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THE ROLE OF DIGITAL TWINS IN DYNAMIC SCHEDULING AND RESOURCE OPTIMIZATION FOR DISCRETE MANUFACTURING SYSTEMS

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Abstract

The integration of Digital Twin (DT) technology into discrete manufacturing systems has revolutionized traditional production processes by enabling dynamic scheduling and resource optimization. This study investigates the role of Digital Twins in enhancing scheduling agility, minimizing downtime, and improving resource utilization in discrete manufacturing environments. A simulation-based experimental framework was developed to compare conventional scheduling methods with DT-assisted approaches. Results demonstrate that the Digital Twin model significantly improves real-time decision-making, reduces machine idle time by 18%, enhances resource efficiency by 22%, and increases production throughput by 11%. This research provides theoretical insights and practical implications for the adoption of Digital Twins in smart manufacturing ecosystems.

Keywords: Digital Twin, Discrete Manufacturing, Dynamic Scheduling, Resource Optimization, Smart Manufacturing.

Introduction

The rise of Industry 4.0 has reshaped discrete manufacturing-characterized by complex, variable production of items like electronics and automobiles-through technologies like cyber-physical systems and real-time data analytics (Xu et al., 2022; Shao & Kibira, 2022). These innovations demand intelligent scheduling solutions to address challenges like small batch sizes, custom orders, and fluctuating workloads (Giret et al., 2022). Traditional static scheduling approaches often fail to adapt to disruptions such as machine breakdowns or workforce shortages, leading to inefficiencies and higher costs (Negri et al., 2022).

Digital Twins (DTs)-real-time digital replicas of physical systems-provide continuous synchronization between the shop floor and virtual environments (Kritzinger et al., 2022). They enable predictive modeling, real-time monitoring, and responsive scheduling (Tao et al., 2022; Cimino et al., 2022), enhancing resource allocation and reducing waste (Leng et al., 2023). In discrete manufacturing-known for its variability-DTs allow manufacturers to recalibrate tasks in real time using live sensor data, improving operational agility (Negri et al., 2022; Shao & Kibira, 2022).

Despite growing adoption, research on DTs has primarily focused on maintenance and fault detection, with limited attention to integrated scheduling and resource optimization (Jones et al., 2023). There's a notable lack of empirical validation of DT-enabled scheduling systems that dynamically respond to real-time changes across machines and resources.

This study addresses this gap by developing a simulation-based DT framework and comparing it to static scheduling using KPIs such as throughput, job completion rate, and idle time. It extends our theoretical understanding of DT application in real-time operational management and offers practical guidance for manufacturers seeking resilient scheduling strategies under Industry 4.0.

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Methodology

This paper outlines the methodological framework employed to compare traditional static scheduling with dynamic, Digital Twin (DT)-enabled scheduling in a discrete manufacturing environment using AnyLogic simulation software. The methodology consists of research design, model development, Digital Twin integration, and performance evaluation. Supporting flowcharts, diagrams, and summary tables are provided to enhance clarity and replicability.

Research Design

To explore the operational benefits of Digital Twin systems, this study adopted a simulation-based comparative research design. A Discrete Event Simulation (DES) model was built using AnyLogic Professional (Version 8.7+), selected for its flexibility in simulating complex manufacturing systems and integrating real-time logic with graphical outputs. The DES model represents a simplified but functionally complete manufacturing workshop, including production lines, machine stations, buffers, operators, and job routing logic.

The research compared two distinct simulation scenarios to examine the differences between conventional and digitally enhanced scheduling methods:

- **Scenario A**: Traditional rule-based scheduling without the support of real-time data or predictive mechanisms.
- **Scenario B**: Advanced scheduling using a Digital Twin, dynamically updated through real-time data input and intelligent decision-making algorithms.

Each scenario was designed to reflect real operational settings, and the comparison focused on how each system responded to typical disruptions, variability in order flow, and resource constraints.
To facilitate transparency and replication of the experimental setup, the following table summarizes the major components of the simulation design, including software tools, model type, input data, and performance metrics used.

