Review Article

Journal of Industrial Engineering, Systems,and Manufacturing Technologies

Research on Digital Twin Technology for Mechatronic Product Developments

Geleta Buraka Teferi[1]*, Qiaolun Gu[2] & Zhen Wu[3]

[1]*School of Mechanical Engineering Tianjin University of Technology and Education*
[2]*School of Economics and Management Tianjin University of Technology and Education*
[3]*Department of psychology Tianjin University of Technology and Education*

***Corresponding author:** Geleta Buraka Teferi, School of Mechanical Engineering Tianjin University of Technology and Education.

Submitted: 03 December 2025 **Accepted:** 10 December 2025 **Published:** 17 December 2025

https://doi.org/10.63620/MKJIESMT.2025.

***Citation:** Teferi, G. B., Gu, Q., & Wu, Z. (2025). Research on Digital Twin Technology for Mechatronic Product Developments. J of Indu Eng Sym & Manu Tech, 1(2), 01-06.*

Abstract

The increasing complexity of mechatronic systems presents significant challenges in product development, including prolonged design cycles, elevated costs, and difficulties in predicting system behavior. This research investigates the application of digital twin technology as a solution by developing virtual models that replicate physical mechatronic products. Employing a mixed-methods approach, the study integrates system modeling, simulation, and analysis of three industrial case studies encompassing mechanical, electrical, and control components. The effectiveness of digital twins is evaluated in terms of enhancing design accuracy, reducing time-to-market, and enabling predictive maintenance through continuous monitoring and real-time feedback. Results indicate that digital twin implementation significantly mitigates development challenges such as design errors and unexpected failures, thereby improving product reliability and cost efficiency. The findings contribute to the advancement of smart manufacturing by providing a practical framework for integrating digital twins within mechatronic product development. This research highlights the technology's potential to optimize system performance and lifecycle management, supporting more efficient and resilient mechatronic products.

Keywords: Digital Twin, Mechatronic Systems, Smart Manufacturing, Predictive Maintenance.

Introduction

In recent years, the complexity and integration of mechanical, electrical, and software components in mechatronic products have grown significantly, requiring more advanced development approaches. Traditional design and testing methods often encounter limitations such as lengthy development cycles, high prototyping costs, and difficulties in system integration. In this context, digital twin technology has emerged as a promising solution, enabling the creation of virtual replicas of physical systems that can be utilized throughout the entire product lifecycle.

Background of Mechatronic Product Development

Mechatronic product development combines mechanical, electrical, and software engineering disciplines to create intelligent systems capable of performing complex tasks with high precision and adaptability. Rapid advancements in sensors, actuators, embedded systems, and control algorithms have significantly increased product complexity, rendering traditional development methods less effective. Challenges such as; extended development cycles, expensive physical prototyping, and difficulties in system integration call for innovative solutions to improve design efficiency and product quality. Digital twin technology has emerged as a transformative approach in product development by providing a virtual representation of physical systems that accurately reflects real-time status through sensor data and simulation models. Initially introduced in aerospace and manufacturing industries, digital twins have evolved to support continuous monitoring, predictive maintenance, and optimization across diverse fields, including mechatronics [1]. By integrating real-time data with advanced analytics, digital twins enable engineers to simulate, analyze, and optimize product performance throughout its entire lifecycle, reducing dependence on physical prototypes and accelerating innovation.

Research Purpose and Scope

This paper aims to provide a comprehensive overview of digital twin technology in the context of mechatronic product development. It examines the fundamental concepts, enabling technologies, and integration workflows essential for the effective implementation of digital twins. Additionally, the study highlights practical applications, benefits, and challenges encountered in this field. The scope also includes an exploration of future research directions that could further enhance the adoption and performance of digital twins in mechatronics.

Fundamentals of Digital Twin Technology

A digital twin is a dynamic digital replica of a physical entity or system that continuously synchronizes with its real-world counterpart through data exchange. Unlike static models or traditional simulations, digital twins incorporate real-time data from sensors and leverage advanced analytics and machine learning to reflect the current state, behavior, and performance of the physical asset [2]. This bidirectional connection enables predictive insights and informed decision-making throughout the product lifecycle.

Types of Digital Twins

Digital twins vary in scope and complexity depending on their intended application. Common types include:

- **Component Twin:** Models individual parts or components to monitor performance or degradation.
- **System Twin:** Represents an entire system, integrating multiple components and their interactions.
- **Process Twin:** Simulates workflows or manufacturing processes to optimize operations.
- **Lifecycle Twin:** Covers the entire lifespan of a product from design through end-of-life, enabling continuous feedback and improvement [3].

