ORIGINAL PAPER VW Applied Sciences

DOI: 10.36297/vw.applsci.v1i3.110 ISSN: 2582-5615

VW Applied Sciences, Volume: 1, Issue: 3, 05-08

Digital Twin Frameworks for Predictive Maintenance and Autonomous Decision-Making in Industry 5.0

Arjun Sen[1*] Hiba Rashid[2*] Nikhil Joshi[3*]

[1]Department of Industrial Engineering, Central University of Karnataka, Kalaburagi, India
[2]Department of Computer Science, Islamic University of Science and Technology, Awantipura, India
[3]Department of Mechanical Engineering, Rajasthan Technical University, Ahmedabad, India
email: arjun.sen@cukr.ac.in, hiba.r@iust.ac.in, nikhil.j@rti.ac.in

Received: Nov 10, 2019
Accepted: Nov 11, 2019
Published online: Nov 12, 2019

Abstract: The transition from Industry 4.0 to Industry 5.0 emphasizes human-centric, resilient, and sustainable manufacturing systems where intelligent machines collaborate with people rather than merely automating tasks. Digital twin frameworks have emerged as a foundational technology for this transformation by creating dynamic virtual replicas of physical assets, processes, and production environments. These virtual models continuously synchronize with real-world data to support predictive maintenance, optimization, simulation, and autonomous decision-making. This paper investigates digital twin frameworks for predictive maintenance and autonomous decision-making in Industry 5.0. It examines enabling technologies including Internet of Things sensors, cyber-physical systems, cloud-edge computing, artificial intelligence, augmented reality, and real-time analytics. Applications in machinery health monitoring, quality assurance, energy management, robotics coordination, supply-chain visibility, and adaptive production planning are analyzed. Particular attention is given to failure prediction, remaining useful life estimation, human-machine collaboration, sustainability performance, and resilience under disruptions. Benefits include reduced downtime, improved asset utilization, lower maintenance cost, faster innovation cycles, and safer operations. Major barriers include data interoperability, cybersecurity, model fidelity, integration with legacy equipment, workforce skill gaps, and governance concerns. A future roadmap is proposed involving cognitive twins, federated industrial intelligence, self-optimizing factories, and ethical AI oversight. The paper concludes that digital twin ecosystems can become the operating intelligence of Industry 5.0 by combining predictive insight, autonomous response, and human expertise within adaptive industrial environments.

Keywords: Digital Twin, Predictive Maintenance, Industry 5.0, Autonomous Decision-Making, Smart Manufacturing

1. Introduction

Manufacturing systems are becoming more connected, data-intensive, and responsive than at any point in industrial history. Earlier automation waves focused on mechanization, mass production, and programmable control. Industry 4.0 introduced cyber-physical systems, IoT connectivity, advanced analytics, and smart factories. The emerging Industry 5.0 paradigm extends this model by emphasizing human-centric design, resilience, sustainability, and collaborative intelligence between people and machines [1]. In complex industrial environments, managers must continuously make decisions regarding maintenance schedules, production planning, quality control, workforce allocation, energy usage, and risk response. Conventional decision processes often rely on periodic reports and reactive maintenance, leading to downtime, waste, and delayed adaptation. Digital twins offer a new operating model. A digital twin is a living virtual representation of a physical asset, system, or process that is continuously updated using real-world data. Unlike static simulations, twins evolve with operational conditions and can forecast future states. This paper explores how digital twin frameworks enable predictive maintenance and autonomous decision-making in Industry 5.0 environments.

 DOI: 10.36297/vw.applsci.v1i3.110 ISSN 2582-5615

2. Evolution of Digital Twin Concepts

The idea of mirroring physical systems through virtual models originated in aerospace and systems engineering, where simulations supported mission planning and fault analysis. As sensors, connectivity, and computing power advanced, these models became increasingly dynamic and data-driven. Modern digital twins differ from traditional computer-aided design models because they are connected to live operational data. Machine temperatures, vibration signals, throughput rates, quality metrics, and environmental conditions continuously refine the model state [2]. This evolution transforms digital twins from engineering tools into operational intelligence platforms capable of monitoring, predicting, and optimizing industrial systems in real time.

