Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 142 (2026) 410–415

www.elsevier.com/locate/procedia

36th CIRP Design Conference (CIRP Design 2026)

AI-Driven Product-Production-CoDesign through digital manufacturing change management in PLM systems

Julia Kausler[a], Alexander Jacob[b], Marvin Carl May*[c,]

[a] *wbk Institute of Production Science, Karlsruhe Institute of Technology (KIT), Kaiserstr. 12, 76131 Karlsruhe, Germany*
[b] *Siemens AG, Östliche Rheinbrückenstr. 50 , 76187 Karlsruhe , Germany*
[c] *School of Mechanical and Aerospace Engineering, Nanyang Technological University (NTU), 50 Nanyang Avenue, Singapore 639798, Singapore*

* Corresponding author: Marvin Carl May, *E-mail address:* marvin.may@ntu.edu.sg

Abstract

Contemporary manufacturing faces unprecedented challenges driven by accelerated time-to-market demands, stringent quality standards, and mass customization requirements. This complexity necessitates seamless integration between product design and production planning, particularly within Product Lifecycle Management (PLM) systems, that current change management approaches lack. This research presents an AI-driven architecture for change management in PLM systems, specifically addressing Product-Production-Co-Design challenges. The proposed framework integrates Machine Learning algorithms with cyber-physical production systems to enable real-time adaptations to design modifications while maintaining manufacturing efficiency and sustainability considerations. Through data-driven analysis of existing PLM workflows, critical bottlenecks in change propagation are identified and targeted for automation. The methodology applies AI-based predictions to anticipate the manufacturing implications of design changes. This enables proactive adjustment of production systems, parts and processes, reducing waste and improving resource utilization - key factors in design for sustainability. The cyber-physical architecture facilitates bidirectional communication between design and production domains, ensuring that manufacturing constraints inform design decisions while design changes are seamlessly integrated into production planning. Results demonstrate significant improvements in change response time and manufacturing adaptability both in the short and long run. The AI-enhanced system reduces manual intervention in change management processes by up to 98% for instance in deriving the MBOM and BOP from the EBOM. This research contributes to the advancement of intelligent manufacturing systems that support sustainable production practices through optimized Product-Production-CoDesign methodologies, establishing a foundation for future autonomous manufacturing environments.

Keywords: Product-Production-CoDesign; Production Planning; Artificial Intelligence; Product Lifecycle Management

1. Introduction

Digital transformation is driven by the rapid pace, uncertainty, and complexity of modern manufacturing environments. Contemporary markets demand continuous adaptation as companies face evolving customer preferences, emerging technologies, and shifting requirements that necessitate frequent modifications to processes and business models [1]. This dynamic landscape is complicated by shorter product development cycles, expanding product diversity and growing customization demands that must be delivered efficiently, in which many companies are currently facing significant challenges [2]. The proliferation of product variants has intensified the complexity of managing product and production information across multiple systems and stakeholders. Manufacturing organizations must handle vast interconnected data spanning the entire product lifecycle, from concept development through production to disposal [3]. This exponential growth in data volume creates substantial challenges for efficient management of the Product-Production-CoDesign interface, requiring sophisticated approaches to ensure information accuracy and accessibility, to ensure holistic improvements [4].

Product Lifecycle Management (PLM) systems manage products from development through disposal [5], generating Bill of Processes (BOP) and Bill of Materials (BOM) while serving as the central hub for product change management [3, 6]. PLM interconnects with Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) systems as shown in Figure 1.

2212-8271 © 2026 The Authors. Published by Elsevier B.V.

10.1016/j.procir.2026.05.283

PLM distributes technical production data to MES and material master data to ERP [7]. ERP plans, manages and controls business resources and financial operations, autonomously calculating costs and relaying information back to PLM [6]. Production schedules from ERP are forwarded to MES, which integrates real-time machine status with PLM data to execute orders and continuously analyze production[8]. Post-production, PLM receives production data and process deviation reports while ERP obtains production and resource consumption data [7].

