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| RESEARCH ARTICLE

Smart Manufacturing, Digital Twins, and Advanced Additive Technologies for Next-Generation Engineering Systems

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| ABSTRACT

The advent of Industry 4.0 is changing the way that manufacturing is done, turning traditional manufacturing into intelligent, connected and data-driven engineering environments. This review discusses the convergence of smart manufacturing, the digital twin, the advanced additive manufacturing and the computational aspects for next generation engineering systems. By combining cyber physical systems, Industrial Internet of Things, cloud and edge computing, automation, robotics, and advanced analytics, smart manufacturing provides enhanced production visibility, efficiency, quality, and flexibility. Digital twins represent a virtual, dynamic counterpart of physical assets, processes and systems, allowing for real-time monitoring, predictive maintenance, simulation, optimization and lifecycle management. Advanced additive manufacturing contributes to this transition by providing digitally controlled fabrication, in situ monitoring, hybrid manufacturing, rapid prototyping and closed loop process control. Under complex and uncertain operating conditions, reliable prediction and adaptive decision making are enabled by computational frameworks which integrate data fusion, machine learning, surrogate modeling, uncertainty quantification, and model predictive control. The review also emphasizes the need for digital twin architectures, interoperability, unified data environments, governance and cybersecurity, validation and standardization for scalability in the industrial world. Huge data challenges, computing power, model trustworthiness, legacy system integration, cyber security risks and staff adaptation are all great hurdles. The future research should focus on trustworthy artificial intelligence, uncertainty aware digital twins, multimodal sensing, adaptive online simulation, standardized frameworks, and approaches based on human-centred Industry 5.

| KEYWORDS

Smart Manufacturing; Digital Twins; Additive Manufacturing; Industry 4.0; Computational Intelligence.

| ARTICLE INFORMATION

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1. Introduction

The Fourth Industrial Revolution (Industry 4.0) is changing manufacturing by connecting systems including cyber physical systems, the Industrial Internet of Things, cloud computing, advanced analytics, automation and additive manufacturing. This transformation is the step from the traditional automation to a smart, interlinked and more often than not, self-optimizing production. The application of these technologies allows for the support of real-time decision making, optimisation of production processes, better product quality, greater operational flexibility and efficient lifecycle management [Aivaliotis, 2019]. It also meets some of the biggest industry goals including decreasing downtime, reducing energy consumption, decreasing material waste, decreasing production lead time and meeting the requirements of more and more customized products. Smart manufacturing is key to this change

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as it brings machines, sensors, production systems, information technologies and enterprise operations together in a combined digital world [Jacoby, 2020]. Data is collected by advanced sensors and embedded software from manufacturing equipment and processes, and data analysis and AI transform the data into actionable insights. With IOT technologies, machines and production assets communicate with each other and information moves continuously throughout the manufacturing environment [He, 2021]. If production data is connected to enterprise systems like resource planning, inventory management, quality management and customer service it becomes possible to create a stronger picture of industrial operations. This integration helps to break down silos, enabling better coordination of production, maintenance, quality and supply chain decisions. Cloud computing and distributed digital infrastructures further extend the smart manufacturing capabilities [Akhtaruzzaman, 2025]. Hybrid and multicloud architectures can enable scalability for data processing while providing access to powerful analytics and computational capabilities. Edge computing can be used in conjunction with cloud computing to handle time-sensitive data near the production equipment. This is especially critical for any application that demands quick responses, such as machine condition monitoring, automated quality inspection, process control and anomaly detection. Digital twins provide an important connection between physical manufacturing systems and their digital representations [Zhong, 2017]. A digital twin can be defined as a dynamic simulation model of a physical asset or process, a product or a production system, which is continuously updated thanks to the information provided by sensors and operational systems. While static computer aided models are designed to represent a physical asset or process at a single point in time, digital twins are expected to change or evolve over time to represent the changing conditions of the physical asset or process. Combination of sensor measurements, historical production data, simulation results and operational data can thus be achieved, within a single digital environment [Mourtzis, 2021]. The quality of data and models is one of the key drivers for the reliability of a digital twin. Therefore, sensor integration, data acquisition, communication networks, documentation, model validations, are all vital. Predictions made using a digital twin should be compared to measurements made in the physical system to see if the digital twin represents real operating conditions. For safety critical systems or automated decision making, calibration and validation becomes especially critical when digital twins are implemented [Brunheroto, 2021]. The apparent need is for ongoing communication between the physical asset, sensing infrastructure, computational model, and decision making system for a reliable implementation. Combined, smart manufacturing, dynamic physical-virtual connection via digital twins and flexible and digitally integrated production power via additive manufacturing make up the infrastructure needed to shape the future of manufacturing [Kenett, 2022].