3. Architecture of Digital Twin Frameworks

A robust digital twin framework typically includes physical assets, sensing infrastructure, communication layers, data platforms, analytics engines, and user interfaces. Physical assets may include machines, robots, conveyors, warehouses, vehicles, or entire plants. Sensors collect variables such as vibration, pressure, torque, acoustic signatures, temperature, current draw, and production counts. IoT gateways transmit these data streams securely to edge or cloud platforms. Data management layers clean, store, and contextualize information. Analytics engines run simulations, machine learning models, anomaly detection algorithms, and optimization routines. Visualization interfaces may include dashboards, 3D environments, or augmented reality tools for technicians [3].

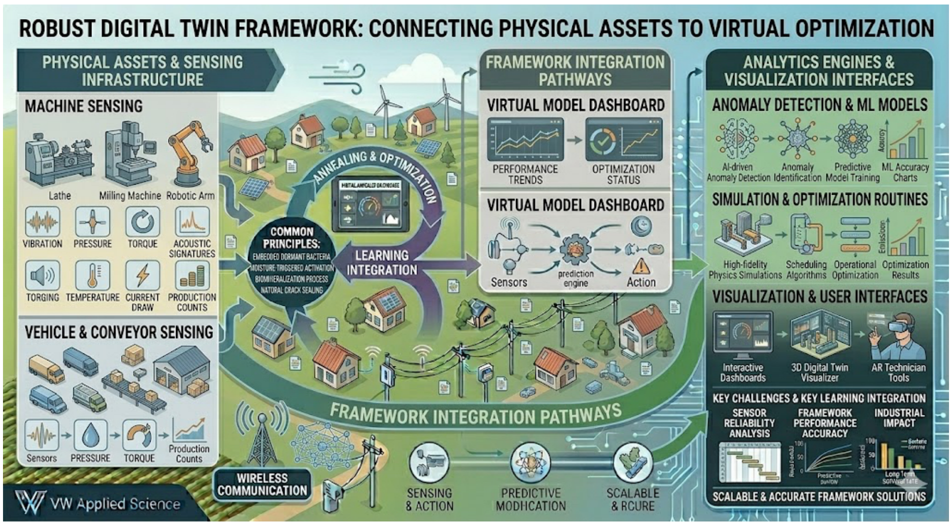

Fig. 1

4. Predictive Maintenance Foundations

Maintenance strategies have historically progressed from reactive repair to preventive schedules and now toward predictive intelligence. Reactive maintenance waits for failure, often causing costly downtime. Preventive maintenance uses time-based intervals but may replace components unnecessarily. Predictive maintenance uses condition data to estimate equipment health and forecast failure before breakdown occurs. Digital twins improve this approach by combining sensor readings with physics models, historical records, and operational context [4]. Instead of asking whether a machine should be serviced every six months, organizations can ask when the actual probability of failure becomes unacceptable.

5. Remaining Useful Life Estimation

One of the most valuable predictive maintenance outputs is remaining useful life estimation. This predicts how long a component can continue operating before maintenance or replacement is required. Machine learning models trained on degradation patterns can estimate remaining life from vibration signatures, temperature drift, lubricant quality, or electrical anomalies. Physics-informed twins improve reliability by incorporating wear mechanisms and engineering constraints [5]. Accurate remaining life estimation reduces spare part waste, prevents unexpected stoppages, and supports better workforce scheduling.

6. Autonomous Decision-Making in Production Systems

Digital twins are increasingly used not only to predict but also to decide. In autonomous decision-making systems, the twin evaluates multiple possible actions and recommends or executes the best option based on current objectives. For example, if a machine shows early failure signs, the twin may reschedule jobs to alternate lines, order replacement parts, and assign maintenance crews automatically. If demand changes suddenly, the system can simulate production scenarios and adjust output plans. Human approval may remain necessary for critical decisions, especially in Industry 5.0 environments where autonomy must remain accountable and human-centered.

7. Quality Assurance and Process Optimization

Manufacturing quality depends on precise control of materials, machine settings, timing, and environmental conditions. Digital twins can simulate how process variables influence defect rates and recommend optimal parameter settings. In continuous production lines, twins can detect drift before products fall outside tolerance. In discrete manufacturing, they can compare actual process traces with ideal digital signatures to identify hidden inefficiencies [6]. This reduces scrap, rework, and warranty costs while accelerating continuous improvement.

8. Human-Machine Collaboration in Industry 5.0

A defining feature of Industry 5.0 is that technology should augment human capability rather than replace it blindly. Digital twins support this goal by providing contextual intelligence to operators, engineers, and managers. Augmented reality interfaces may overlay maintenance instructions directly onto equipment. Operators can explore what-if scenarios without disrupting production. Engineers can test process changes virtually before applying them physically. The result is a collaborative environment where humans contribute judgment, creativity, and ethics while intelligent systems provide speed, prediction, and precision [7].