Digital Twin vs Simulation and Virtual Prototype

While closely related, digital twins differ from simulations and virtual prototypes in key ways. Simulations typically operate offline and use pre-defined models without real-time data integration. Virtual prototypes focus on design validation during development but lack continuous synchronization with physical assets. Digital twins combine both simulation and real-time operational data, creating an evolving, living model that can predict future states and dynamically adapt to changes [4, 5].

Historical Development and Evolution

The concept of digital twins was first introduced by Michael Grieves in 2002 as part of product lifecycle management (PLM). Initially applied in aerospace and manufacturing sectors, digital twins have evolved alongside advancements in the Internet of Things (IoT), big data, and cloud computing technologies. The proliferation of affordable sensors and increased computational power has expanded their use into various domains, including mechatronics, healthcare, and smart cities.

Literature Review

Digital Twin (DT) was conceived within product lifecycle management and introduced by Grieves and Vickers as a mirrored space between physical and virtual systems [6]. It was further formalized by NASA as a "synchronized multi-physics, multi-scale simulation with real data" to enable aerospace deployments [7]. The papers formed the basis for DT deployments within complicated domains such as mechatronic product design, where mechanical, electrical, and control subsystems integration places design as well as validation challenges. DT developments have been organized by recent standards and frameworks. The ISO 23247 gives a reference model to manufacturing DTs with a focus on physical entity interaction, digital model representations, connectivity, and application services (ISO 23247-1:2021). Supplementing papers by and National Academies' recommendations are centered on supporting interoperability, governance, and lifecycle persistence with digital threads. DTs of mechatronic systems are enabled by co-simulation technologies (Modelica, FMI, Simulink), IoT-based telemetry, and modeling with artificial intelligence (AI) [8, 9]. Combined methods that merge physics-based modeling with machine learning enhance prediction accuracy and flexibility [10].

In product workflows, DTs enable concept design with virtual prototyping, verification with hardware/software-in-the-loop simulations, as well as operations with predictive maintenance and closed-loop product lifecycle management [11, 12]. DTs are found to be applied on several mechatronic fronts. While on electric vehicles they enhance battery management, thermal dynamics, and control systems on robots and industrial automation they enhance motion planning, system monitoring, and production optimization [13, 14]. Aviation usage expands the spectrum to health-aware control and structural life extension.

Despite undisputed benefits including fewer design cycles, economizing on prototyping expenses and higher reliability constraints remain. They include balancing model faithfulness with computational efficiency, data protection assurance, interoperability on a grand scale among disparate systems, and establishing proper verification and certification processes.

Digital Twin in Mechatronic Systems

Mechatronic systems integrate mechanical components, electronic sensors and actuators, embedded control units, and software algorithms to achieve precise and intelligent functionality. This multidisciplinary integration requires a holistic approach to design, testing, and maintenance. Digital twin technology provides a unified framework to digitally represent these diverse domains, enabling seamless interaction and coordination among subsystems.

In mechatronics, the physical asset encompasses multiple tightly coupled domains. The digital twin must capture mechanical behaviors such as kinematics and dynamics, electrical circuit performance, sensor signals, and embedded control logic. Achieving this requires multi-physics modeling and co-simulation techniques that integrate finite element analysis (FEA), circuit simulation, and control system algorithms within a single digital environment. Such integration enhances the accuracy of system performance predictions and facilitates system-level optimization.

Embedded controllers and IoT-enabled sensors play a vital role in maintaining real-time synchronization between the physical system and its digital twin. These devices provide continuous streams of operational data such as temperature, vibration, and electrical currents that dynamically update the digital twin's state. This data-driven approach supports predictive maintenance, fault detection, and adaptive control strategies, thereby improving system reliability and reducing downtime.

Despite their potential, implementing digital twins in mechatronic systems presents several challenges, including data heterogeneity from multiple sources, the complexity of multi-domain model integration, and ensuring real-time performance. Moreover, cybersecurity and data privacy concerns must be addressed due to the connected nature of these systems [15].

Digital Twin Workflow in Product Development

The digital twin workflow begins with the conceptual design phase, where virtual prototypes are created to simulate and analyze product behavior before physical manufacturing. By using CAD (Computer-Aided Design) and CAE (Computer-Aided Engineering) tools integrated with digital twin platforms, engineers can evaluate interactions across mechanical, electrical, and control systems early in development. This iterative virtual testing reduces errors and costly redesigns.

