

# Digital Twin Models for Intelligent Engineering Process Optimization

**Wen-Ren Jong**

Professor, Chung Yuan Christian University, Taiwan

## **Abstract**

Digital twin technology has emerged as an important approach for improving the monitoring, simulation, prediction, and optimization of complex engineering processes. A digital twin establishes a dynamic digital representation of a physical asset, process, or system and connects it with operational data to support continuous analysis and decision-making. The integration of digital twins with artificial intelligence, machine learning, Internet of Things technologies, simulation, and optimization algorithms provides opportunities for intelligent engineering process optimization. This paper examines digital twin models for intelligent engineering process optimization, focusing on their architecture, data integration mechanisms, predictive capabilities, optimization functions, and applications across modern engineering domains. A structured review-based methodology is employed to analyze digital twin approaches used in manufacturing, energy, mechanical systems, process engineering, infrastructure, and industrial operations.

The analysis indicates that digital twins can improve engineering optimization by enabling virtual experimentation, real-time performance assessment, predictive analysis, condition monitoring, and adaptive decision-making. AI-enabled digital twins can further enhance optimization by learning from operational data and identifying improved process configurations. However, practical implementation is affected by challenges involving data interoperability, model synchronization, cybersecurity, computational complexity, scalability, model fidelity, and integration with existing engineering infrastructure. The study highlights the importance of hybrid digital twin architectures that combine physics-based simulation, data-driven models, real-time sensing, and optimization algorithms. Future development should emphasize autonomous adaptation, explainable AI, uncertainty management, interoperable architectures, and human-centered decision support. Digital twin models therefore represent a significant foundation for developing more intelligent, adaptive, efficient, and sustainable engineering processes.

**Keywords:** Digital Twin, Engineering Optimization, Intelligent Manufacturing, Process Optimization, Artificial Intelligence, Machine Learning, Simulation, Smart Engineering.

## **1. Introduction**

Modern engineering processes increasingly involve interconnected physical assets, automated operations, complex workflows, and continuously changing operating conditions. Engineers must optimize these systems while simultaneously considering productivity, quality, energy consumption, cost, reliability, safety, and environmental performance. Conventional engineering optimization generally depends on mathematical models, numerical simulations, historical data, and expert knowledge. Although these approaches remain important, they can become difficult to manage when

engineering systems contain multiple interacting components and dynamic operating conditions. Digital twin technology provides a new framework for connecting physical engineering systems with continuously updated digital representations.

A digital twin can be understood as a digital representation of a physical object, process, or system that maintains a connection with its physical counterpart through data and communication mechanisms. The concept has developed substantially with advances in sensors, Internet of Things technologies, cloud computing, artificial intelligence, and simulation. Digital twins can provide engineers with a virtual environment in which system behavior can be observed, predicted, tested, and optimized without repeatedly interfering with the physical process.

The optimization potential of digital twins becomes particularly important when they are combined with artificial intelligence and machine learning. A conventional digital model may represent the physical behavior of a system, whereas an intelligent digital twin can additionally learn from operational data. Machine learning algorithms can identify patterns in sensor observations, estimate future performance, detect deviations, and recommend improved operating parameters. This creates a continuous relationship between monitoring, prediction, simulation, and optimization.

Digital twin applications have expanded across manufacturing, mechanical engineering, energy systems, infrastructure, aerospace, transportation, and process industries. In manufacturing, digital twins can represent production equipment and processes, enabling engineers to evaluate process configurations and production conditions. In energy systems, digital twins can support performance monitoring, predictive maintenance, load management, and system optimization. Infrastructure applications can use digital representations for structural monitoring, asset management, and lifecycle optimization.

The effectiveness of digital twin-based optimization depends heavily on synchronization between the physical and digital environments. If the digital representation does not accurately reflect the physical system, optimization decisions may become unreliable. Therefore, data acquisition, communication, model updating, validation, and uncertainty management are essential components of digital twin architectures. Real-time or near-real-time synchronization also introduces computational and communication requirements that must be addressed.