9. Sustainability and Energy Management

Industrial sustainability requires reducing energy use, emissions, waste, and resource intensity. Digital twins can model energy consumption across machines, shifts, and production scenarios. A plant twin may recommend shifting energy-intensive tasks to lower-tariff periods, optimizing HVAC settings, minimizing idle runtime, or balancing loads across equipment. Material flow twins can reduce waste through better sequencing and inventory control. Because sustainability goals increasingly influence competitiveness and regulation, such optimization capabilities are strategically important.

10. Supply Chain and Resilience Applications

Digital twins are expanding beyond factory walls into supply chains. A supply-chain twin may integrate inventory levels, shipment status, supplier risk, weather disruptions, and market demand. During disruptions, the system can simulate alternate sourcing strategies, transport routes, or production priorities. This enhances resilience in an era of geopolitical uncertainty, pandemics, and climate-related shocks [8]. Connected enterprise twins may ultimately synchronize procurement, production, logistics, and customer service in one decision environment.

11. Challenges and Implementation Barriers

Despite major potential, digital twin deployment is complex. Many factories operate legacy equipment not originally designed for connectivity. Retrofitting sensors and integrating heterogeneous data sources can be costly. Model fidelity is another challenge. Oversimplified twins may mislead decisions, while overly detailed twins become expensive to maintain. Cybersecurity risks increase when operational technology becomes networked. Workforce readiness is equally important. Engineers, operators, and managers need new skills in data interpretation, system thinking, and human-AI collaboration [9].

12. Governance, Ethics, and Trust

As twins gain decision authority, governance becomes critical. Organizations must define accountability for automated actions, thresholds for human intervention, and audit trails for recommendations. Bias in optimization objectives can also create unintended outcomes. A system focused only on productivity may neglect worker well-being or sustainability targets. Transparent design and ethical oversight are therefore essential in Industry 5.0 contexts. Trust grows when users understand system logic and can challenge or refine decisions.

13. Future Directions

 DOI: 10.36297/vw.applsci.v1i3.110 ISSN 2582-5615

The future of digital twins lies in cognitive and autonomous systems. Cognitive twins will combine reasoning, language interfaces, and contextual learning. Federated industrial intelligence may allow multiple facilities to improve models collaboratively without exposing sensitive raw data. Self-optimizing factories could continuously adapt production, maintenance, and energy systems with minimal delay. Integration with robotics, additive manufacturing, and circular economy platforms will broaden impact. As standards mature, digital twins may become core infrastructure rather than optional innovation.

14. Conclusion

Digital twin frameworks are rapidly becoming the operating intelligence of advanced industry. By continuously synchronizing physical assets with virtual models, they enable predictive maintenance, quality optimization, resilient planning, and autonomous decision-making. Their alignment with Industry 5.0 is especially strong because they can combine automation with human-centered collaboration and sustainability goals. Although challenges remain in integration, cybersecurity, governance, and skills development, the trajectory is clear. Organizations that successfully deploy digital twins will gain faster learning cycles, lower downtime, stronger resilience, and smarter decision systems for the future of manufacturing.

References

1. European Commission, Industry 5.0: Towards a Sustainable, Human-Centric and Resilient European Industry, Brussels, Belgium, 2021.
2. M. Grieves and J. Vickers, “Digital twin: Mitigating unpredictable outcomes,” in Transdisciplinary Perspectives on Complex Systems, Cham, Switzerland: Springer, 2017.
3. F. Tao and M. Zhang, “Digital twin shop-floor,” IEEE Access, vol. 5, pp. 20418–20427, 2017.
4. A. Heng, S. Zhang, A. Tan, and J. Mathew, “Rotating machinery prognostics,” Mechanical Systems and Signal Processing, vol. 23, pp. 724–739, 2009.
5. K. Jardine, D. Lin, and D. Banjevic, “Condition-based maintenance review,” Mechanical Systems and Signal Processing, vol. 20, pp. 1483–1510, 2006.
6. Y. Lu, X. Xu, and L. Wang, “Smart manufacturing process optimization,” Journal of Manufacturing Systems, vol. 49, pp. 157–171, 2018.
7. E. Topol, The Creative Destruction of Medicine, New York, USA: Basic Books, 2012.
8. World Economic Forum, Resilient Supply Chains in Manufacturing, Geneva, Switzerland, 2023.
9. OECD, The Future of AI in Advanced Manufacturing, Paris, France, 2024.