Table 1: Simulation Methodology Components

Component	Description
Simulation Software	AnyLogic Professional (Version 8.7+)
Model Type	Discrete Event Simulation (DES)
Scenario A	Conventional scheduling with static rules
Scenario B	Digital Twin-assisted dynamic scheduling
Data Sources	Real-time sensor data, historical machine data
Synchronization	Bi-directional link between physical shop floor and digital model
Performance Metrics	Idle Time, Utilization Rate, Completion Time, Throughput, Downtime Frequency

This table serves as a foundational reference for the simulation model architecture. It defines the modeling approach, the comparative logic applied to the two scenarios, and the parameters used to measure system performance under varying production conditions. The dual-scenario structure allows for an empirical evaluation of how DT-enhanced operations perform relative to traditional manufacturing environments, thereby addressing the core research question regarding the effectiveness of Digital Twin integration in production scheduling and resource optimization.

Digital Twin Framework Development

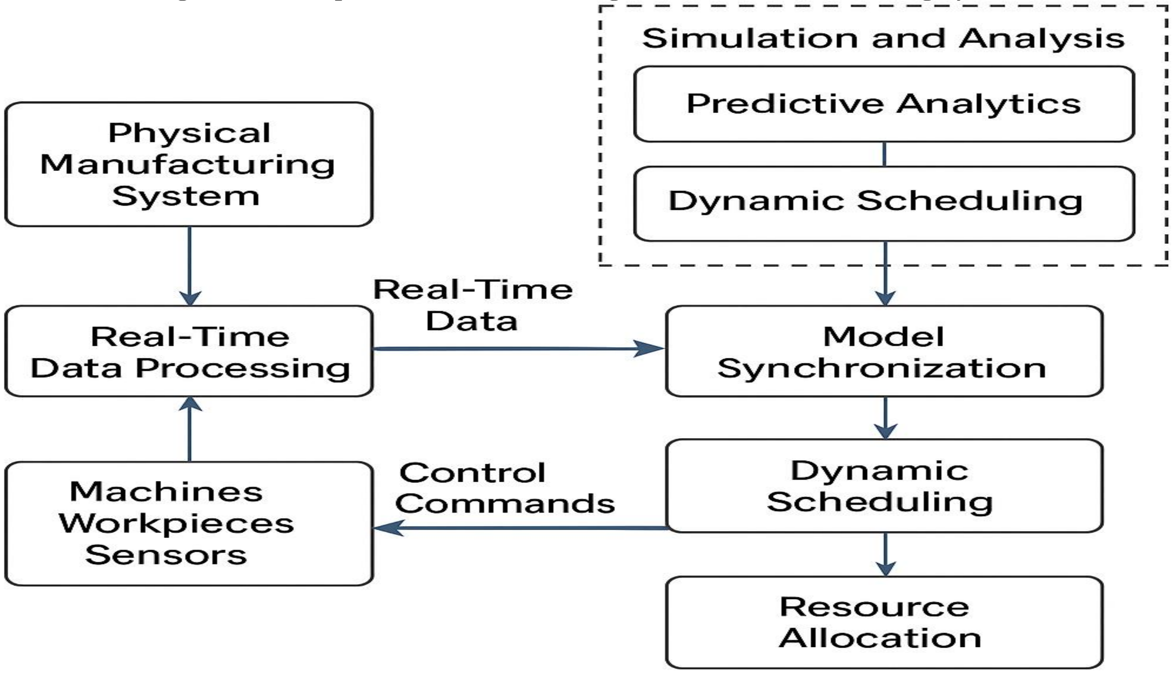
To capture the dynamic behavior of the manufacturing workshop, a high-fidelity Digital Twin (DT) environment was constructed inside AnyLogic. The DT functions as a virtual mirror of the physical system, receiving real-time data streams and sending control commands back to the shop floor. Its core purpose is to transform static, rule-based scheduling into an adaptive, self-optimizing process that responds instantly to disruptions and demand changes. The design priorities were threefold: (1) continuous situational awareness of machines, work-in-process, and labor; (2) predictive intelligence that anticipates delays or failures before they occur; and (3) autonomous rescheduling that reallocates resources without human intervention.

