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Integrating production and maintenance planning in process industries using Digital Twin: A literature review

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Abstract: Among the Industry 4.0 technologies transforming manufacturing environments, the Digital Twin (DT) technology is gaining attention as a driver for improving manufacturing performance and a platform to enhance collaboration. While the advantages of leveraging DT for supporting decision-making in production planning and maintenance planning are recognized, research taking an integrated perspective is scarce. In addition, besides the growing trend, recent studies highlight the limited adoption of DTs in process industries, emphasizing the necessity to address the unique features of their production processes. Through a literature review, this paper points out the main obstacles encountered during the implementation of DT in process manufacturing industries, as well as shows the research gap in exploiting DT to support the integration of decisions concerning production and maintenance and underscores the need for further investigation in this direction to discover its full potential.

Keywords: Digital Twin, process industry, production planning, maintenance planning, literature review

1. INTRODUCTION

Decisions within production planning (PP) are made to fulfill customer demand on time, ensuring the required product quantity and quality while simultaneously minimizing production expenses. Maintenance planning (MP) is concerned with decisions to maximize system availability and reliability while keeping maintenance costs at a minimum. These managerial responsibilities are delegated to distinct departments, namely production and maintenance, which traditionally operate independently within companies. Nevertheless, many researchers claim that overcoming established barriers and improving communication are essential to enhancing overall business performance (Arena et al., 2022), commonly assessed through comprehensive key performance indicators (KPIs), such as overall equipment effectiveness (OEE) and throughput (Maheshwari et al., 2022).

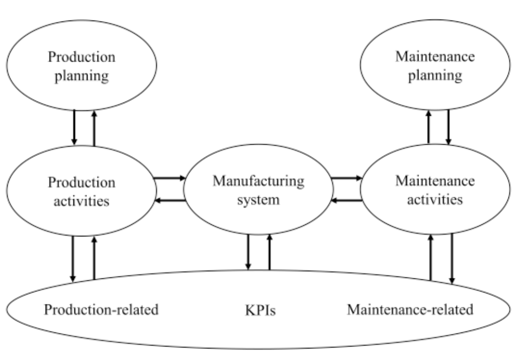

Figure 1. Production and maintenance interdependency

The benefits of the integration directly stem from the intrinsic interdependencies characterizing these decisions and their impact on the manufacturing system, consequently affecting overall KPIs, as illustrated in Figure 1.

For this study, the manufacturing system is limited to the set of operations, resources, and technologies directly involved in the transformation of raw materials into final products.

Decisions within PP inevitably influence the manufacturing system's performance by executing production activities, such as processing work orders. This directly affects production-related KPIs, including availability, utilization efficiency, and throughput rate (Maheshwari et al., 2022). At the same time, production tasks indirectly influence maintenance-related KPIs, such as mean time to failure (MTTF), as a result of the manufacturing system's usage.

Adopting the opposite perspective can lead to similar considerations. Decisions within MP affect the manufacturing system's performance through the execution of maintenance activities, such as inspection, repair, and replacement. Effective planning of maintenance activities directly leads to enhanced maintenance-related KPIs. Nevertheless, carrying out maintenance tasks indirectly affects production-related KPIs, either by requiring production stoppages or by ensuring the smooth operation of the manufacturing system.

Considering these relationships, it becomes evident that decisions made within one department can have varying impacts on the performance of the other. Hence, it is advisable to approach such decisions in an integrated manner to enhance overall KPIs.

This consideration holds even stronger in the context of process industries. What distinguishes them from discrete manufacturing is the production of non-assembled products obtained from transforming raw materials through a series of operations connected in a continuous flow (Storm et al., 2013). As a result, they have distinctive characteristics, including elevated downtime costs, high safety risks, strict quality requirements, high investment costs, and low product margins (Zhu & Ji, 2023b). Because of these distinctive features, manufacturing system reliability and production efficiency are critical, as well as characterized by closer interdependency.