Maintaining consistent and synchronized data across multiple manufacturing systems and the entire lifecycle has emerged as both essential and increasingly challenging in this complex environment [3]. Organizations struggle to ensure that product modifications, process changes, and operational updates are accurately reflected across all relevant systems without delays or inconsistencies that could compromise product quality or operational efficiency [9].

Machine Learning (ML), as a subfield of AI, develops customized solutions for specific tasks through autonomous learning rather than explicit programming [10]. ML's capacity for independent adaptation to new situations creates significant opportunities for advancing digital manufacturing planning and PLM systems [11, 12].

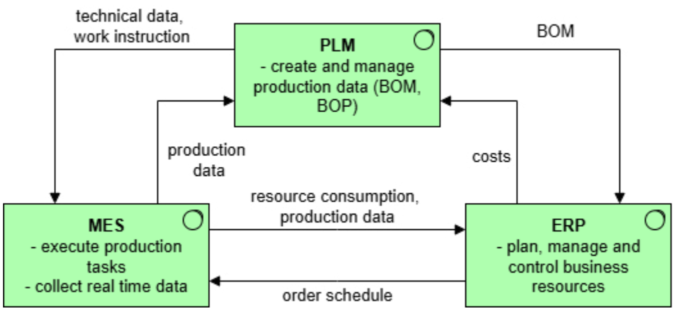

Fig. 1. Interaction of PLM, ERP and MES

This research optimizes digital manufacturing planning through a future-oriented target architecture for PLM-based product change management. The approach ensures consistent data representation across expanding datasets, accelerates product change implementation, and enables seamless inter-system data transfer while integrating ML capabilities. This paper is organized as follows: Section 2 examines current research on AI and ML applications in digital manufacturing planning, establishing the research proposal. Section 3 outlines the methodology for developing the architecture and identifying automation and ML improvements during the change management procedure. Section 4 applies this methodology on a general level. In section 5 the general process is applied in an industrial use-case, where the created automation and ML solutions undergo a cost-benefit analysis, culminating in a future-oriented PLM change management architecture.

2. State-of-the-art

This section overviews current research on AI applications in manufacturing and digital production. Research indicates

	Product-related processes				
Approach from	Development	Design	Process Planning	Manufacturing	Quality Control
Arinez et al., 2020 [21]	○	○	○	●	○
Wang et al., 2021 [24]	●	○	○	○	○
Denkena et al., 2021 [19]	●	●	●	○	●
Xu et al., 2022 [23]	○	○	○	○	●
Stark, 2022 [5]	●	●	○	○	○
Tsirigotirs, 2024 [25]	○	○	●	○	○

Fig. 2. State-of-the-art in the product-related process

AI integration actively advances to address increasing product complexity and customer demands [10]. Industry 4.0's emphasis on data collection and digital infrastructure has enhanced AI's industrial significance [13]. In the general big picture of Product-Production-CoDesign, which aims at jointly, interconnectedly and holistically developing products, there features and the there from derived production systems across the product life-cycle but also across their variants and generations, an interconnected database is key [4].

Product engineering processes categorize into order-related (production planning, scheduling, maintenance) [10, 14] and product-related (design, process optimization, quality control) processes [15, 16]. Research shows significant AI integration potential in production planning and control [17, 18], enabling predictions for sales, order volumes, and resource utilization [19].

Automatically collected data including machine status, process information, and inventory levels can be analyzed using AI to optimize production systems and workflows [20, 9]. By detecting patterns in large operational datasets, AI provides decision-making insights and enables condition-based maintenance through sensor feedback [21, 22]. Predictive maintenance represents another key application, where AI identifies anomalies, forecasts equipment failures, and creates intelligent maintenance plans [23].

Since this work addresses product changes within PLM systems, the focus centers on product-related processes, which divide into five areas as shown in Figure 2 [19].

Product-related processes encompass development, design, process planning, manufacturing, and quality control. The first three constitute virtual production (product creation), while the latter two represent physical production utilizing generated information [3, 19].

