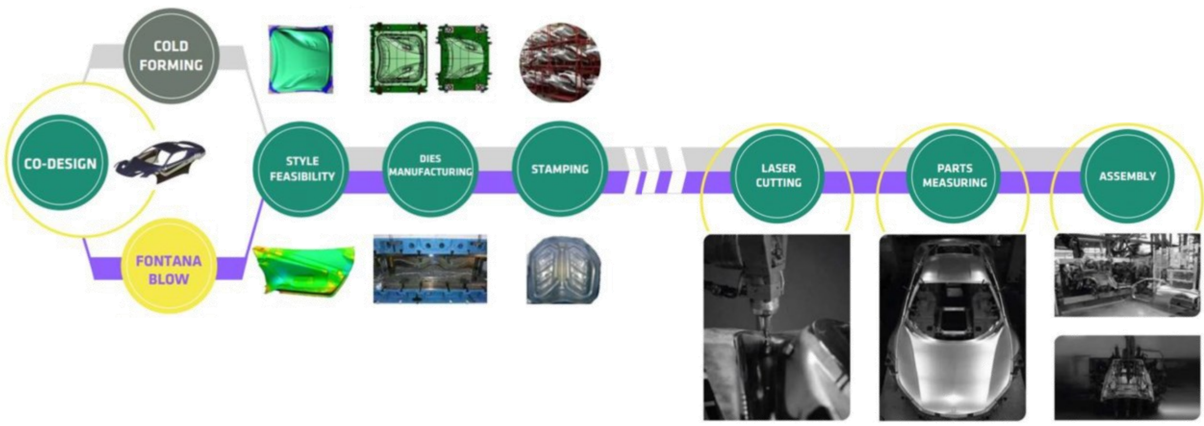

Figure 2. Fontana Group Production Steps

at the end. Furthermore, currently, the single cells are 100% saturated only for a brief time period, while the rest of the time they are stationary. Multi-product cells can resolve this problem.

iv) Process stability issues, where temperature and deformation rate must remain constant throughout super plastic forming process, and shrinkage of metal sheets due to uncontrolled cooling asks for rework operations for deviated parts.

DTs carry immense importance to Fontana not only to predict the forming behaviour but also to simulate the assembly processes in order to anticipate any deviation from nominal feature values, activate downstream compensation by means of feed-forward control and reduce assembly setup time. To enable higher flexibility and resilience of Fontana Group's manufacturing system, the DTs of the proposed architecture are explained in the following.

Product-level DT: Constantly monitors the material database for the availability and type of raw materials. The impact of variability in mechanical properties of different materials is reduced by back-and-forth information exchange with product meta-model and optimisation algorithm that searches the solution domain constrained by inventory availability to adjust the product configuration.

Process-level DT: The numerical model with an accurate digital description of the production processes. Simulation of forming, hemming and assembly processes in order to obtain quality improvements and best tooling performance under optimal process parameters for the next operation within a feasible range based on product-level DT outputs. Indeed, part FEM model is utilized for the automatic configuration of boundary conditions and loads. In addition to that, the lessons learned at the end deepen the product and process know-how that mainly depends on operator expertise (e.g., qualified or non-qualified), and provides valuable feedback for operator learning.

System-level DT: In order to obtain a sub-assembled part "family", a Multi-Product Line (MPL) is needed. MPL includes all the necessary manufacturing processes like hemming, bonding, self-piercing, spot welding and clinching for bodyside and door. This allows to optimise the MPL associated costs (investments, management and maintenance), part handling and assembly cycle time, and ultimately the overall cell performance for the production mixes and batches involved in the same MPL. The Discrete Event Simulation (DES) of the process chain is developed to foresee, through historical data and peculiar system dynamics, system operation, reachable throughput and bottlenecks: enabling the optimisation of resources and storage. Afterwards, when the system is working, the DES can be used to verify how the production capacity is affected by modifications of the different parameters or shop-floor layouts, to highlight possible criticalities and to evaluate the benefit of potential improvements that can be performed on the equipment. All those actions can be conducted by the simulation before proceeding with any physical activity.

System of systems-level DT: Cross-enterprise supply-chain and manufacturing cooperation. It includes various stages of the product lifecycle, where the data from all these cycles are combined. Thanks to system of system level DTs, possible value streaming scenarios for defective (3-4%), scrapped (0.5%) or post-use returned products are identified and based on the economic feasibility of the alternatives, in-line defect compensation, recycling or post-use returned product value retention strategies such as remanufacturing, reuse, repair are selected as a basis for reconfiguration.