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Therefore, adopting a comprehensive perspective when dealing with the above-mentioned decisions in these industries can yield even more significant benefits.
Digital technologies are revolutionizing manufacturing environments nowadays. Within this transformation, there is an increasing interest in the Digital Twin (DT) technology for its role in real-time decision support in manufacturing through monitoring, simulation, prediction, and optimization.
Among the applications in manufacturing, DT is commonly used to simulate and optimize production or to predict the manufacturing system's condition to define maintenance measures (Spindler et al., 2021).
Importantly, being a virtual replica and providing a shared view of the manufacturing system, the DT holds the potential to improve collaboration between departments in an enterprise (Singh et al., 2021).
Despite the growing number of studies on this technology, the exploration of DT in process industries remains limited (Perno et al., 2022). However, the distinct features of these industries present unique challenges in DT implementation, deserving specific consideration (Perno et al., 2023). Hence, this study is limited to encompassing these manufacturing sectors. Additionally, within this context, literature addressing the use of DT to improve the collaboration between production and maintenance is lacking.
Therefore, through a literature review, this paper investigates the development of DT to support PP and MP within process industries. The goal is to investigate the already mentioned research gap while highlighting the specific challenges associated with its implementation in process industries, especially for improving the integration between production and maintenance.
The following sections of this paper are structured as follows: Section 2 illustrates how the literature review was conducted, Section 3 includes a descriptive analysis of the selected publications, Section 4 presents a content analysis of the DT applications, Section 5 highlights the challenges associated with the DT implementation, and Section 6 summarizes the insights gained from the study.

2. METHODOLOGY

A literature review was conducted to explore the implementation of DT in process manufacturing, explicitly focusing on PP and MP as application areas.
The PRISMA procedure, illustrated in Figure 2, was followed for this purpose (Page et al., 2021).

2.1 Literature identification

The first step consisted of the search for articles in the Scopus Database using this search string:

TITLE-ABS-KEY ("digital twin*") AND TITLE-ABS-KEY (production OR maintenance) AND TITLE-ABS-KEY ("process industr*" OR "oil and gas" OR chemical OR pharmaceuticals OR food OR steel OR iron OR mining OR metal OR aluminum OR glass OR ceramic OR clay OR cement OR concrete OR stone OR beverage OR paper OR pulp)

The industrial sectors specified in the search string refer to Storm et al. (2013). Following an initial search iteration, the word "paper" was excluded from the string due to its meaning of research publication. The results were further constrained to include only articles and reviews as document types, and the language criterion was set to English.
The final output consisted of 280 papers meeting the specified criteria.

2.2 Literature screening

The studies resulting from the literature identification were first screened based on their title, abstract, and journal.
During this phase, 246 records were excluded based on the following criteria:

i. Scimago Journal Rank (SJR) index lower than 0.7;
ii. Lack of explicit reference to the DT concept;
iii. Lack of focus on process industries or pertinent to other sectors.

As a result of this first screening process, 34 articles were selected for a full-text analysis.
During this subsequent evaluation, 6 papers were further excluded due to the criteria mentioned above ii and iii. Additionally, 5 studies were removed for the additional criterion:

iv. Scope of the DT extended beyond the manufacturing process.

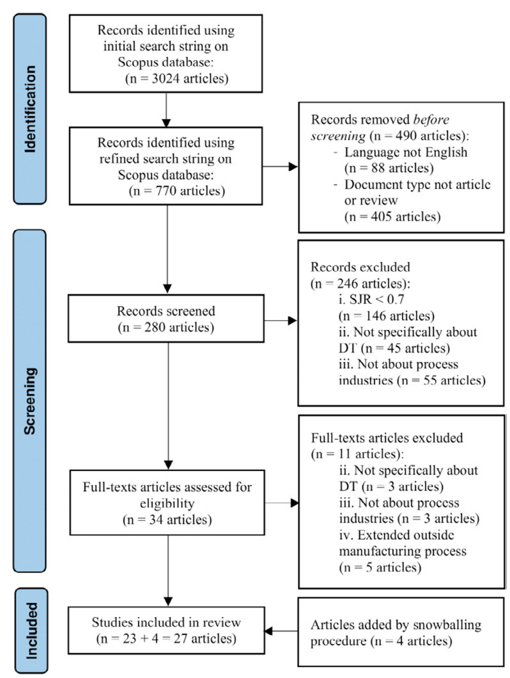

Figure 2. PRISMA flow diagram

2.3 Literature included

A total of 23 papers emerged as particularly relevant from the literature screening process.
Lastly, employing a backward snowballing procedure, 4 more studies were included. Some were incorporated because they relate to DT implementation in process industries; others were considered key publications concerning DT implementation for these application areas, even if not directly addressing the process industries.