AI application within PLM remains limited from a product-oriented perspective. However, AI significantly contributes to product improvement through task automation, dataset analysis, and decision support. In development and design, AI analyzes market trends and provides actionable suggestions, accelerating prototyping and enhancing competitiveness [5, 24]. For process planning, AI automates process steps, proposes optimal actions, and optimizes parameters [19].

Within PLM change management, AI analyzes historical data to identify impactful changes and predict future effects. Individual change management steps can be automated, with AI expediting complex approval processes by automatically verifying component availability [25]. In manufacturing, AI enables human-machine collaboration, though requiring careful implementation [21]. Quality control benefits from AI-enhanced process monitoring using sensor data to detect deviations and improve error detection [19].

AI implementation opportunities exist across all areas, but development varies. Most research focuses on manufacturing, quality assurance, and production control. Product-related AI primarily targets development and design for parameter optimization, as shown in Figure 2. However, research overlooks product transition processes within IT systems, concentrating solely on product or process improvements rather than change implementation support.

3. Method

This paper employs a structured, systematic approach to identify current process inefficiencies in PLM change management and explore new technologies. The focus centers on improving adaptability to product changes and fostering innovation in manufacturing systems through ML integration. The methodology is summarized in Figure 3. Note that the focus of this approach is on operational performance, however, the same method can be applied to achieve a higher sustainability in Product-Production-CoDesign [26].

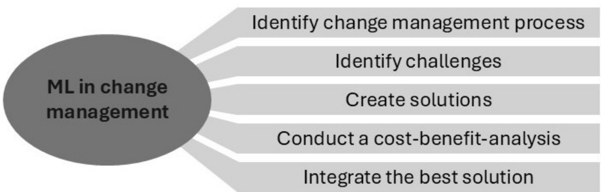

Fig. 3. Methodic approach

To effectively integrate machine learning into change management, it is essential to first conduct a comprehensive analysis of the overarching change management processes in Product Lifecycle Management Systems. This analysis provides detailed process step overviews derived from various PLM systems, including Teamcenter, PTC Windchill, and SAP PLM. ArchiMate, a vendor-neutral standard for enterprise architecture modeling, facilitates the visualization of business processes through which key challenges can be identified in subsequent stages [5]. These identified challenges serve as a foundation for determining appropriate solutions such as automation and ML applications in general. In the following Use-Case these generalized solutions were subsequently tailored to the specific context of an industry partner. In collaboration with the industry partner, their processes and challenges can be identified by workers who engage in this process daily. Leveraging their precise data, a comprehensive Cost-Benefit Analysis (CBA) was conducted to evaluate and compare the two proposed solutions, automation and machine learning, assessing their economic feasibility and identifying the most effective approach according to [5]. The detailed results of this analysis will be examined in the following sections, serving as the foundation for designing a forward-looking architecture for the change management process in PLM-systems, using ArchiMate as a modeling language.

4. Machine Learning in change management

The process begins representing product change management within PLM systems by using ArchiMate modeling language. Current process challenges are then identified, followed by exploration of automation and machine learning solutions.

4.1. General Change Management Process

The general change management process in PLM is modeled in Figure 4 using ArchiMate, which comprises three layers: business, application and technology. The business layer represents processes executed by business actors, the application layer describes supporting services and applications, and the technology layer represents technological services required for application support. The typical ArchiMate color scheme applies: yellow for business, blue for application, and green for technology layers [27].

At the business layer of the PLM change management process, manufacturing planners manage and plan products and therefore the change management, producing modified products as outcomes. The technology layer encompasses three main systems: PLM, ERP, and MES, each operating with independent databases accessible via computer interfaces. Core operations execute in PLM with subsequent data transfer to ERP and MES through interface databases. The PLM-to-ERP database is designated ”P2E” while the PLM-to-MES connection is termed ”P2M”.