Significance: Integrated digital technologies enable predictive, adaptive, efficient, sustainable, and resilient manufacturing through real time monitoring, optimization, and intelligent decision making.

2. Connected Manufacturing Operations

Connected manufacturing operations are a key part of Industry 4.0, where machine-to-machine, machine-to-sensor, machine-to-software, machine-to-production system and machine-to-enterprise network communications are facilitated under a single digital umbrella. Through the use of connected hardware, modular software platforms, automation solutions and real-time data analytics, manufacturing plants can be continuously collecting, sharing and analyzing operational data [Chinesta, 2020]. The connectivity enhances the transparency of production and allows more efficient management of equipment, processes and resources. Connected operations are systems that are not largely dependent on manual inspection or planned interventions, but rather respond to varying conditions based on continually generated data. One of the most prevalent connected manufacturing uses is intelligent asset management and maintenance [Glaessgen, 2012]. Equipment powered by IoT can deliver information on operating conditions, the health of the equipment, energy consumption, vibration, temperature, pressure and other equipment performance characteristics continuously. These data may be used to determine if there is any abnormal behavior, and if an abnormality, what maintenance is required. Scheduled maintenance can thus be supported by proactive and predictive methods. Predictive maintenance models predict equipment damage or failure and enable maintenance to be carried out before any major equipment failure, which allows for maintenance more than a year ahead of time [Kritzinger, 2018]. This can help to minimise unwanted downtime, maximise equipment lifespan, utilise assets more effectively and decrease unnecessary maintenance work. Another benefit of connected manufacturing is the shift from reactive to proactive asset management. In traditional manufacturing, maintenance

work is often triggered by failures or on a fixed schedule. These can lead to unexpected production stops or the replacement of components which are still working. In a connected world, the condition of the equipment can be assessed on a continuous basis and maintenance decisions can be made according to the actual condition of the equipment [Cai, 2017]. Maintenance can then be performed at a time that is best suited for production thereby minimizing disruption and maximizing use of manpower, spare parts, and maintenance resources. Cyber-security is one of the biggest challenges in connected manufacturing. With more and more machines, sensors, controllers, databases and enterprise systems connected via an industrial network and the Internet of Things, new cyber vulnerabilities are also opening up [Ahmadi-Assalemi, 2020]. Manufacturing companies need to secure their intellectual property, production data, operational technologies, and critical infrastructure from unauthorized access, manipulation, and disruption. Cyberattacks can impact information systems, but they can also cause systems to fail in the production process, the operation of systems and equipment, system product quality, and the safety of workers.

3. Digital Twins in Engineering

In the engineering context, a digital twin is an improved virtual copy of a physical asset, process, or system that allows engineers to visualize, analyze, simulate, and optimize performance before changes are made to the physical asset, process or system. Digital twins are not only continually connected to systems in the real world, but they can also include historical, operational and real-time data that are not available in traditional computer-aided design models or simulations (Figure 1) [Björnsson, 2020]. This connection allows the virtual representation to change along with the physical asset and gives a dynamic way of engineering analysis and decision making. Digital twins can be used at various levels of engineering systems, such as a component, a production facility, a supply chain and a system. A digital twin at the component level is the representation of individual components like sensors, motors, valves, pumps, electrical circuits, or any other equipment (Table 1) [Hossain, 2025]. Component Twins can provide detailed information in relation to operating history and current condition of individual elements. This information can be used to gain insight into the behavior of components, detect abnormal conditions, and determine the impact of a modification of one part of a system on the behavior of another part of the system. An asset twin is a physical product or machine that is considered complete and usually comprises multiple interrelated component twins [Guo, 2022]. They offer a wider range of equipment running on the factory floor, and can be used to look at interactions between individual components. The use of asset twins can enable the performance of equipment to be tracked, operational efficiency to be measured, potential failure conditions to be identified and resource consumption to be optimized. They can help to enhance reliability, energy efficiency, maintenance planning, and equipment usage by giving information on the state and activity of an entire asset [Agalianos, 2020].