3. DESCRIPTIVE ANALYSIS

A descriptive analysis of the selected papers was performed. Coherently with the scope of the research, most of the articles included in the review (21 out of 27) deal with the process manufacturing industry or address a specific process industry. These papers offer valuable insights into the challenges of implementing DT technology in this industrial setting, summarized in Section 5.
Besides the manufacturing industry, the following factors were considered relevant for the analysis:

- Area of application: Papers are categorized according to their specific application area, distinguishing between studies concerning the implementation of DT to support PP and those related to DT for MP.

- Real case application: Implementing the DT concept in a real industrial scenario was considered an additional criterion for distinguishing purely theoretical articles from those providing practical implications based on a real application. A distinction was made between digital models and real DTs, which are characterized by a connection with the physical system and can dynamically adjust and represent changes in the system over time (Maheshwari et al., 2022).

- Type of DT: Papers with a real DT application were additionally classified as those that provide feedback to assist users in decision-making processes and those that enable intelligent system adjustments.

Figure 3 shows the distribution of the literature by area of application. Research on the use of DT for integrating production and maintenance is scarce, with only one paper addressing this aspect. This underscores the need for further investigation to examine the potential benefits. Within the remaining articles, 17 focus on employing DT to support PP, while 9 explore its advantages in MP.

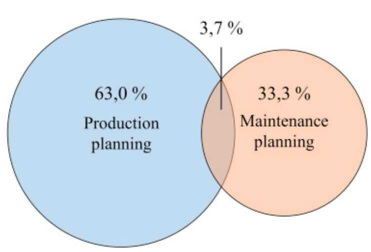

Figure 3. Literature distribution by area of application

Among the articles in the literature review, 13 papers include the DT implementation in a real industrial scenario. Notably, all but one pertain to applications within the process industry setting, with the exception being applied in discrete manufacturing. Of these papers, 9 present DTs providing feedback to operators, facilitating their decision-making processes. Meanwhile, the manufacturing system's intelligent control and adjustment of process parameters are observed in only 4 cases. Benefits stemming from the DT development are recognized independently of the specific type of DT.

4. CONTENT ANALYSIS

The factor area of application primarily guides the content analysis. Sections 4.1 and 4.2 present the findings related to the development of DT to support PP and MP independently, while Section 4.3 focuses on their integration and emphasizes the need for additional research.

4.1 Digital Twin for production planning

PP is a comprehensive managerial task involving a wide range of decisions. DT implementation mirrors this complexity, with various purposes driving its adoption in this domain.
Among the most common applications within PP, leveraging the DT to simulate the manufacturing process and enable predictions emerges as a valuable tool to support several decisions in this area. Timely anticipating deviations in final product properties facilitates the adoption of corrective measures to ensure product quality and minimize the number of outputs failing to meet quality standards, thus contributing to reducing overall production costs (Martin et al., 2021; Ralph et al., 2022; Zhu & Ji, 2022; Song et al., 2023). On the other hand, dynamically predicting critical process parameters allows for proactively adjusting technical parameters and improving production efficiency (Perno et al., 2023).
Additionally, DT can facilitate adaptive production scheduling by evaluating the optimal schedule once changes in the system are detected, enhancing both production efficiency and product quality (Liu et al., 2019; Koulouris et al., 2021).
By leveraging real-time data collection and simulation, it can support dynamic production control and optimization while concurrently reducing the reliance on expert knowledge for making related decisions through a continuous self-learning process (Min et al., 2019; Zhou et al., 2021; Zhu & Ji, 2023a; Zhu & Ji, 2023b; Kasper et al., 2024; Carlo Tancredi et al., 2023).
Finally, the DT development can be extended to consider external factors, such as market demand or supply chain changes, enabling dynamic adjustments to production plans to respond to evolving requirements (Müller-Zhang et al., 2023).
The outlined studies analyze the potential of DT to better approach PP decisions. Although this indirectly contributes to improved manufacturing system lifespan, consequently enhancing maintenance-related KPIs, targeting this outcome is not the explicit objective of the DT implementation in this area, which remains centered around increasing production-related KPIs (Figure 4).