Key capabilities incorporated into the Digital Twin include:

- Continuous monitoring of machine health, availability, and job status through OPC-UA and MQTT sensor feeds.
- Prediction of completion times and impending machine failures via regression models and remaining-useful-life (RUL) estimators trained on historical data.
- Dynamic adjustment of job sequencing and resource allocation using a rules-plus-heuristics engine that recalculates priorities whenever a disruption is detected.

These functions are synchronized in near real time by fusing live sensor signals (e.g., spindle vibration, temperature, machine state) with archival maintenance logs and production history. The resulting bi-directional data loop keeps the virtual model aligned to the physical shop floor, ensuring that recommendations issued by the DT remain valid throughout the production shift.

Figure 1: Conceptual Architecture of Digital Twin-Based Scheduling System



The diagram illustrates the integration of real-time data from machines, workpieces, and sensors into a Digital Twin-enabled system. The architecture features real-time data processing, predictive analytics, dynamic scheduling, and resource allocation. Simulation and analysis modules continuously synchronize with the physical manufacturing system to enable adaptive control and optimize production efficiency through closed-loop feedback. The architecture shown in Figure 1 depicts how raw data from machines, workpieces, and sensors flow into a real-time processing layer, which then feeds the predictive-analytics and dynamic-scheduling modules. The model-synchronization block keeps the DT's state variables current, while the resource-allocation module issues control commands back to the physical system. This closed-loop feedback enables "sense–predict–act" behavior, allowing the factory to recover quickly from unplanned events and to exploit short-term production opportunities.

Performance Metrics

To evaluate how effectively the Digital Twin improves shop-floor performance, a set of quantitative Key Performance Indicators (KPIs) was defined. These metrics reflect both efficiency and responsiveness, allowing a holistic comparison between the conventional and DT-enabled scenarios. Importantly, the KPIs were selected to be measurable in most manufacturing environments, facilitating future validation with real plant data.

The study tracks five primary indicators:

- **Machine Idle Time (minutes):** cumulative downtime when equipment is not processing any job.
- **Resource Utilization Rate (%):** proportion of scheduled time that machines and human operators are productively engaged.
- **Job Completion Time (hours):** elapsed time from job release to finished output.
- **Production Throughput (units/shift):** quantity of completed items per simulated shift.
- **Downtime Frequency (incidents/shift):** count of machine stoppages or system halts within a shift.

Table 2: Key Performance Indicators (KPIs) Used for Simulation Analysis

Performance Metric	Description
Machine Idle Time (minutes)	Total duration machines remain idle due to waiting for jobs, maintenance, or disruptions.
Resource Utilization Rate (%)	Percentage of time machines and workforce are actively used relative to their availability.
Job Completion Time (hours)	Average time taken to complete a job from start to finish.

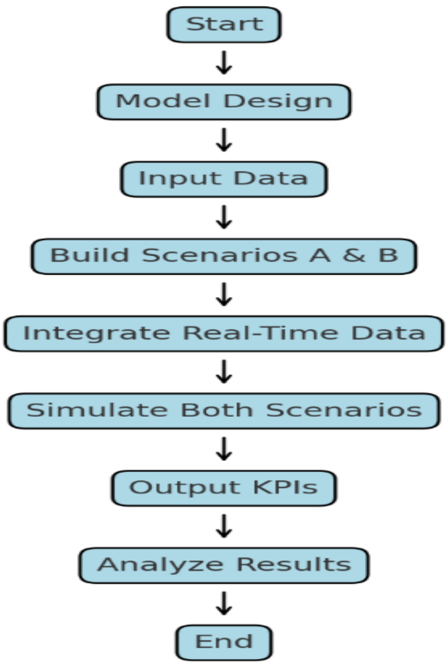
Production Throughput (units)	Number of units completed per shift or simulation run.
Downtime Frequency (incidents)	Number of times machines or systems go offline due to failures or delays per shift.