Another important consideration is the integration of engineering knowledge with data-driven intelligence. Purely data-driven models may provide strong predictive performance but may lack physical consistency, particularly when operating conditions differ from historical data. Physics-based models can provide physical constraints and system understanding, while machine learning can improve prediction and adaptability. Hybrid digital twins can therefore combine these complementary capabilities to support more reliable optimization.

This paper examines digital twin models for intelligent engineering process optimization. It investigates their architecture, major technologies, engineering applications, optimization capabilities, implementation challenges, and future research directions. The study emphasizes the role of digital twins as an integrated engineering framework capable of connecting physical systems, digital models, operational data, predictive analytics, and optimization processes.

## 2. Objectives

The primary objective of this study is to examine the role of digital twin models in intelligent engineering process optimization. The study focuses on how digital twins can integrate real-time data, simulation, machine learning, and optimization algorithms to improve engineering process performance, reliability, resource utilization, and operational decision-making.

## 2.1 Evaluation of Digital Twin Optimization Models

The first objective is to analyze major digital twin modeling approaches used for engineering optimization, including physics-based, data-driven, hybrid, and AI-enabled models. The study evaluates how these models represent physical systems, integrate operational information, and support prediction and optimization under changing conditions.

The second objective is to examine the contribution of real-time data synchronization, simulation, artificial intelligence, and optimization algorithms to digital twin performance. Particular attention is given to how these technologies enable virtual experimentation, predictive analysis, process parameter optimization, and adaptive engineering decision-making.

## 2.2 Assessment of Engineering Applications

The study also aims to assess digital twin applications across manufacturing, mechanical engineering, energy systems, process industries, infrastructure, and industrial operations. It considers their potential contributions to productivity, efficiency, reliability, quality, sustainability, and lifecycle management.

A further objective is to identify the major technical and organizational challenges affecting practical implementation. These include model fidelity, data integration, interoperability, computational requirements, cybersecurity, scalability, synchronization, and engineering validation.

## 3. Review of Literature

### 3.1 Digital Twin Concepts and Engineering Systems

The digital twin concept has developed into an important framework for representing physical systems through digital models connected to operational information. Digital twins differ from static simulations because they are designed to maintain an ongoing relationship with physical assets or processes. This connection allows digital models to be updated as system conditions change.

Tao et al. identified digital twin technology as an important component of intelligent manufacturing and emphasized its relationship with physical entities, virtual models, services, data, and connections. Digital twin research has subsequently expanded beyond manufacturing toward product development, maintenance, energy, infrastructure, and complex engineering systems.

### 3.2 Digital Twins and Intelligent Optimization

Optimization is a major function of advanced digital twin systems. A digital twin can reproduce system conditions in a virtual environment and allow engineers to test alternative configurations without directly modifying the physical system. Optimization algorithms can then search for improved solutions based on predefined objectives such as energy efficiency, production rate, quality, cost, or reliability.

The combination of digital twins and AI strengthens this capability. Machine learning can use historical and real-time information to estimate system behavior, while optimization algorithms can determine suitable operating parameters. Consequently, the digital twin can become an active optimization environment rather than simply a monitoring tool.

### 3.3 AI and Machine Learning Integration

Artificial intelligence has become increasingly important in digital twin development. Machine learning models can identify patterns in sensor data, predict system states, and detect deviations from expected behavior. Deep learning can support complex nonlinear prediction, while reinforcement learning can enable adaptive decision-making in dynamic environments.

AI-enabled digital twins can therefore provide a feedback loop involving data collection, prediction, simulation, optimization, and physical implementation. However, the reliability of this loop depends on data quality and model validity. Physics-based constraints remain important to prevent AI models from generating physically unrealistic recommendations.

### 3.4 Digital Twins for Smart Manufacturing

Smart manufacturing is one of the most developed application areas for digital twin technology. Digital twins can represent machines, production lines, products, and manufacturing processes. They can support process monitoring, quality prediction, production scheduling, predictive maintenance, and resource optimization.

Research has identified digital twins as an important technology for integrating cyber-physical systems, IoT, data analytics, and intelligent manufacturing. Their ability to provide virtual representations of production processes allows engineers to examine alternative process configurations before implementation.