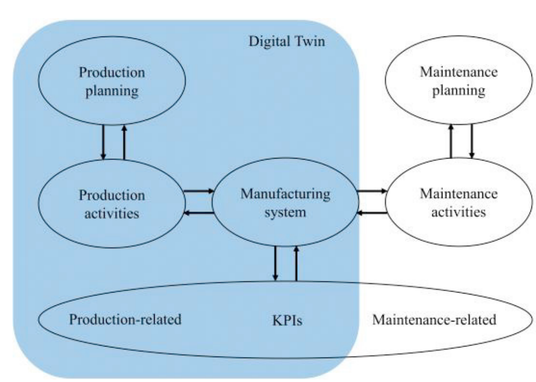

Figure 4. DT implementation for production planning

4.2 Digital Twin for maintenance planning

Similarly, adopting a DT within the area of MP can have different purposes.
A prevalent application, particularly relevant for this research, is supporting predictive maintenance and optimizing maintenance schedules. In this sense, DT allows the dynamic prediction of the system's remaining useful life depending on its actual condition (Aivaliotis et al., 2019). Additionally, it can be employed to generate data for developing the predictive models through simulation, notably in scenarios where failure data are not available or installing sensors on the actual system poses challenges (D'Urso et al., 2024). When adopting a predictive maintenance approach, the DT allows dynamic adjustments of the optimal maintenance schedule to minimize maintenance costs while guaranteeing the required production capacity (Feng et al., 2023) or considering environmental variables (Savolainen & Urbani, 2021).
On the other hand, DT is commonly developed to support fault diagnosis (Yang et al., 2023a; Yang et al., 2023b) or optimization of control strategies (He et al., 2019; Saraeian & Shirazi, 2022; Yang et al., 2022).
While the effective use of a DT in MP indirectly improves production-related KPIs by ensuring the continuous functioning of the manufacturing system, the primary objective behind its implementation in this domain is to improve maintenance-related KPIs (Figure 5).

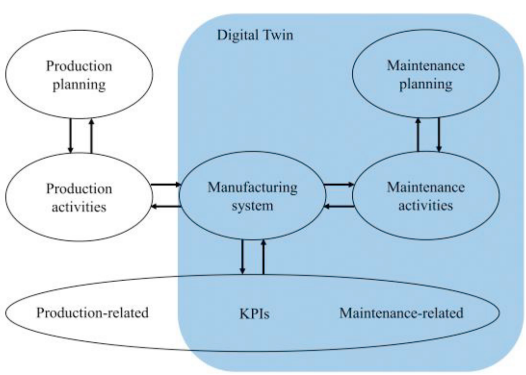

Figure 5. DT implementation for maintenance planning

4.3 Digital Twin for integrating production and maintenance planning

Arena et al. (2022) adopt a more comprehensive approach in their study. DT is leveraged to predict the remaining useful life of the system for each task in the production schedule and to identify the critical ones whose execution potentially leads to system failure. The maintenance department receives feedback regarding the alternative time slots for performing maintenance activities that align with the production schedule, accompanied by a comprehensive cost evaluation for each scenario.
Nevertheless, the integration remains limited, as the tool is specifically designed to support maintenance operators, considering the production schedule as input for the optimization. This means that decisions concerning MP rely on prior PP decisions rather than being evaluated simultaneously. Furthermore, the approach lacks validation in a real industrial setting and is not specifically tailored to the unique requirements of process industries.
Utilizing DT for dynamic maintenance planning and avoiding conflicts with the production schedule is just one possible application for improving the integration among these functions.
DT enables the possibility of testing the effect of a production job on the system condition before its execution (Aivaliotis et al., 2019) or similarly evaluating the impact of different values of process parameters. Therefore, it provides a means to assess how different decisions concerning the production process affect the remaining useful life of the system, other than the associated production performance. In parallel, it allows the evaluation of maintenance activity costs at different points in the production cycle and the varying effects on the manufacturing system's performance and production performance.
This underscores the need for further research to fully assess the potential of leveraging DT to integrate production and maintenance decisions (Figure 6).