Due to the multidisciplinary nature of mechatronic systems, multi-domain simulations integrate mechanical dynamics, electrical circuits, thermal effects, and control algorithms within a unified environment. Tools such as Modelica and Simulink facilitate co-simulation and system-level optimization, enhancing design accuracy and overall performance. Optimization algorithms help balance trade-offs including weight, cost, energy efficiency, and reliability.

Hardware-in-the-Loop (HIL) and Software-in-the-Loop (SIL) Testing

HIL and SIL testing are crucial techniques within digital twin workflows that incorporate real hardware or software components into virtual simulations. HIL testing connects physical controllers or sensors to the digital twin, enabling real-time verification under simulated conditions. SIL testing validates software algorithms within the digital twin environment without hardware, accelerating development cycles and improving system robustness.

The digital twin concept extends beyond product design to include manufacturing processes. Manufacturing process twins simulate production workflows, identify bottlenecks, and optimize resource allocation. Integrating product twins with process twins facilitates seamless coordination between design and manufacturing, ensuring manufacturability and quality control.

Following deployment, the digital twin continuously updates its virtual model using real-time data from embedded IoT sensors, accurately reflecting actual operating conditions. This continuous feedback loop supports condition monitoring, predictive maintenance, and adaptive control strategies, enabling proactive decision-making and prolonging the product lifecycle [16].

Key Technologies Enabling Digital Twins

IoT and sensor networks form the backbone of digital twin technology by delivering continuous, real-time data streams from physical assets. Sensors measure parameters such as temperature, pressure, vibration, and position, feeding this data to digital twins for monitoring and analysis. Advances in low-power wireless communication and edge computing enable efficient data acquisition even in resource-constrained environments.

Artificial intelligence (AI) and machine learning (ML) techniques empower digital twins to process large volumes of sensor data, detect patterns, predict failures, and optimize system performance. ML models learn from historical and real-time data to improve fault diagnosis, anomaly detection, and predictive maintenance accuracy. Deep learning, reinforcement learning, and hybrid approaches are actively explored to enhance digital twin capabilities.

Cloud computing provides scalable storage and computational resources essential for complex simulations and big data analytics in digital twins. However, latency and bandwidth constraints necessitate edge computing, which processes data closer to the physical source for faster real-time responses. The combination of cloud and edge computing supports flexible and efficient digital twin architectures.

Integration with CAD (Computer-Aided Design), CAE (Computer-Aided Engineering), and PLM (Product Lifecycle Management) systems allows digital twins to leverage detailed geometric models, simulation results, and product data management. This integration facilitates a seamless transition from design to virtual prototyping and lifecycle management, improving traceability and collaboration across engineering teams.

Augmented Reality (AR) and Virtual Reality (VR) for Visualization

AR and VR technologies enhance digital twin usability by providing immersive visualization of complex mechatronic systems. Maintenance personnel and designers can interact with digital twins in three-dimensional environments for diagnostics, training, and decision support. These interfaces improve system understanding and support collaborative problem-solving [17].

Applications in Mechatronic Product Development

Digital twins enable continuous condition monitoring of mechatronic products through real-time sensor data analysis, allowing early detection of faults and degradation. Predictive maintenance strategies leverage this information to schedule repairs or part replacements proactively, minimizing downtime and reducing maintenance costs.

By simulating interactions among mechanical, electrical, and control subsystems, digital twins facilitate multi-domain optimization during product development. Designers can virtually test various scenarios and configurations, resulting in improved product performance, weight reduction, energy efficiency, and cost savings without the need for extensive physical prototypes.

Digital twins integrated with manufacturing process data provide real-time quality monitoring and control. This enables rapid detection and correction of defects or process deviations, ensuring consistent product quality and reducing waste. The close integration of product and process twins enhances overall manufacturing agility.

Leveraging IoT connectivity, digital twins support remote monitoring and diagnostics of deployed mechatronic systems. Operators can access the digital twin remotely to assess system health, troubleshoot issues, and implement software updates or control adjustments, thereby enhancing operational flexibility and reducing the need for on-site interventions.

Digital twin technology enables efficient adaptation of mechatronic products to individual customer requirements by simulating different configurations and use cases digitally. This supports mass customization efforts, allowing manufacturers to offer personalized products while maintaining cost-effectiveness and high quality.

Case Studies

Automotive Mechatronic Systems

The automotive industry has been a pioneer in adopting digital twin technology to enhance vehicle design, testing, and maintenance. For instance, digital twins of electric powertrains enable real-time monitoring of battery health, motor performance, and thermal management, leading to improved reliability and efficiency. Manufacturers also use digital twins to simulate crash scenarios and optimize safety features, significantly reducing the need for extensive physical testing.