The application layer centers on PLM systems as the primary interface for manufacturing planners accessing various applications. PLM serves as the central platform for managing Bill of Materials (BOM) and Bill of Processes (BOP) changes. Product data structures include Engineering BOM (EBOM), Manufacturing BOM (MBOM), and BOP, with EBOM and MBOM connected, as well as MBOM containing BOP information.

Product changes initiate when development teams provide new EBOMs, necessitating corresponding MBOM and BOP creation. This process involves four manual steps executed by manufacturing planners: MBOM and BOP creation based on existing data, adjustment to reflect required changes, component assignment linking MBOM components to BOP steps, and the calculation of new process times. Updated documents undergo approval before being transferred to integrated systems and synchronized with interface databases.

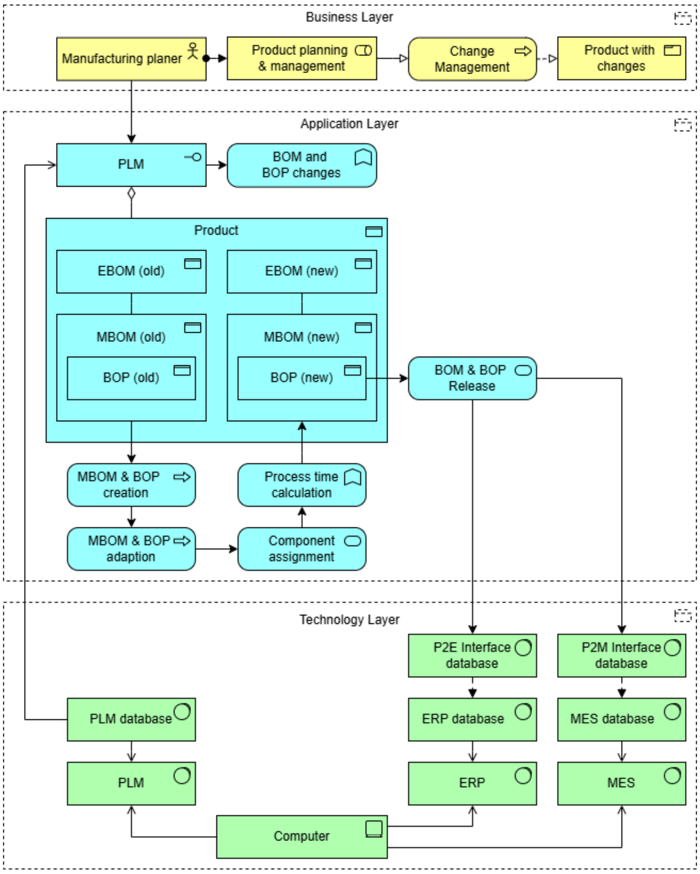

Fig. 4. Current change management process

4.2. Current Challenges and Proposed Solutions

Current challenges center on manual process execution requiring extensive product and process knowledge from manufacturing planners. This time-intensive approach necessitates expert involvement and individual product handling, significantly increasing complexity for large-scale production changes. Several common challenges have been identified through specialist interviews: Fragmented data connectivity, high manual effort, no mass change capabilities, IT performance issues, historic mistakes in data and non-conformance with target processes.

Two solutions address these challenges. Automation involves developing algorithms for individual workflow optimization and mass change capabilities, automatically adjusting MBOM and BOP based on EBOM modifications while requiring expert verification. Machine Learning solutions employ supervised learning on existing EBOM, MBOM, and BOP relationships. Trained ML systems automatically generate MBOM and BOP from new EBOM inputs, enabling full automation with continuous online training for improved accuracy over time.

5. Industrial Use Case

This use case, conducted with an industrial partner, examined detailed change management processes, analyzed problems, and developed tailored solutions. The general solutions from Chapter 4.2 were adapted to partner-specific needs, defining framework conditions for automation algorithms and ML training to enable a cost-benefit comparison. Analysis focused exclusively on changes within PLM systems as the master data source.