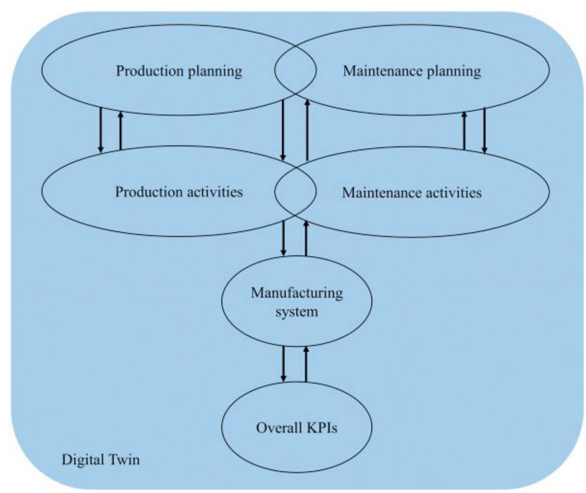

Figure 6. DT implementation for integrating production and maintenance planning

5. CHALLENGES FOR DT IMPLEMENTATION IN PROCESS INDUSTRIES

Given the inherent characteristics of process industries, the advantages of incorporating the DT concept into their manufacturing processes are demonstrated (Maheshwari et al., 2022).
The severe operating conditions and the possible exposure to hazardous substances underscore the importance of risk management and process safety (He et al., 2019). Because of the continuous and irreversible nature of the production processes, deviations from normal conditions lead to the accumulation of quality problems, resulting in financial losses and potential system damages (Zhu & Ji, 2022).
Adopting DT technologies emerges as a solution to mitigate these issues, as it enables intelligent monitoring and control of the production process. Moreover, it allows for testing, through simulation, the impact of different decisions and scenarios without the associated safety concerns and high costs (Zhu & Ji, 2023a).

Nonetheless, the development of DT in process manufacturing faces several challenges. Perno et al. (2022) provide a review of barriers to the implementation. It is worth noting, however, that the authors identified the scarcity of literature explicitly addressing these sectors as a study limitation.

Drawing from the publications reviewed, the common obstacles identified when using DT in process industries include:

- The complexity in accurately modeling the physical and chemical reactions involved in the production processes;
- The difficulty in effectively merging high volumes of data coming from different sensors, leading to delayed feedback and adjustments;
- The involvement of many correlated process parameters, making it challenging to identify the key indicators and requiring optimization of several conflicting objectives.

Consequently, additional research is necessary to explore solutions for overcoming these barriers and validate their effectiveness through practical implementations.

In addition to the general challenges above, implementing DT to improve the integration of production and maintenance planning necessitates collecting data about critical parameters essential for both decision-making processes while avoiding redundancies. Moreover, it requires feeding the DT with data from both departments' information systems and developing a model with a comprehensive perspective, thus considering multiple objectives for the optimization. Additionally, there is a need to develop a shared platform accessible to both production and maintenance operators, where they can interact and make decisions. Thus, achieving the integration is expected to pose additional challenges concerning data collection and integration, modeling system behavior and effects of different decisions, and optimizing conflicting objectives.

Further research and practical implementation efforts are necessary to explore the requirements and challenges of a similar DT.

6. CONCLUSIONS

Given the different and often contrasting objectives of the production and maintenance functions and their interdependencies, adopting an integrated management approach is essential, particularly in process industries, where production efficiency and system reliability are critical for companies' competitiveness. Integrating digital technologies into manufacturing has shown its benefits in enhancing performance. An increasing number of studies are investigating the benefits of adopting DTs. However, the number of applications explicitly focusing on process industries is limited. Through a literature review, this study aimed to summarize DT implementation in process manufacturing industries to support decision-making processes related to PP and MP. The findings underscore the need for additional research to overcome general challenges encountered in DT development in process industries. Moreover, the lack of an integrated perspective for the implementation lays the groundwork for further research to explore the full potential of DT to support the integration of production and maintenance. The scarce existing literature addressing this aspect stands as the primary limitation of this study. Therefore, it is crucial to acknowledge that its scope is confined to theoretical considerations and that there is a need for additional research and practical applications to gain deeper insights into the additional challenges associated with the DT implementation for this purpose.