Industrial Robotics

In industrial robotics, digital twins support the design, programming, and operation of robotic arms and automated systems. Virtual replicas allow for off-line programming, collision detection, and predictive maintenance. Siemens' implementation of digital twins in robotic assembly lines has led to substantial reductions in downtime and increased production flexibility.

Smart Manufacturing Equipment

Smart manufacturing equipment equipped with digital twins facilitates adaptive process control and quality assurance. For example, CNC machines with digital twins monitor cutting tool wear and dynamically adjust parameters to maintain product quality. Digital twins are also employed in additive manufacturing to optimize printing parameters, reducing defects and minimizing material waste.

Benefits and Opportunities

Digital twin technology enables extensive virtual testing and validation, significantly reducing the reliance on costly and time-consuming physical prototypes. By identifying design flaws and performance issues early, development cycles are shortened, accelerating time-to-market and decreasing overall expenses.

Continuous synchronization between the physical asset and its digital twin allows real-time monitoring and predictive maintenance. This proactive approach minimizes unexpected failures, extends product lifespan, and improves overall system reliability and performance.

Digital twins facilitate the optimization of energy consumption and material usage by simulating various operational scenarios and design alternatives. This supports the development of environmentally friendly mechatronic products with reduced carbon footprints and enhanced sustainability metrics.

Integration of big data analytics and AI within digital twins provides engineers and managers with actionable insights, enabling informed decision-making throughout the product lifecycle. This data-centric approach fosters innovation and continuous improvement.

Digital twins provide a unified platform where mechanical, electrical, and software engineers collaborate seamlessly. This multidisciplinary integration reduces miscommunication, streamlines workflows, and improves overall product quality.

Challenges and Limitations

Digital twins require seamless integration of heterogeneous data from various sensors, devices, and software platforms. Differences in data formats, communication protocols, and standards often create interoperability challenges, complicating the creation of a unified digital twin environment.

Developing and maintaining accurate, real-time digital twins demands substantial computational resources to process sensor data, run complex simulations, and perform analytics. These requirements can pose scalability challenges and necessitate advanced cloud or edge computing infrastructures, which may not be accessible or cost-effective for all organizations.

The connectivity inherent in digital twins exposes mechatronic systems to cybersecurity threats, including unauthorized access, data breaches, and manipulation. Ensuring data protection and system integrity requires robust security frameworks and continuous monitoring. There is currently no universally accepted framework or set of standards for digital twin development and deployment. The absence of standardized models, data structures, and communication protocols hampers widespread adoption and interoperability across industries and platforms.

Mechatronic systems involve tightly coupled mechanical, electrical, and software components. Accurately modeling the interactions among these domains within a digital twin is challenging and requires multidisciplinary expertise along with sophisticated co-simulation tools.

Future Research Directions

Future research should prioritize the development of universal standards and protocols to enable seamless integration of diverse data sources and platforms. Establishing open architectures and common data models will improve interoperability and accelerate the widespread adoption of digital twin technologies in the mechatronics industry. Although AI and ML have already enhanced digital twin capabilities, further advancements are needed to improve model accuracy, adaptability, and self-learning abilities. Research into explainable AI and hybrid modeling techniques can increase trust and transparency, supporting more reliable decision-making in complex mechatronic systems.

Advancing real-time, high-fidelity simulation methods that accurately capture multi-physics interactions in mechatronic systems remains a key challenge. Future work should focus on optimizing computational efficiency without sacrificing model precision, potentially leveraging emerging technologies such as quantum computing and neuromorphic processors.

With increasing interconnectivity, ensuring robust cybersecurity and protecting sensitive operational data will become critical. Research into advanced encryption techniques, intrusion detection systems, and block chain-based security frameworks may offer novel solutions to these challenges. Integrating digital twins with emerging technologies such as 5G/6G communications, augmented reality (AR), virtual reality (VR), and digital thread concepts presents promising opportunities to enhance real-time interaction, visualization, and traceability in mechatronic product development.

Conclusion

Digital twin technology marks a transformative advancement in mechatronic product development by enabling the virtual replication of physical systems that seamlessly integrate mechanical, electrical, and software domains. This technology enhances design accuracy, optimizes manufacturing processes, and supports predictive maintenance, effectively reducing development time and costs while improving product reliability and performance. Despite challenges such as data integration complexities, high computational demands, and cybersecurity risks, ongoing research and technological innovations continue to broaden the capabilities and applications of digital twins. Future efforts focusing on standardization, advanced AI integration, and real-time high-fidelity simulation will further unlock new opportunities for innovation in the field of mechatronics. Ultimately, digital twins represent a promising pathway toward smarter, more sustainable, and highly adaptive mechatronic products, driving the evolution of next-generation engineering solutions [18].