## 4. Methodology

### 4.1 Research Design

This study adopts a structured review-based methodology to investigate digital twin models for intelligent engineering process optimization. Relevant literature was conceptually examined according to digital twin architecture, modeling methodology, optimization function, engineering application, and implementation challenges. Publications available up to 2024 were considered to maintain consistency with the specified reference-period requirement.

The reviewed literature was classified into four principal digital twin categories: physics-based models, data-driven models, hybrid models, and AI-enabled models. Engineering applications were subsequently organized according to manufacturing, mechanical systems, energy, process engineering, infrastructure, and industrial operations. This classification enabled comparative analysis of digital twin capabilities across different engineering environments.

### 4.2 Analytical Framework

The analytical framework evaluates digital twin models according to their ability to represent physical systems, synchronize operational data, predict system behavior, support optimization, and adapt to changing conditions. Model fidelity is considered alongside computational efficiency because highly detailed digital representations can require substantial resources for real-time operation.

The framework also considers the interaction between digital and physical environments. A useful digital twin must maintain an appropriate level of synchronization and provide outputs that are sufficiently reliable for engineering decisions. Consequently, data quality, model validation, interoperability, and uncertainty management are considered important components of digital twin effectiveness.

### 4.3 Evaluation Criteria

**The following criteria were used to evaluate digital twin models:**

- **Model fidelity:** accuracy of the digital representation.
- **Data synchronization:** consistency between physical and digital states.
- **Prediction capability:** ability to estimate future system behavior.

- **Optimization capability:** ability to identify improved process configurations.
- **Real-time performance:** responsiveness to operational changes.
- **Scalability:** ability to represent larger and more complex systems.
- **Interoperability:** compatibility with different engineering platforms.
- **Security:** protection of engineering and operational data.
- **Adaptability:** ability to update models as system conditions change.

## 5. Analysis

### 5.1 Digital Twin Modeling Approaches

Digital twin models can differ significantly according to their representation mechanisms and data requirements. Physics-based models rely primarily on mathematical and simulation representations of physical behavior. Data-driven twins use historical and real-time data to learn system relationships. Hybrid twins combine physical modeling with machine learning, while AI-enabled twins integrate predictive and optimization algorithms for intelligent decision-making.

**Table 1: Comparative Characteristics of Digital Twin Models**

| Digital Twin Model    | Primary Basis                | Optimization Capability   | Major Strength                          | Main Limitation               |
|-----------------------|------------------------------|---------------------------|-----------------------------------------|-------------------------------|
| Physics-Based Twin    | Mathematical/physical models | High for known systems    | Strong physical interpretability        | Computationally demanding     |
| Data-Driven Twin      | Operational data             | High with sufficient data | Flexible prediction                     | Data dependent                |
| Hybrid Twin           | Physics + data               | Very high                 | Combines physical and data intelligence | Model complexity              |
| AI-Enabled Twin       | AI/ML + digital model        | Very high                 | Adaptive optimization                   | Requires extensive validation |
| Simulation-Based Twin | Numerical simulation         | High                      | Supports virtual experimentation        | May require high computation  |
| Real-Time Twin        | Live sensor data             | High                      | Rapid operational feedback              | Communication requirements    |

The comparison indicates that hybrid and AI-enabled digital twins provide considerable potential for intelligent engineering optimization. Physics-based twins remain essential where physical behavior is well understood, while data-driven approaches provide flexibility when analytical modeling is difficult.

Hybrid models can bridge these approaches by incorporating physical knowledge while benefiting from data-driven learning.

### 5.2 Engineering Process Optimization Applications

Digital twins can support optimization across multiple engineering activities. In manufacturing, they can optimize machine parameters, production scheduling, material utilization, and quality control. In mechanical systems, digital twins can support equipment performance optimization and maintenance planning. Energy-sector twins can optimize generation, distribution, storage, and consumption.

Infrastructure applications include structural condition monitoring, lifecycle planning, and resource management. Process engineering applications can use digital twins to evaluate operating conditions, detect deviations, and optimize process parameters. The ability to test alternative scenarios virtually reduces the need for expensive physical experimentation.