CONCLUSIONS AND FUTURE WORKS

This paper puts modular DTs deployed on different manufacturing levels, from bottom (product and process) to top (system and system of systems level), into a unique human-centric framework to be used for short and long-term reconfiguration of manufacturing systems. The current challenges in a real case study from automotive industry and what possible benefits the proposed framework can bring by integrating the vertical solution are discussed. To tackle the vague standards of interfaces and software for interoperable design and use of DTs and to guarantee the data flow between multiple system layers, Industrial Internet of Things (IIoT) based on integrated data gateways, edge computing or Data Quality Management (DQM) platforms are considered.

Future research will be focused on the implementation of a collaboration platform for capability-based matchmaking between the required production capabilities for reconfiguration scenarios under consideration and available skills in the local ecosystem for dynamic and agile production network cocreation. Based on the prognosis of the needed capabilities, additional production modules (machines) to be acquired in order to satisfy the new production needs will be identified. The platform will then provide the environment to enable the fast generation of focused connections among different actors of the value chain, where the end-users will be able to identify potential suppliers in their local ecosystems or outside, and adjust the production module configuration, product recipes and production flow in their manufacturing system, while minimizing their costs.

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REFERENCES

Barth, L.; Ehrat, M.; Fuchs, R.: and Haarmann, J. 2020. “Systematization of digital twins,” in *ICISS 20: Proceedings of the 3rd International Conference on Information Science and Systems (New York, United States of America, Mar. 2020)*, 13–23. doi:https://doi.org/10.1145/3388176.3388209.

Boschert, S. and R. Rosen. 2016. "Digital Twin—The Simulation Aspect." In *Mechatronic Futures*, P. Hehenberger and D. Bradley (Eds.), Springer, Cham. 59-74. doi:https://doi.org/10.1007/978-3-319-32156-1_5.

Ceglarek, D.; Franciosa, P.; Sokolov, M.; Sinha, S; and Sun T. 2020. "Deep learning enhanced digital twin for Closed-Loop In-Process quality improvement." *CIRP Annals - Manufacturing Technology* 69(1): 369-372. doi:https://doi.org/10.1016/j.cirp.2020.04.110.

Cinar, Z.M.; Nuhu, A.A.; Zeeshan, Q.; and Korhan, O. 2020. "Digital Twins for Industry 4.0: A Review," in *Industrial Engineering in the Digital Disruption Era*. Calisir, F., Korhan, O. (Eds.), GJCIE 2019. Lecture Notes in Management and Industrial Engineering. Springer, Cham. 193-203. doi:https://doi.org/10.1007/978-3-030-42416-9_18.

Colledani, M.; Yemane, A.; Lugaresi, G.; Borzi, G.; and Callegaro, D. 2018. "A software platform for supporting the design and reconfiguration of versatile assembly systems." *Procedia CIRP - 51st CIRP Conference on Manufacturing Systems (Stockholm, Sweden, May 16-18).* 808-813. doi:https://doi.org/10.1016/j.procir.2018.03.082.

Hänel, A.; Seidel, A.; Frieß, U.; Teicher, U.; Wiemer, H.; Wang, D.; Wenkler, E.; Penter, L.; Hellmich, A.; and Ihlenfeldt, S. 2021a. "Digital Twins for High-Tech Machining Applications—A Model-Based Analytics-Ready Approach." J*ournal of Manufacturing and Materials Processing* 5(3): 80. doi:https://doi.org/10.3390/jmmp5030080

Hänel, A.; Seidel, A.; Mehling, C.W.; Dementyev, A.; Kozak, K.; Seidel, R.; Teicher, U.; Hellmich, A.; Drossel W.G.; and Ihlenfeldt, S. 2021b. "Impact of Cyber-physically enhanced manufacturing on the product requirement documentation in high-tech applications" *Procedia CIRP - 18th CIRP Conference on Modeling of Machining Operations (Ljubljana, Slovenia, Jun. 15-17)*. 210-215. doi:https://doi.org/10.1016/j.procir.2021.09.036

Ivanov, D. and Dolgui A. 2021. "A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0." *Production Planning & Control* 32(9): 775-788. doi:https://doi.org/10.1080/09537287.2020.1768450.

Koren, Y.; Gu, X.; and Guo, W. 2018. "Reconfigurable manufacturing systems: Principles, design, and future trends." *Frontiers of Mechanical Engineering* 13(2): 121-136. doi:https://doi.org/10.1007/s11465-018-0483-0.

Longo, F.; Nicoletti, L.; and Padovano, A. 2022. " New perspectives and results for Smart Operators in industry 4.0: A human-centered approach" *Computers & Industrial Engineering*, vol. 163, 107824. doi:https://doi.org/10.1016/j.cie.2021.107824

Magnanini, M.; Colledani, M.; and Caputo, D. 2020. "Reference Architecture for The Industrial Implementation of Zero-Defect Manufacturing Strategies." *Procedia CIRP, 93*, 646-651. doi:https://doi.org/10.1016/j.procir.2020.05.154

Magnanini, M.C. and Tolio, T. 2021a. "A model-based Digital Twin to support responsive manufacturing systems." *CIRP Annals - Manufacturing Technology* 70(1): 353-356. doi:https://doi.org/10.1016/j.cirp.2021.04.043.