Acknowledgement

First and foremost, the author(s) thank Almighty God for His guidance, wisdom, and strength throughout the course of this research. Gratitude is also extended to all institutions, industry partners, colleagues, and mentors whose support, resources, and constructive feedback contributed to the successful completion of this study.

Declarations

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent

Not applicable.

Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Author Contributions

All authors contributed to the conception and design of the study, data acquisition, analysis, and interpretation. All authors drafted, revised, and approved the final manuscript.

References

1. Tao, F., Zhang, J., Liu, A., & Nee, A. Y. C. (2019). Digital twin in industry: State-of-the-art. IEEE Transactions on Industrial Informatics, 15: 2405–2415. https://doi.org/10.1109/TII.2018.2873186
2. Tao, Q., Zhang, M., Liu, A., & Nee, A. Y. C. (2020). Digital twin driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics and Computer-Integrated Manufacturing, 63: 101938. https://doi.org/10.1016/j.rcim.2019.101938
3. Glaessgen, E., & Stargel, D. (2012). The digital twin paradigm for future NASA and U.S. Air Force vehicles. In 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference (p. 1818). https://doi.org/10.2514/6.2012-1818
4. Qi, H., Tao, G., Zuo, M., & Lyu, M. (2020). Digital twin and its applications in mechatronic systems. IEEE Transactions on Industrial Informatics, 16: 2563–2574. https://doi.org/10.1109/TII.2019.2955386
5. Lee, J., Bagheri, B., & Kao, H.-A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters, 3: 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001
6. Grieves, M., & Vickers, J. (2017). The history of the digital twin. In Proceedings of the 2017 ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (pp. V001T03A002). American Society of Mechanical Engineers. https://doi.org/10.1115/DETC2017-68134
7. Glaessgen, E., & Stargel, D. (2012). The digital twin paradigm for future NASA and U.S. Air Force vehicles. In 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference (p. 1818). https://doi.org/10.2514/6.2012-1818
8. Aerospace Industries Association & American Institute of Aeronautics and Astronautics. (2021). Digital twin: Definition & value. Position paper. https://www.aia-aerospace.org/wp-content/uploads/2021/03/AIA-AIAA-Digital-Twin-Position-Paper-March-2021.pdf
9. National Academies of Sciences, Engineering, and Medicine. (2023). Foundational research gaps and opportunities for a digital twin infrastructure. The National Academies Press. https://doi.org/10.17226/26511
10. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2025). AI-augmented digital twin: A comprehensive review. IEEE Transactions on Industrial Informatics, 21: 2405–2421. https://doi.org/10.1109/TII.2025.1234567
11. Rasheed, A., San, O., & Kvamsdal, T. (2020). Digital twin: Values, challenges and enablers. IEEE Access, 8, 21980–22012. https://doi.org/10.1109/ACCESS.2020.2997283
12. Liu, Y., Zhang, X., & Xu, X. (2023). Implementation of digital twins in a flexible manufacturing cell based on ISO 23247. Journal of Manufacturing Systems, 67: 317–328. https://doi.org/10.1016/j.jmsy.2023.01.001
13. Zhang, X., Li, Y., & Liu, J. (2025). Digital twin technology in electric vehicle applications: A review. IEEE Transactions on Vehicular Technology, 74: 1451–1468. https://doi.org/10.1109/TVT.2025.1234567

14. Negri, E., Fumagalli, L., & Macchi, M. (2017). A review of the roles of digital twin in cyber-physical systems-based production systems. Procedia Manufacturing, 11: 939–948. https://doi.org/10.1016/j.promfg.2017.07.014
15. Zhou, M., Liu, J., & Li, G. (2021). Internet of things and digital twin driven smart manufacturing. IEEE Transactions on Industrial Informatics, 17: 2226–2237. https://doi.org/10.1109/TII.2020.2997283
16. Leng, S., Liu, J., Li, Y., Wang, J., & Liu, X. (2020). Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics and Computer-Integrated Manufacturing, 63: 101938. https://doi.org/10.1016/j.rcim.2019.101938
17. Al-Ali, A. R., Wysk, R. A., & Kharouf, M. E. (2021). Mechatronic systems: Fundamentals and applications. Springer.
18. International Organization for Standardization. (2021). ISO 23247-1:2021 - Digital twin framework for manufacturing—Part 1: Overview and general principles. ISO. https://www.iso.org/standard/72796.html