5.1. Cost-Benefit Analysis: Automation versus Machine Learning

The cost-benefit analysis compares the two approaches: The automation solutions for individual process steps, enabling mass changes and overall integration and the ML-based approach to create MBOMs and BOPs from an EBOM based on training. In fact, the proposed ML-based approach builds on some requirements from the automation to be implemented.

To analyze the different solutions estimating implementation benefits and costs are required. The duration of the current process was recorded to assess the potential time savings for each solution. The current change effort multiplied by the annual change frequency yielded a total annual effort, establishing a 100% baseline for all calculations. Savings and implementation efforts were calculated as percentage shares of the total annual effort.

Automation solutions enable simultaneous multi-product adjustments through individual process step automation, achieving 89% benefit in this use case. The ML-based solution, automatically generating a MBOM and BOP from an EBOM, achieved 98% savings as shown in Figure 5. ML creates new MBOMs and BOPs upon the availability of EBOMs through training-based generation, requiring only manual final approval. However, ML implementation demanded 26% of annual total effort whereas automation only demanded 2% , as illustrated in Figure 5.

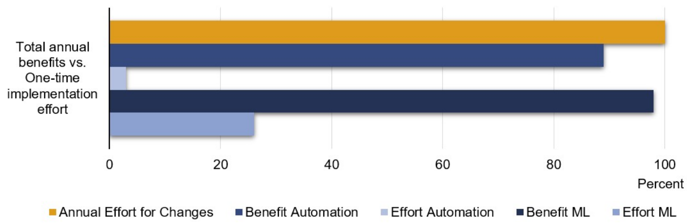

Fig. 5. Total annual benefits vs. One-time implementation effort

Relative benefit comparison considering first-year implementation costs, as shown in Figure 6, displays automation delivering 87% benefit, while ML achieves 72% despite higher implementation costs. Since ML targets future-proof architecture, relative benefits were calculated over five years, adjusting annual effort and benefit by corresponding yearly factors while maintaining constant implementation effort.

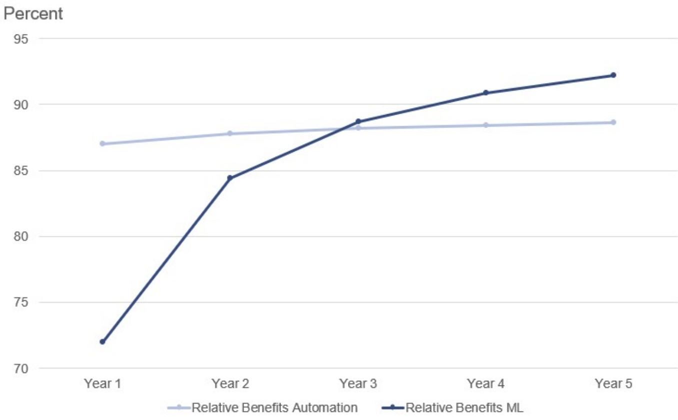

Fig. 6. Relative Benefits over Five Years

A five-year analysis reveals that automation is achieving 88.9% overall benefit, approaching its 89% theoretical maximum. ML approaches absolute benefit more gradually due to higher initial costs, reaching 92.2% process effort reduction after five years. From the third year onward, ML benefits exceed automation benefits, providing significantly higher returns in subsequent years.

5.2. Architecture Development

Solution selection depends on company strategy. Companies seeking rapid process changes favor automation, while future-oriented architecture development supports ML implementation. Based on these findings, ML-based solutions are recommended for optimal, future-ready architecture development.

The ML solution autonomously handles processes previously executed manually by manufacturing planners. Since only application layer modifications (see Figure 4 application layer) occur across four process steps, Figure 7 depicts current architecture: The creation and adaption of BOM & BOP is partially assisted by the system. Component Assignment is done manually. Process time calculations are manually transferred from external tools into PLM.