**Table 2: Engineering Applications of Digital Twin-Based Optimization**

| <b>Engineering Domain</b> | <b>Optimization Focus</b>         | <b>Supporting Technologies</b> | <b>Expected Outcome</b>   |
|---------------------------|-----------------------------------|--------------------------------|---------------------------|
| Smart Manufacturing       | Production and process parameters | IoT, AI, simulation            | Higher productivity       |
| Mechanical Engineering    | Equipment performance             | Sensors, ML, simulation        | Improved reliability      |
| Energy Engineering        | Generation and consumption        | AI, IoT, forecasting           | Better efficiency         |
| Process Engineering       | Operating parameters              | ML, simulation                 | Reduced operating cost    |
| Civil Engineering         | Infrastructure lifecycle          | Sensors, digital models        | Improved asset management |
| Aerospace Engineering     | System performance                | Simulation, AI                 | Enhanced reliability      |
| Industrial Engineering    | Scheduling and resources          | Optimization, AI               | Better utilization        |
| Maintenance Engineering   | Asset condition                   | Predictive analytics           | Reduced downtime          |

The analysis shows that digital twin optimization can connect operational monitoring with engineering decision-making. Rather than evaluating performance after a process has occurred, the digital twin can continuously assess current conditions and estimate the consequences of alternative decisions.

## 5.3 Intelligent Optimization Cycle

An intelligent digital twin can operate through a continuous cycle. First, sensors and operational systems collect information from the physical engineering process. Second, the data are transferred to the digital environment and used to update the virtual representation. Third, predictive models estimate future performance or identify potential deviations. Fourth, optimization algorithms evaluate alternative decisions. Finally, selected recommendations can be transferred back to the physical system.

This cycle can substantially improve engineering responsiveness. However, each stage must operate reliably. Poor sensor data can affect model updating, inaccurate models can produce incorrect predictions, and inappropriate optimization constraints can result in impractical recommendations. Therefore, the complete digital twin ecosystem must be validated rather than evaluating individual components in isolation.

## 6. Discussion

### 6.1 Digital Twins as Engineering Decision-Support Systems

Digital twins can transform engineering decision-making by providing a continuously updated virtual representation of physical processes. Engineers can use the digital environment to examine current system conditions and simulate potential decisions before implementing them. This capability reduces dependence on trial-and-error experimentation and supports more informed process management.

The integration of optimization algorithms further expands digital twin functionality. Instead of merely showing what is happening within an engineering system, the digital twin can identify possible improvements. This transition from monitoring to predictive and prescriptive analysis represents an important development in intelligent engineering.

### 6.2 Integration of AI and Simulation

AI and simulation provide complementary capabilities within digital twin environments. Simulation provides a mechanism for representing physical behavior and testing hypothetical conditions, whereas AI can rapidly approximate complex relationships and identify patterns within operational data. Combining both approaches can reduce simulation requirements while retaining physical knowledge.

Hybrid approaches are particularly promising for complex engineering processes. A physics-based model can provide constraints and system relationships, while machine learning can capture residual or difficult-to-model behavior.

### 6.3 Contribution to Efficiency and Sustainability

Digital twin-based optimization can contribute to sustainability by reducing unnecessary energy consumption, material waste, downtime, and inefficient operating conditions. Virtual experimentation can also reduce the number of physical prototypes and tests required during engineering development.

The sustainability benefits become more significant when optimization considers multiple objectives simultaneously. An intelligent digital twin can potentially balance productivity, cost, energy use, reliability, and environmental performance rather than focusing exclusively on one performance measure.

## 7. Challenges

A major challenge in digital twin implementation is maintaining accurate synchronization between physical and digital systems. Engineering processes can change rapidly because of equipment

degradation, environmental conditions, production changes, and unexpected disturbances. If the digital representation is not updated appropriately, optimization decisions may become inconsistent with the physical system.

Data integration represents another significant challenge. Digital twins can receive information from multiple sensors, enterprise systems, simulation platforms, and operational databases. Differences in data formats, communication protocols, sampling frequencies, and system architectures can make integration difficult. Interoperability standards are therefore important for large-scale digital twin deployment.

Computational complexity is also a concern. High-fidelity digital twins may require substantial computational resources, particularly when simulations must operate in near real time. AI models can reduce computational requirements in some situations, but training and updating complex models may also be resource intensive.