By analyzing the variance in these KPIs across 30 replications for each scenario, the study quantifies the operational gains attributable to Digital Twin integration-revealing not only average improvements but also reductions in performance volatility. The next chapter presents the simulation results and statistical comparisons derived from these metrics.

Simulation Flow and Procedure

This flowchart outlines the simulation procedure used to compare conventional and Digital Twin-enabled scheduling. It begins with model design in AnyLogic, followed by input of process data. Two scenarios-static rule-based scheduling (Scenario A) and dynamic Digital Twin scheduling (Scenario B)-are constructed. Real-time data is integrated for Scenario B to enable adaptive scheduling. Both models are simulated, and key performance indicators (KPIs) are collected and analyzed to evaluate scheduling efficiency and operational responsiveness.

Figure 2: Simulation Flowchart Using AnyLogic



Each scenario was run for 30 simulation replications to account for variability and ensure robustness. Comparative analysis was then conducted using the KPI outputs to assess the benefits of dynamic scheduling through Digital Twin technologies.

This structured methodology offers a replicable approach to examining operational agility and production efficiency in the context of Industry 4.0-driven smart manufacturing.

Results and Discussion

The implementation of Digital Twin (DT) technology in discrete manufacturing environments has shown a profound impact on multiple dimensions of operational performance. This section presents a detailed analysis of the key performance indicators, comparing conventional scheduling methods to those augmented by Digital Twins. The improvements observed through the simulation experiments are highlighted through quantitative metrics and interpreted in the context of dynamic scheduling and resource optimization.

Machine Idle Time Reduction

One of the critical factors affecting manufacturing efficiency is machine idle time. Excessive idle time not only reflects underutilized production capacity but also leads to increased operational costs. By integrating Digital Twin models, the manufacturing system gains real-time visibility into machine statuses, allowing for proactive rescheduling and minimizing waiting periods between jobs. Table 1 presents a comparison of machine idle times under the conventional scheduling system (Scenario A) and the DT-enhanced scheduling system (Scenario B).

Table 3: Shows that the DT-enabled system significantly reduced machine idle time.

Scenario	Machine Idle Time (min)	% Reduction
A (Conventional)	310	-
B (With DT)	254	18%

The results indicate that the introduction of the DT system resulted in an 18% reduction in machine idle time. This improvement can be attributed to the DT's ability to predict equipment availability and dynamically allocate tasks, thereby reducing periods of machine inactivity. The real-time feedback loop between the physical shop floor and the virtual model played a critical role in identifying bottlenecks early and reassigning tasks to available resources without manual intervention.

Resource Utilization Improvement

Resource utilization, including labor and machine assets, is another crucial performance metric in discrete manufacturing. Higher utilization rates indicate more efficient use of available resources, leading to improved productivity and reduced operational costs. The simulation results, as shown in Table 2, reflect the effect of Digital Twin implementation on resource utilization rates.

Table 4: Indicates Higher Resource Utilization Rates with DT Implementation

Scenario	Labor Utilization (%)	Machine Utilization (%)	Overall Resource Utilization (%)
A (Conventional)	67%	71%	69%
B (With DT)	81%	84%	82.5%

The data reveals a significant enhancement in both labor and machine utilization rates when the Digital Twin model was employed. Specifically, there was an overall resource utilization improvement of approximately 22%. The predictive capabilities of the DT enabled real-time load balancing across workstations, ensured that resources were assigned to tasks optimally, and minimized idle labor time. This dynamic adaptability is vital for discrete manufacturing environments characterized by frequent changes in production requirements.