Figure 8 shows ML system integration directly within PLM systems. Upon new EBOM introduction, ML generates corresponding MBOM and BOP, adjusting for development team changes including component assignment and process time calculations. Following process completion, manufacturing planners approve outputs for ERP and MES system forwarding. Foundation of the ML-Application is a PLM-data-model in the PLM database (see Fig 4, Technology Layer) which is depicting all product data (EBOM, MBOM, BOP) available in the PLM. This enables training of ML to solve product generation development as well as handling of new product types based on similarity analysis's. This comprehensive ML-driven solution ensures efficient automation while guaranteeing continuous improvement through ongoing training, establishing sustainable long-term production and PLM optimization strategies.

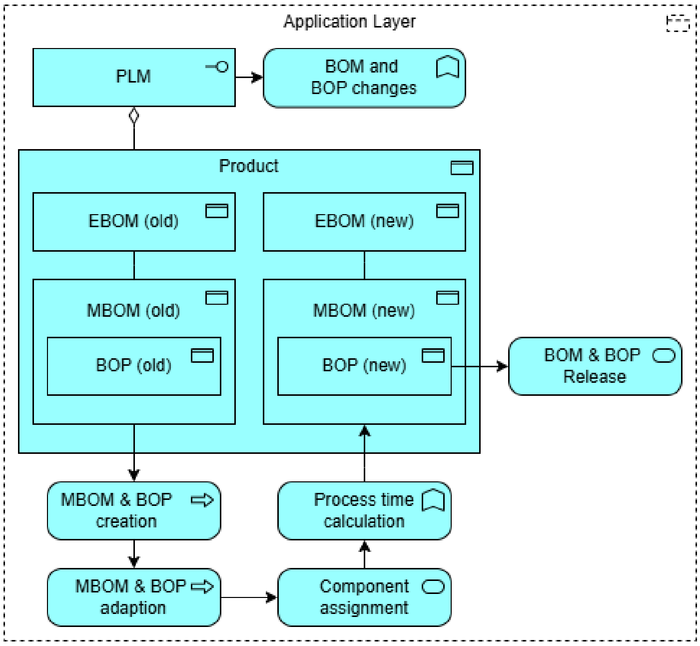

Fig. 7. Current change management architecture

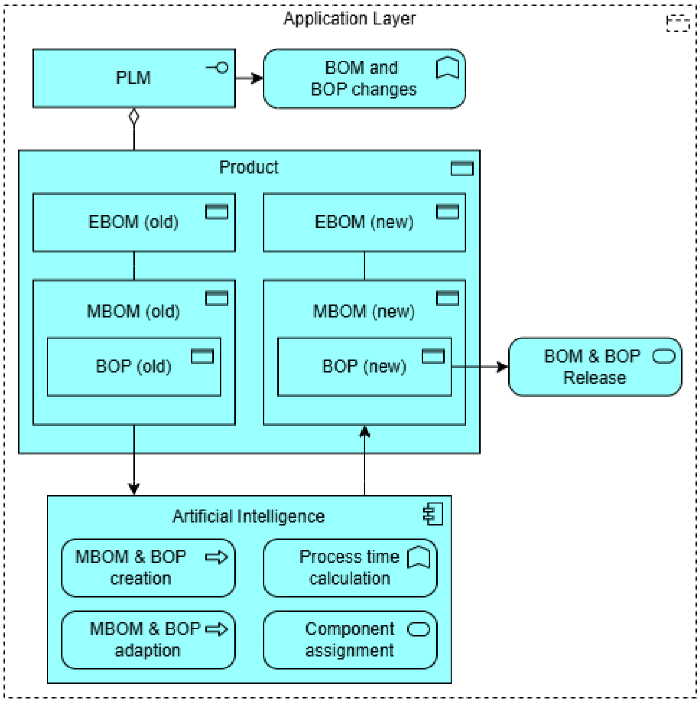

Fig. 8. Future change management architecture

6. Summary and Outlook

This research examines PLM change management processes where new MBOM and BOP are manually created from EBOM inputs, adjusted according to changes, and transferred to ERP and MES systems. Current challenges including high manual effort were identified, leading to automation and ML integration solutions for MBOM and BOP creation, implementing the dream of Product-Production-CoDesign.