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REFERENCES

Aivaliotis, P., Georgoulias, K., and Chryssolouris, G. (2019). The Use of Digital Twin for Predictive Maintenance in Manufacturing. *International Journal of Computer Integrated Manufacturing,* 32 (11), 1067–1080. https://doi.org/10.1080/0951192X.2019.1686173

Arena, M., Di Pasquale, V., Iannone, R., Miranda, S., and Riemma, S. (2022). A Maintenance Driven Scheduling Cockpit for Integrated Production and Maintenance Operation Schedule. *Advances in Manufacturing,* 10 (2), 205–219. https://doi.org/10.1007/s40436-021-00380-z

Carlo Tancredi, G. P., Bottani, E., and Vignali, G. (2023). Digital twin-enabled process control in the food industry: proposal of a framework based on two case studies. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2023.2260495

D'Urso, D., Chiacchio, F., Cavalieri, S., Gambadoro, S., and Khodayee, S. M. (2024). Predictive Maintenance of Standalone Steel Industrial Components Powered by a Dynamic Reliability Digital Twin Model with Artificial Intelligence. *Reliability Engineering & System Safety*, 243. https://doi.org/10.1016/j.ress.2023.109859.

Feng, Q., Zhang, Z., Sun, B., Guo, X., Fan, D., Ren, Y., Song, Y., and Wang, Z. (2023). Multi-Level Predictive Maintenance of Smart Manufacturing Systems Driven by Digital Twin: A Matheuristics Approach. *Journal of Manufacturing Systems*, 68, 443–454. https://doi.org/10.1016/j.jmsy.2023.05.004.

He, R., Chen, G., Dong, C., Sun, S., and Shen, X. (2019). Data-Driven Digital Twin Technology for Optimized Control in Process Systems. *ISA Transactions,* 95, 221–234. https://doi.org/10.1016/j.isatra.2019.05.011.

Kasper, L., Schwarzmayr, P., Birkelbach, F., Javernik, F., Schwaiger, M., and Hofmann, R. (2024). A Digital Twin-Based Adaptive Optimization Approach Applied to Waste Heat Recovery in Green Steel Production: Development and Experimental Investigation. *Applied Energy,* 353. https://doi.org/10.1016/j.apenergy.2023.122192

Koulouris, A., Misailidis, N., and Petrides, D. (2021) Applications of Process and Digital Twin Models for

Production Simulation and Scheduling in the Manufacturing of Food Ingredients and Products. *Food and Bioproducts Processing*, 126, 317–333. https://doi.org/10.1016/j.fbp.2021.01.016

Liu, L., Wan, X., Gao, Z., Li, X., and Feng, B. (2019). Research on Modelling and Optimization of Hot Rolling Scheduling. *Journal of Ambient Intelligence and Humanized Computing,* 10 (3), 1201–1216. https://doi.org/10.1007/s12652-018-0944-7

Maheshwari, P., Kamble, S., Belhadi, A., Mani, V., and Pundir, A. (2022). Digital Twin Implementation for Performance Improvement in Process Industries- A Case Study of Food Processing Company. *International Journal of Production Research,* 61 (23), 8343–8365. https://doi.org/10.1080/00207543.2022.2104181

Martin, N. L., Schomberg, A. K., Finke, J. H., Abraham, T. G., Kwade, A., and Herrmann, C. (2021). Process Modeling and Simulation of Tableting—An Agent-Based Simulation Methodology for Direct Compression. *Pharmaceutics,* 13 (7), 996. https://doi.org/10.3390/pharmaceutics13070996

Min, Q., Lu, Y., Liu, Z., Su, C., and Wang, B. (2019). Machine Learning Based Digital Twin Framework for Production Optimization in Petrochemical Industry. *International Journal of Information Management*, 49, 502–519. https://doi.org/10.1016/j.ijinfomgt.2019.05.020

Müller-Zhang, Z., Kuhn, T., and Antonino, P. O. (2023). Towards Live Decision-Making for Service-Based Production: Integrated Process Planning and Scheduling with Digital Twins and Deep-Q-Learning. *Computers in Industry,* 149, 103933. https://doi.org/10.1016/j.compind.2023.103933

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hofmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaf, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., McGuinness, L. A., Stewart, L. A., Thomas, J., Tricco, A. C., Welch, V. A., Whiting, P., McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. *BMJ,* 372: n160. https://doi.org/10.1136/bmj.n160

Perno, M., Hvam, L., and Haug, A. (2022). Implementation of Digital Twins in the Process Industry: A Systematic Literature Review of Enablers and Barriers. *Computers in Industry*, 134. https:10.1016/j.compind.2021.103558