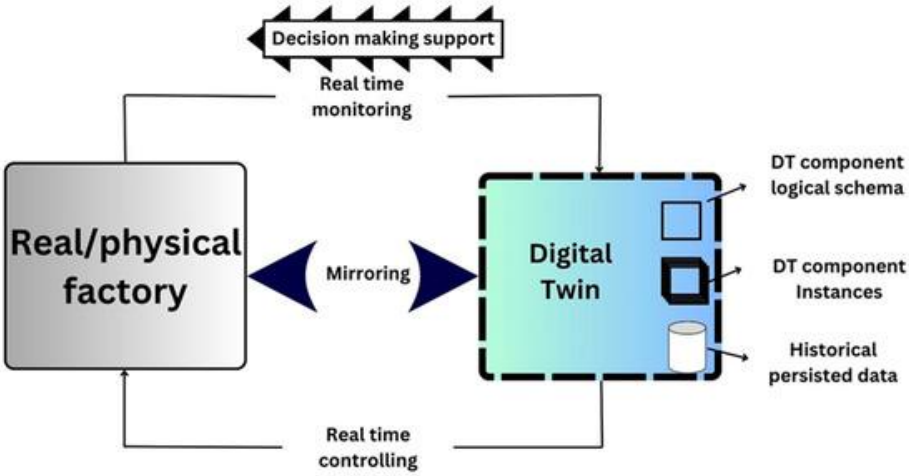


Figure 1. Impact of Digital Twins on Real Practices in Manufacturing Industries [Bertola, 2018]

Table 1. Smart Manufacturing, Digital Twins, and Advanced Additive Manufacturing

Technology	Key features	Main applications	Reference
Smart manufacturing	Integration of cyber physical systems, IIoT, cloud computing, analytics, automation, and AM	Real time decision making, process optimization, quality improvement, flexibility, reduced downtime and waste	[1], [2]
Industrial Internet of Things	Continuous communication between machines, sensors, software, and production systems	Real time data collection, equipment monitoring, production coordination	[3]
Cloud computing	Distributed and scalable computing infrastructure	Large scale data processing, advanced analytics, computational support	[4]
Edge computing	Processing of time sensitive data near production equipment	Machine condition monitoring, automated inspection, process control, anomaly detection	[4]
Digital twins	Dynamic virtual representation continuously updated using sensor and operational data	Real time monitoring, simulation, prediction, optimization, and lifecycle management	[5], [6]

4. Advanced Additive Technologies

Additive manufacturing (AM), also called 3D printing, is an umbrella term that describes a family of digitally controlled manufacturing processes where objects are created by the successive deposition of material, typically in layers, to form the object shape according to a digital model. Additive manufacturing is a method of producing components based on the desired geometry in contrast to subtractive manufacturing where material is removed from a larger piece of material [Casciani, 2022]. This characteristic offers significant product development flexibility, and allows for the creation of complex structures, customisation of components, lightweight designs and geometries that can prove challenging to achieve through traditional manufacturing processes. With close ties to the digital design, automation, sensing, simulation and data analytics, advanced additive manufacturing has become an important element of the smart manufacturing. Process families are categorized as binder jetting, powder bed fusion, directed energy deposition, material extrusion, material jetting and other specialized applications (Figure 2) [Xu, 2019]. The material requirements, operating conditions, advantages and limitations are different in each process. Powder bed fusion is well suited for manufacturing high precision metal and polymer parts and directed energy deposition is more suited to repair, coating, and large-scale part manufacture. With material extrusion having the advantage of relative simplicity and accessibility, it is widely used, while binder jetting and material jetting offer the potential for higher throughput and more complex applications. The digital nature of additive manufacturing allows a strong connection to be established between product design, process planning, production, inspection, and subsequent operation [Khajavi, 2019]. Information may be associated with a digital model that represents a component either prior to manufacturing, or as it is manufactured. This forms a seamless digital thread spanning from design to manufacturing and to performance while in use. This integration makes it easier to track, and can be the basis for lifecycle based engineering [Grieves, 2016]. In the world of advanced additive manufacturing, digital twins are among the most significant advances. The machine, material, process parameters, environmental factors and changing geometry of the component can be all represented by a digital twin of the AM process. In production, sensor data can be fed into the digital twin for continuous comparison with the expected behavior [Hossain, 2023]. An extra quality assurance tool for in situ inspection exists. Sensors and cameras around the build area can track layer formation, material deposition, geometry, surface characteristics and even possible defect formation. In process monitoring, quality information is collected continuously, rather than being a post-production activity.