Cybersecurity presents an additional challenge because digital twins connect physical engineering systems with digital networks. Unauthorized access, manipulation of sensor data, or attacks on optimization systems could have direct operational consequences. Strong security mechanisms are therefore required throughout the digital twin architecture.

Finally, model validation and trust remain important. Engineers must be able to determine whether digital twin outputs are sufficiently accurate for operational decisions. Differences between simulated and actual system behavior can reduce confidence, making continuous validation, uncertainty quantification, and human oversight essential.

## 8. Future Research

### 8.1 Autonomous Digital Twin Optimization

Future research should investigate autonomous digital twins capable of continuously learning from physical systems and adjusting optimization strategies as conditions change. Such systems could use reinforcement learning, adaptive machine learning, and real-time optimization to respond to operational disturbances.

Autonomous optimization should nevertheless remain within predefined engineering constraints. Future frameworks should therefore combine learning algorithms with safety boundaries, physical rules, and human supervision to prevent inappropriate automated decisions.

### 8.2 Physics-Informed and Explainable Digital Twins

Physics-informed digital twins represent another important research direction. Integrating physical equations and engineering knowledge with machine learning can improve model reliability, particularly when operational data are limited. Such approaches may also reduce the likelihood of physically unrealistic predictions.

Explainability should be incorporated alongside physical consistency. Engineers should be able to understand why an optimization recommendation was generated, which variables influenced it, and what uncertainty surrounds the predicted outcome. This can increase trust in AI-enabled digital twins.

### 8.3 Scalable and Interoperable Digital Twin Ecosystems

Future digital twin systems should support interoperability across machines, production lines, organizations, and engineering platforms. Standardized data structures and communication mechanisms can allow multiple digital twins to exchange information and support system-level optimization.

Research should also investigate scalable cloud-edge architectures. Edge computing can support rapid local processing, while cloud environments can provide extensive computational resources for large-scale optimization and simulation. Combining these capabilities could enable responsive digital twins for complex engineering environments.

## 9. Limitations

This study is based on a structured literature-oriented analysis rather than an experimental implementation of a digital twin within a specific engineering facility. Therefore, the findings provide conceptual and comparative insights rather than direct measurements of optimization performance. Actual digital twin effectiveness depends on system complexity, sensor infrastructure, model quality, data availability, and computational resources.

Another limitation is the multidisciplinary scope of the study. Digital twin requirements differ substantially between manufacturing, energy, infrastructure, mechanical systems, and process industries. A digital twin architecture suitable for one domain may require significant modification before being applied to another domain because of differences in physical processes, data structures, and operational requirements.

The study also focuses on literature available through 2024. Consequently, developments published after this period are outside the defined scope. In addition, digital twin performance can be strongly influenced by synchronization quality and model fidelity, which cannot be completely evaluated through literature-based analysis alone. Practical validation through engineering case studies remains necessary.

## 10. Conclusion

Digital twin models provide an important foundation for intelligent engineering process optimization by connecting physical systems with dynamic digital representations, operational data, simulation, predictive analytics, and optimization algorithms. Unlike static engineering models, digital twins can continuously incorporate information from physical systems and provide updated assessments of system behavior. This capability supports virtual experimentation, performance prediction, process monitoring, and optimization across manufacturing, energy, mechanical, civil, process, and industrial engineering applications.

The integration of artificial intelligence and machine learning can further strengthen digital twin capabilities. AI can identify patterns in operational data, predict future performance, detect deviations, and support adaptive optimization. However, successful implementation depends on accurate model representation, reliable data synchronization, interoperability, computational efficiency, cybersecurity, and engineering validation. Hybrid approaches that combine physics-based models with data-driven intelligence appear particularly valuable because they can balance physical consistency with predictive flexibility.

Future digital twin research should emphasize autonomous optimization, physics-informed learning, explainable AI, uncertainty management, scalable architectures, and interoperable digital ecosystems. Digital twins should increasingly function as intelligent engineering decision-support systems capable of continuously learning from physical environments while operating within established engineering constraints. When appropriately designed and validated, digital twin technology can support more efficient, reliable, adaptive, and sustainable engineering processes.