Perno, M., Hvam, L., and Haug, A. (2023). A Machine Learning Digital Twin Approach for Critical Process Parameter Prediction in a Catalyst Manufacturing Line. *Computers in Industry,* 151, 103987. https://doi.org/10.1016/j.compind.2023.103987

Ralph, B., J., Sorger, M., Hartl, K., Schwarz, A., Messner, F., and Stockinger, M. (2022). Transformation of a Rolling Mill Aggregate to a Cyber Physical Production System: From Sensor Retrofitting to Machine Learning. *Journal of Intelligent Manufacturing*, 33, 493-518. https://doi.org/10.1007/s10845-021-01856-2

Saraeian, S., and Shirazi, B. (2022). Digital Twin-Based Fault Tolerance Approach for Cyber–Physical Production System. *ISA Transactions,* 130, 35–50. https://doi.org/10.1016/j.isatra.2022.03.007

Savolainen, J., and Urbani, M. (2021). Maintenance Optimization for a Multi-Unit System with Digital Twin Simulation: Example from the Mining Industry. *Journal of Intelligent Manufacturing,* 32 (7), 1953–1973. https://doi.org/10.1007/s10845-021-01740-z

Singh, M., Fuenmayor, E., Hinchy, E., Qiao, Y., Murray, N., and Devine, D. (2021). Digital Twin: Origin to Future. *Applied System Innovation*, 4 (2), 36. https://doi.org/10.3390/asi4020036

Song, C., Shen, X., and Xia, J. (2023). A Digital Twin Model for Automatic Width Control of Hot Rolling Mill. *IEEE Access,* 11, 90613–90621. https://doi.org/10.1109/ACCESS.2023.3306782

Spindler, J., Kec, T., and Ley, T. (2021). Lead-Time and Risk Reduction Assessment of a Sterile Drug Product Manufacturing Line Using Simulation. *Computers & Chemical Engineering,* 152, 107401. https://doi.org/10.1016/j.compchemeng.2021.107401

Storm, P., Lager, T., and Samuelsson, P. (2013) Managing the Manufacturing–R&D Interface in the Process Industries. R&D Management, 43 (3), 252–70. https://doi.org/10.1111/radm.12010

Yang, H., Kuang, Z., Zhu, J., Xu, F., Nie, F., and Sun, S. (2022). Digital Twin Key Technology on Rare Earth Process. *Scientific Reports,* 12 (1), 14727. https://doi.org/10.1038/s41598-022-19090-y

Yang, C., Cai, B., Wu, Q., Wang, C., Ge, W., Hu, Z., Zhu, W., Zhang, L., and Wang, L. (2023a). Digital Twin-Driven Fault Diagnosis Method for Composite Faults by Combining Virtual and Real Data. *Journal of Industrial Information Integration,* 33, 100469. https://doi.org/10.1016/j.jii.2023.100469

Yang, C., Cai, B., Zhang, R., Zou, Z., Kong, X., Shao, X., Liu, Y., Shao, H., and Akbar Khan, J. (2023b). Cross-Validation Enhanced Digital Twin Driven Fault Diagnosis Methodology for Minor Faults of Subsea Production Control System. *Mechanical Systems and Signal Processing*, 204, 110813. https://doi.org/10.1016/j.ymssp.2023.110813

Zhou, H., Yang, C., and Sun, Y. (2021). Intelligent Ironmaking Optimization Service on a Cloud Computing Platform by Digital Twin. *Engineering,* 7 (9), 1274–1281. https://doi.org/10.1016/j.eng.2021.04.022

Zhu, X., and Ji, Y. (2022). A Digital Twin–Driven Method for Online Quality Control in Process Industry. *The International Journal of Advanced Manufacturing Technology,* 119 (5–6), 3045–3064. https://doi.org/10.1007/s00170-021-08369-5

Zhu, X., and Ji, Y. (2023a). A Digital Twin-Based Multi-Objective Optimization Method for Technical Schemes in Process Industry. *International Journal of Computer Integrated Manufacturing,* 36 (3), 443–468. https://doi.org/10.1080/0951192X.2022.2126013

Zhu, X., and Ji, Y. (2023b). A Reduced Order Model Based on Adaptive Proper Orthogonal Decomposition Incorporated with Modal Coefficient Learning for Digital Twin in Process Industry. *Journal of Manufacturing Processes,* 102, 780–794. https://doi.org/10.1016/j.jmapro.2023.07.061