These general solutions were developed for a specific application case, evaluating benefits through time savings and implementation effort via cost-benefit analysis. The analysis revealed ML provides superior long-term benefits with 98% process effort savings compared to 89% for automation alone. However, ML requires higher initial implementation resources (26% of total annual effort versus 2% for automation). Relative benefits adjust over time to match absolute benefits, establishing ML as the preferred solution for future-proof architectures. In Practice, since not every task can be handle by ML or justifies the necessary technological complexity of ML applications, a hybrid approach yields the highest potential. Gradually identifying and implementing ML solutions, if advantageous, is handable for large and small scale companies.

Beyond measurable cost savings, ML offers additional advantages not captured in traditional cost-benefit evaluations. ML significantly reduces extensive training requirements for new manufacturing planners by ensuring process accuracy and efficiency without requiring deep product and process knowledge. Continuous training enables ML systems to propose innovative product designs, optimize workflows, and leverage synergies for specialized processes—capabilities exceeding isolated automation solutions limited to specific process steps with static algorithms. Beyond classical ML, the investigation of Generative AI, Large Language Models and their embodiment into Agentic AI deserves more work, not only in control and planning, but also design and product related areas [14, 18, 17].

ML represents an inevitable element of future manufacturing [10], with benefits confirmed through this study. Future focus should shift toward potential-analysis, recognizing synergies beyond cost considerations and examining smaller application areas demonstrating significant impact. Continuous process improvement remains essential to ensure optimized processes and consistent data generation for future ML implementations.

Acknowledgements

This research was partially funded by NTU StartUp Grant on "Holistic I4.0 and Industrial AI" (ID:025861-00001).

References

[1] J. Knorr, Treiber der Digitalisierung, Springer Fachmedien, 2024. doi:10.1007/978-3-658-45979-6_1.

[2] Siemens Digital Industries Software, The executive's guide to digital manufacturing - transforming business to achieve strategic objectives, Tech. rep., Siemens AG (2021).

[3] W. Boos, E. Zancul, PPS-System als Bestandteil des Product Lifecycle Management, Schuh, G.; Stich, V., 2012. doi:10.1007/978-3-642-25427-7.

[4] M. C. May, L. Schäfer, A. Frey, C. Krahe, G. Lanza, Towards product-production-codesign for the production of the future, Procedia CIRP 119 (2023) 944–949. doi:10.1016/j.procir.2023.02.172.

[5] J. Stark, Product Lifecycle Managemnet (Volume1): 21st Century Paradigm for Product Realisation, Springer International Publishing, 2022. doi:10.1007/978-3-030-98578-3.

[6] V. Avvaru, G. Bruno, P. Chiabert, E. Traini, Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook, Vol. 142, Nyffenegger, F.; Rios, J.; Rivest, L.; Bouras, A., 2020.

[7] C. Willmann, A. Mazoochi, E. Horn, Ein leitfaden zu vernetzten systemen in der diskreten fertigung: Plm, erp, mes und darüber hinaus, PTC Inc. Whitepaper (2023).

[8] J. Kletti, MES - Manufacturing Execution System: Moderne Informationstechnologie unterstützt die Wertschöpfung, Klett, J., 2015.

[9] M. C. May, D. Glatter, D. Arnold, D. Pfeffer, G. Lanza, Iiot system canvas—from architecture patterns towards an iiot development framework, Journal of Manufacturing Systems 72 (2024) 437–459. doi:10.1016/j.jmsy.2023.12.001.

[10] T. Chen, V. Sampath, M. C. May, S. Shan, O. J. Jorg, J. J. Aguilar Martín, F. Stamer, G. Fantoni, G. Tosello, M. Calaon, Machine learning in manufacturing towards industry 4.0: From 'for now'to 'four-know', Applied Sciences 13 (3) (2023) 1903. doi:10.3390/app13031903.

[11] P. Krauss, Das komplexeste System im Universum, Springer, 2023. doi:10.1007/978-3-662-67179-5_2.