Magnanini, M.C.; Melnychuk, O.; Yemane, A.; Strandberg, H.; Ricondo, I.; Borzi, G.; and Colledani; M. 2021b. "A Digital Twin-based approach for multi-objective optimization of short-term production planning" *IFAC-PapersOnLine* 54(1): 140-145. doi:https://doi.org/10.1016/j.ifacol.2021.08.077

Makris, S.; Aivaliotis, P.; Georgoulias, K.; and Arkouli, Z. 2019. "Methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance." *Procedia CIRP - 52nd CIRP Conference on Manufacturing Systems (Lugano, Switzerland, Jun.29-Jul.1).* 417-422. doi:https://doi.org/10.1016/j.procir.2019.03.072.

Matta, A. and Lugaresi, G. 2021. "Automated manufacturing system discovery and digital twin generation." *Journal of Manufacturing Systems* 59: 51-66. doi:https://doi.org/10.1016/j.jmsy.2021.01.005.

Moshood, T.D.; Nawanir, G.; Sorooshian, S.; and Okfalisa, D. 2021. "Digital twins driven supply chain visibility within logistics: A new paradigm for future logistics." Applied System Innovation 4(2): 29. doi:https://doi.org/10.3390/asi4020029

Schleich, B.; Anwer, N.; Mathieu, L.; and Wartzack, S. 2017. "Shaping the digital twin for design and production engineering." *CIRP Annals - Manufacturing Technology* 66(1): 141-144. doi:https://doi.org/10.1016/j.cirp.2017.04.040.

Seidel, A.; Wenzel, K.; Hänel, A.; Teicher, U.; Weiß, A.; Schäfer, U.; Ihlenfeldt, S.; Eisenmann, H.; and Ernst, H. 2022. "Towards a Seamless Data Cycle for Space Components - Considerations from the growing European future Digital Ecosystem GAIA-X" Deutscher Luft- und Raumfahrtkongress (Dresden, Germany, Sep. 27-29).

Tao, F.; Qi,Q.; Wang, L.; and Nee, A.Y.C. 2019. " Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and

Comparison", Engineering 5(4): 653-661. doi:https://doi.org/10.1016/j.eng.2019.01.014.

Tolio, T.; Ceglarek, D.; ElMaraghy, H.A.; Fischer, A.; Hu, S.J.; Laperrière, L.; Newman, S.T; and Vancza, J. 2010. "SPECIES — Co-evolution of products, processes and production systems." *CIRP Annals - Manufacturing Technology* 59(2): 672-693. doi:https://doi.org/10.1016/j.cirp.2010.05.008.

Tolio, T.; Colledani, M.; Fischer, A.; Iung, B.; Lanza, G.; Schmitt, R.; and Vancza, J. 2014. "Design and Management of Manufacturing Systems for Production Quality." *CIRP Annals - Manufacturing Technology* 63(2): 773-796. doi:https://doi.org/10.1016/j.cirp.2014.05.002.

Tomiyama, T.; Lutters E.; Stark, R.; and Abramovici, M. 2019. "Development capabilities for smart products." *CIRP Annals - Manufacturing Technology* 68(2): 727-750. doi:https://doi.org/10.1016/j.cirp.2019.05.010.

Wanasinghe, T. R.; Wroblewski, L.; Petersen, B.K.; Gosine, R.G.; James, L.A.; De Silva, O.; Mann, G.K.I.; and Warrian, P.J. 2020. "Digital Twin for the Oil and Gas Industry: Overview, Research Trends, Opportunities, and Challenges," *IEEE Access*, vol. 8, pp. 104175–104197. doi:https://doi.org/10.1109/ACCESS.2020.2998723.

Wang, J.; Ye, L.; Gao, R.X; Li, C.; and Zhang, L. 2019. "Digital Twin for rotating machinery fault diagnosis in smart manufacturing." *International Journal of Production Research* 57(12): 3920-3934. doi:https://doi.org/10.1080/00207543.2018.1552032.

Yemane, A.; Colledani, M.; Lugaresi, G.; Frigerio, N.; Borzi, G.; Bassi, A.; and Callegaro, D. 2018. "A Decision Support Methodology for the Design of Reconfigurable Assembly Systems." *IFAC-PapersOnLine* 51(11): 108-115. doi:https://doi.org/10.1016/j.ifacol.2018.08.243.

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