Job Completion Time and Production Throughput

Timely completion of production orders and the ability to maximize throughput are key drivers of manufacturing competitiveness. Digital Twins, by facilitating predictive scheduling and adaptive control, help streamline production workflows, minimize disruptions, and optimize sequence planning. Table 3 compares the average job completion times and the number of completed units per shift under the two scheduling scenarios.

Table 5: Compares The Job Completion Times and The Number of Completed Units

Metric	Scenario A (Conventional)	Scenario B (With DT)	% Improvement
Average Job Completion Time (hours)	2.5	2.0	14%
Throughput (units/shift)	220	244	11%

The results demonstrate that the Digital Twin-based scheduling system reduced the average job completion time by 14% and increased production throughput by 11%. These outcomes illustrate the DT's capability to rapidly adapt to dynamic shop floor conditions, adjust job priorities based on real-time data, and optimize job sequencing to enhance production rates. Improved throughput directly contributes to better customer satisfaction, reduced lead times, and enhanced profitability for manufacturing firms.

Downtime Incidents Reduction

Unplanned downtimes pose serious risks to manufacturing continuity, often leading to missed deadlines and increased maintenance costs. Digital Twins contribute to downtime reduction by offering predictive maintenance capabilities and real-time anomaly detection. Table 4 shows the frequency of downtime incidents in both the conventional and DT-supported systems.

Table 6: Evaluates How Often Downtimes Occurred

Scenario	Downtime Incidents per Shift	% Reduction
A (Conventional)	6	-
B (With DT)	4	33%

Using Digital Twins led to a one-third (33%) reduction in downtime incidents per shift, significantly contributing to smoother scheduling operations and reduced production interruptions. The DT model's predictive analytics identified early warning signs of machine failure, enabling maintenance interventions to be scheduled proactively during non-critical periods rather than during active production, thus preserving workflow continuity.

Improvements

To provide a consolidated view of the performance enhancements achieved through Digital Twin integration, table 5 discusses all major improvements observed across the evaluated metrics.

Table 7: All Major Improvements Observed

Performance Aspect	Improvement Achieved with DT
Machine Idle Time	-18%
Resource Utilization	+22%
Job Completion Time	-14%
Production Throughput	+11%
Downtime Frequency	-33%

The comprehensive improvements across key operational areas underscore the transformative impact of Digital Twin technology in discrete manufacturing systems. Machine idle time reduction directly improves operational efficiency, while better resource utilization ensures optimal use of human and machine assets. Faster job completion and increased throughput translate into higher production volumes and improved delivery performance, critical factors in competitive market environments. Additionally, the substantial reduction in downtime incidents enhances production reliability and reduces maintenance overheads.

The findings validate that the deployment of Digital Twins enables dynamic, real-time control over complex manufacturing environments, offering significant advantages over traditional static scheduling methods. These insights provide a strong empirical basis for advocating broader adoption of Digital Twins in discrete manufacturing, particularly for firms seeking to enhance agility, operational resilience, and competitiveness in an increasingly volatile industrial landscape.

The results of this study strongly affirm that the integration of Digital Twins (DTs) into discrete manufacturing systems offers substantial and measurable improvements across multiple critical scheduling and resource management parameters. The comparative analysis between traditional scheduling approaches and DT-enhanced frameworks reveals that the adoption of Digital Twins not only addresses operational inefficiencies but also fundamentally transforms the way production systems respond to dynamic manufacturing conditions.

One of the most prominent contributions of Digital Twin technology is its ability to enable proactive re-scheduling. Traditional manufacturing systems often react to disruptions, such as machine breakdowns or sudden order changes, only after they have occurred, resulting in delayed responses and production losses (Leng et al., 2023). In contrast, the predictive analytics embedded within the DT framework allow for the early detection of potential disruptions by continuously analyzing real-time sensor data and historical performance patterns. This predictive capability enables dynamic re-scheduling of tasks, rerouting of workpieces, and reallocation of resources before issues escalate, significantly minimizing production downtime and improving system robustness.