[12] C. Lanquillon, S. Schacht, Künstliche Intelligenz: Ein Überblick, Springer Fachmedien, 2023. doi:10.1007/978-3-658-41689-8_2.

[13] S. Gabriel, A. Kuehn, R. Dumitrescu, Strategic planning of the collaboration between humans and artificial intelligence in production, Procedia CIRP 120 (2023). doi:10.1016/j.procir.2023.09.168.

[14] K. Theuner, T. M. Elmgren, A. Götling, M. C. May, H. Akay, Weaving knowledge graphs and large language models (llms): Leveraging semantics for contextualized design knowledge retrieval, Procedia CIRP 134 (2025) 1125–1130. doi:10.1016/j.procir.2025.03.073.

[15] A. M. Frey, M. C. May, G. Lanza, Creation and validation of systems for product and process configuration based on data analysis, Production Engineering 17 (2) (2023) 263–277. doi:10.1007/s11740-022-01176-1.

[16] J. Gammack, H. Akay, C. Ceylan, S.-G. Kim, Semantic knowledge management system for design documentation with heterogeneous data using machine learning, Procedia CIRP 109 (2022) 95–100.

[17] Y. Tan, B. Wang, W. Yuan, Q. Zhou, W. Ye, M. C. May, X. Li, S.-G. Kim, R. Athinarayanan, Generative ai-driven disruption management in matrix production: A digital twin-based framework for resilient operations towards industry 5.0, in: ASME International Mechanical Engineering Congress and Exposition, Vol. IMECE2025, American Society of Mechanical Engineers, 2025, p. 167119.

[18] T. Körner, M. C. May, M. Huber, Llms as data preprocessors for natural language processing in manufacturing, in: 2025 IEEE 30th International Conference on Emerging Technologies and Factory Automation (ETFA), IEEE, 2025, pp. 1–7.

[19] B. Denkena, M.-A. Dittrich, H. Noske, K. Kramer, M. Schmidt, Anwendungen des maschinellen lernens in der produktion aus auftrags- und produktsicht: Ein Überblick, Zeitschrift für wirtschftlichen Fabrikbetrieb 116 (2021). doi:10.1515/zwf-2021-0068.

[20] M. C. May, T. Kaihara, Large language models for heuristics to solve aggregate production planning, in: IFIP International Conference on Advances in Production Management Systems, Springer, 2025, pp. 387–400.

[21] J. Arinez, Q. Chang, R. X.G., C. Xu, J. Zhang, Artificial intelligence in advanced manufacturing: Current status and future outlook, Journal of Manufacturing Science and Engineering 142 (2020).

[22] F. Ansari, L. Kohl, J. Giner, H. Meier, Text mining for ai enhanced failure detection and availability optimization in production systems, CIRP Annals 70 (1) (2021) 373–376.

[23] J. Xu, M. Kovatsch, D. Mattern, F. Mazza, M. Harasic, A. Paschke, S. Lucia, A review on ai for smart manufacturing: Deep learning challenges and solutions, Applied Sciences 16 (12) (2022).

[24] L. Wang, Z. Liu, A. Liu, F. Tao, Artificial intelligence in product lifecycle management, The international Journal of Advanced Manufacturing Technology 4 (114) (2021) 771–796.

[25] F. Tsirigotis, Artificial Intelligence and Product Lifecycle Management Systems, Stark, J., 2024. doi:10.1007/978-3-031-53521-5_2.

[26] M. C. May, L. Schäfer, T. Lachnit, G. Lanza, Product-production-codesign thinking for sustainable manufacturing, in: Global Conference on Sustainable Manufacturing, Springer, 2023, pp. 185–193. doi:10.1007/978-3-031-77429-4_21.

[27] A. Aldea, M. Iacob, J. Van Hillegersberg, D. Quartel, Bodenstaff, L., H. Franken, Modelling strategy with archimate, Proceedings of the 30th Annual ACM Symposium on Applied Computing (2015) 1211–1218.