## References

1. Aivaliotis, P., Georgoulas, K., & Chrysosolouris, 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>
2. Barricelli, B. R., Casiraghi, E., & Fogli, D. (2019). A survey on digital twin: Definitions, characteristics, applications, and design implications. *IEEE Access*, 7, 167653–167671. <https://doi.org/10.1109/ACCESS.2019.2953499>
3. Birk, W., Hostettler, R., Razi, M., Atta, K., & Tammia, R. (2022). Automatic generation and updating of process industrial digital twins for estimation and control—A review. *Frontiers in Control Engineering*, 3, 954858. <https://doi.org/10.3389/fcteg.2022.954858>
4. Boschert, S., & Rosen, R. (2016). Digital twin—The simulation aspect. In P. Hehenberger & D. Bradley (Eds.), *Mechatronic futures: Challenges and solutions for mechatronic systems and their designers* (pp. 59–74). Springer.
5. Cimino, C., Negri, E., & Fumagalli, L. (2019). Review of digital twin applications in manufacturing. *Computers in Industry*, 113, 103130. <https://doi.org/10.1016/j.compind.2019.103130>
6. 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>
7. Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In F.-J. Kahlen, S. Flumerfelt, & A. Alves (Eds.), *Transdisciplinary perspectives on complex systems* (pp. 85–113). Springer.
8. Kritzing, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, 51(11), 1016–1022. <https://doi.org/10.1016/j.ifacol.2018.08.474>
9. Negri, E., Fumagalli, L., & Macchi, M. (2017). 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.2017.07.198>
10. Ouahabi, N., Chebak, A., Kamach, O., Laayati, O., & Zegrari, M. (2024). Leveraging digital twin into dynamic production scheduling: A review. *Robotics and Computer-Integrated Manufacturing*, 89, 102778. <https://doi.org/10.1016/j.rcim.2024.102778>
11. 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>
12. Schleich, B., Anwer, N., Mathieu, L., & Wartzack, S. (2017). Shaping the digital twin for design and production engineering. *CIRP Annals*, 66(1), 141–144. <https://doi.org/10.1016/j.cirp.2017.04.040>
13. Sharma, A., Kosasih, E., Zhang, J., Brintrup, A., & Calinescu, A. (2022). Digital twins: State of the art theory and practice, challenges, and open research questions. *Journal of Industrial Information Integration*, 30, 100383. <https://doi.org/10.1016/j.jii.2022.100383>
14. Wagner, S., Gonnermann, C., Wegmann, M., Listl, F., Reinhart, G., & Weyrich, M. (2024). From framework to industrial implementation: The digital twin in process planning. *Journal of Intelligent Manufacturing*, 35, 3793–3813. <https://doi.org/10.1007/s10845-023-02268-0>
15. Zhang, B., Ding, G., Zheng, Q., Zhang, K., & Qin, S. (2024). Iterative updating of digital twin for equipment: Progress, challenges, and trends. *Advanced Engineering Informatics*, 62, 102773. <https://doi.org/10.1016/j.aei.2024.102773>

16. Zhang, L., Liu, J., & Zhuang, C. (2024). Digital twin modeling enabled machine tool intelligence: A review. *Chinese Journal of Mechanical Engineering*, 37, 47. <https://doi.org/10.1186/s10033-024-01036-2>
17. Jin, L., Zhai, X., Wang, K., Zhang, K., Wu, D., Nazir, A., Jiang, J., & Liao, W.-H. (2024). Big data, machine learning, and digital twin assisted additive manufacturing: A review. *Materials & Design*, 244, 113086. <https://doi.org/10.1016/j.matdes.2024.113086>
18. Burggräf, P., Adlon, T., & Schäfer, N. (2024). Towards digital-twin-driven factory planning—A systematic review. *Procedia CIRP*, 126, 248–253. <https://doi.org/10.1016/j.procir.2024.08.334>
19. *Analyzing the purpose and technologies of digital twins in distributed manufacturing: A systematic literature review.* (2024). *Procedia Computer Science*, 232, 368–376. <https://doi.org/10.1016/j.procs.2024.01.036>
20. *Digital twins for discrete manufacturing lines: A review.* (2024). *Big Data and Cognitive Computing*, 8(5), 45. <https://doi.org/10.3390/bdcc8050045>