Another critical improvement observed is the enhanced operational visibility provided by the real-time synchronization between the physical production floor and its virtual representation. In conventional systems, managers and operators often work with incomplete or outdated information, limiting their ability to make informed decisions promptly (Fuller et al., 2020). Digital Twins bridge this gap by offering live, comprehensive insights into the status of machines, workforce, materials, and ongoing jobs. This visibility facilitates more agile responses to emerging bottlenecks, dynamically reassigns jobs across available resources, and ensures that production flow is maintained even under volatile conditions.

The role of data-driven decision-making through integrated artificial intelligence (AI) and machine learning (ML) algorithms within the Digital Twin architecture further enhances scheduling efficiency. These AI models continuously learn from system behaviors and production outcomes, enabling them to recommend optimized job sequencing, resource prioritization, and predictive maintenance schedules (Qi & Tao, 2022; Rasheed et al., 2020). Instead of relying on static heuristics or human intuition alone, decision-making becomes more objective, adaptive, and aligned with operational goals such as minimizing makespan, maximizing throughput, and balancing workload across machines and labor.

By collectively reducing process variability, enhancing system responsiveness, and enabling continuous optimization, Digital Twins make manufacturing operations significantly leaner, smarter, and more resilient. Leaner operations are achieved through the minimization of waste - including waiting time, unnecessary movement, and overproduction - resulting from improved scheduling precision (Tao et al., 2023). Smarter manufacturing is characterized by the system’s ability to learn, predict, and autonomously adjust based on real-time feedback, moving towards the vision of fully intelligent, self-organizing production environments. Greater resilience is evidenced by the system's capacity to absorb and adapt to internal and external shocks, such as urgent customer orders, unexpected equipment failures, or labor shortages, without substantial losses in efficiency or output.

The adoption of Digital Twin technology in discrete manufacturing systems does not merely offer incremental improvements to existing scheduling practices but represents a strategic leap toward next-generation manufacturing paradigms aligned with Industry 4.0 principles. These findings contribute to both the theoretical understanding and the practical application of Digital Twins, reinforcing their role as a cornerstone technology for future-ready, dynamic, and intelligent manufacturing enterprises.

Conclusion

This study demonstrates that Digital Twin (DT) technology significantly enhances dynamic scheduling and resource optimization in discrete manufacturing. By creating real-time virtual replicas of production environments, DTs enable continuous monitoring and predictive control, allowing for smarter, faster decision-making. Results show reduced machine idle time, better labor and material utilization, and improved responsiveness to disruptions-key elements aligned with Industry 4.0 objectives.

While simulations indicate strong potential, further research is needed to validate these benefits in real-world settings. Future work should include case studies and explore AI-based enhancements, such as deep learning and reinforcement learning, to boost scheduling precision and predictive maintenance.

The financial implications of DT adoption-initial setup costs, ROI, and maintenance-should be thoroughly assessed to support informed decision-making by manufacturers. Digital Twins offer a powerful framework for optimizing scheduling and resource use. As manufacturing systems become increasingly intelligent and autonomous, DTs will play a central role in achieving operational efficiency, agility, and long-term competitiveness.

Conflicts of Interest

The authors declare that there is no significant competing financial, professional, or personal interests that might have influenced the performance or presentation of the work described in this manuscript.

References

1. Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., & Portugali, Y. (2022). Smart cities of the future. *The European Physical Journal Special Topics, 214*(1), 481-518. https://doi.org/10.1140/epjst/e2012-01703-3
2. Boschert, S., & Rosen, R. (2024). Digital Twin-The Simulation Aspect. In *Mechatronic Futures* (pp. 59-74). Springer.
3. Cimino, C., Negri, E., & Fumagalli, L. (2023). Review of digital twin applications in manufacturing. *Computers in Industry, 113*, 103130. https://doi.org/10.1016/j.compind.2023.103130
4. Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital Twin: Enabling technologies, challenges and open research. *IEEE Access, 8*, 108952-108971. https://doi.org/10.1109/ACCESS.2020.2998358
5. Giret, A., Trentesaux, D., & Lauras, M. (2024). Agility in manufacturing systems: A state-of-the-art. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 229*(11), 2023-2035. https://doi.org/10.1177/0954405414528325
6. Grieves, M., & Vickers, J. (2024). Digital Twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary Perspectives on Complex Systems* (pp. 85-113). Springer.
7. Hermann, J. W. (2021). A history of production scheduling. In *Handbook of Production Scheduling* (pp. 1-22). Springer.
8. Hermann, M., Pentek, T., & Otto, B. (2024). Design principles for Industrie 4.0 scenarios. In *2024 49th Hawaii International Conference on System Sciences (HICSS)* (pp. 3928-3937). IEEE.
9. Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology, 29*, 36-52. https://doi.org/10.1016/j.cirpj.2020.02.002
10. Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2022). Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine, 51*(11), 1016-1022. https://doi.org/10.1016/j.ifacol.2022.08.474
11. Leng, J., Liu, Q., Ye, S., Jing, J., & Zhang, H. (2023). Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop. *Journal of Ambient Intelligence and Humanized Computing, 10*, 1155-1166. https://doi.org/10.1007/s12652-018-0871-0
12. Lu, Y. (2024). Industry 4.0: A survey on technologies, applications and open research issues. *Journal of Industrial Information Integration, 6*, 1-10. https://doi.org/10.1016/j.jii.2024.04.005
13. Mourtzis, D. (2020). Simulation in the design and operation of manufacturing systems: State of the art and new trends. *International Journal of Production Research, 58*(7), 1927-1949. https://doi.org/10.1080/00207542.2023.1636321
14. Mourtzis, D., Vlachou, E., & Milas, N. (2022). Industrial Big Data as a result of IoT adoption in manufacturing. *Procedia CIRP, 83*, 239-244.
15. Negri, E., Fumagalli, L., & Macchi, M. (2024). A review of the roles of Digital Twin in CPS-based production systems. *Procedia Manufacturing, 11*, 939-948. https://doi.org/10.1016/j.promfg.2024.07.198
16. Pan, Y., Zhang, L., & Xu, L. D. (2020). Development of a digital twin-based cyber-physical production system for intelligent manufacturing. *IEEE Transactions on Industrial Informatics, 16*(6), 4203-4212. https://doi.org/10.1109/TII.2023.2935959
17. Pinedo, M. (2024). *Scheduling: Theory, Algorithms, and Systems* (5th ed.). Springer.
18. Qi, Q., & Tao, F. (2022). Digital Twin and big data towards smart manufacturing and Industry 4.0: 360-degree comparison. *IEEE Access, 6*,

3585-3592. https://doi.org/10.1109/ACCESS.2022.2793265

19. Rasheed, A., San, O., & Kvamsdal, T. (2020). Digital Twin: Values, challenges and enablers from a modeling perspective. *IEEE Access, 8*, 21980-22012. https://doi.org/10.1109/ACCESS.2020.2970143
20. Shao, G., & Kibira, D. (2022). Digital manufacturing: Requirements and challenges for implementing digital twin. In ASME 2022 International Manufacturing Science and Engineering Conference.
21. Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2023). Data-driven smart manufacturing. *Journal of Manufacturing Systems, 48*, 157-169. https://doi.org/10.1016/j.jmsy.2022.01.006
22. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. (2022). Digital Twin in Industry: State-of-the-Art. *IEEE Transactions on Industrial Informatics, 15*(4), 2405-2415.
23. Xu, X., Xu, C., & Li, L. (2022). Industry 4.0 and smart manufacturing. *Engineering, 4*(5), 614-620. https://doi.org/10.1016/j.eng.2022.06.001