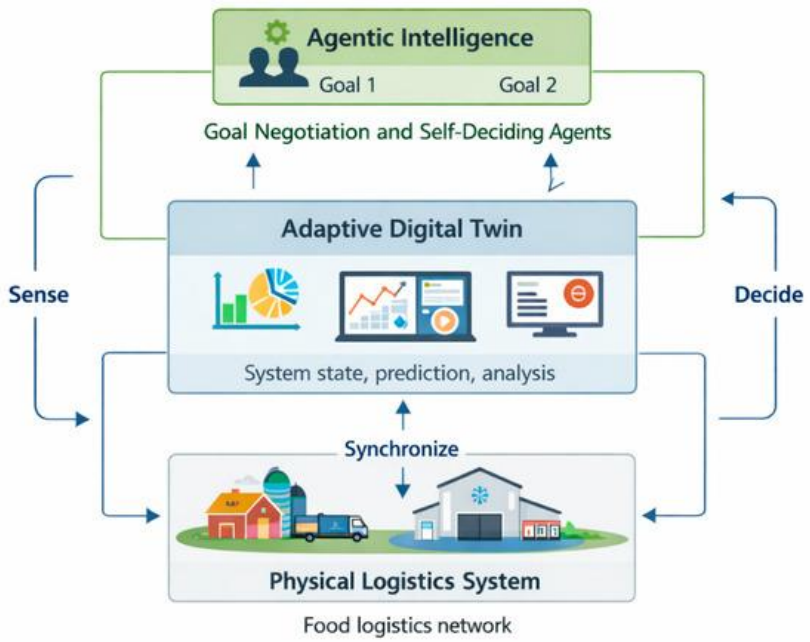


Figure 2. A Self-Deciding Adaptive Digital Twin Framework Using Agentic AI for Fuzzy Multi-Objective Optimization [Spagnoli, 2023]

5. Enabling Computational Frameworks, Governance, Compliance, and Standards

Computational frameworks are essential to support the development of smart manufacturing, digital twins and advanced additive technologies, enabling the seamless integration of physical processes, real-time data, predictive models, and intelligent decision-making [Rasheed, 2020]. These frameworks provide the computational groundings for the conversion of information from machines, sensors, production systems, and digital models into useful operational knowledge. In the recent years, the coupling of sensing, simulation, prediction and control has been increasingly integrated in a synchronized digital environment, rather than adopting them as separated activities. This integration is useful to continuously monitor manufacturing systems, as well as to predict, optimize and adapt control [Qi, 2018]. Digital twins are a valuable computational space for this integration. A digital twin can integrate the data related to the production process, the state of the equipment, environmental parameters, energy consumption and product quality. Production rate and machine temperature could, for instance, be included in an energy analysis model for estimating energy requirements under different operating conditions [Fuller, 2020]. The thermal behavior can affect the energy profile of a manufacturing system, thus temperature is an important variable in both operational health assessment and a sustainability analysis. This computational representation enables one to take into account simultaneously the energy performance, production efficiency and product quality. These technical and organizational components can contribute to the realization of a successful convergence for real time optimization, predictive maintenance, sustainable production, adaptive additive manufacturing and lifecycle based engineering [Chen, 2017]. The next generation of manufacturing systems will continue to evolve, and scalable computational architectures, coupled with trustworthy data governance and human centered design will play an important role in ensuring reliable and intelligent manufacturing operations in the future.

6. Challenges, Research Directions, and Future Outlook

Digital twins, smart manufacturing, and advanced additive technologies are likely to increasingly be a key part of the evolution of intelligent engineering systems. They are evolving and are being increasingly combined with cyber physical systems, the Internet of Things, artificial intelligence, big data analytics, cloud computing, and advanced manufacturing technologies, to offer more responsive and adaptive production systems (Table 2) [Liu, 2018]. But large-scale industrial use is still hindered by technical, computational, organizational, and regulatory issues. But future advances will need to be made simultaneously in the development of reliable digital models, scalable computational equipment, high quality data systems, standards for architectures, and trustworthy mechanisms for decision making [Zheng, 2019]. The data quality challenge is one of the most critical ones. Digital twins and

intelligent manufacturing systems are reliant on real-time data and information obtained via sensors, machines, industrial controllers, production databases and enterprise systems. Digital representations can be less accurate because of errors and missing observations and measurements or communication delays, inconsistencies in measurements [Vrabič, 2018]. These data may be used directly in manufacturing decisions, which can cause poor quality of data to ripple through prediction and control systems and eventually reach to impact on the quality of products, reliability of equipment and operational safety. Accurate data gathering, pre-processing, synchronisation, calibration and quality control as a result are therefore crucial [Madni, 2019]. Research efforts in the future will increasingly focus on embedding surrogate modeling, artificial intelligence, real-time decision making and uncertainty quantification into a single comprehensive digital twin framework. Surrogate models can sometimes alleviate the need to perform high fidelity physical simulations, by offering quicker approximations of complex system behavior. These models can be used with real time sensor information to aid in rapid prediction and optimization without a full scale simulation at each time step [Tao, 2019].

Table 2. Computational Intelligence, Challenges, and Future Directions

Area	Key approach	Main challenge	Reference
Computational frameworks	Integration of sensing, simulation, prediction and control	Scalable computational architectures are required	[23], [24]
Energy modelling	Integration of production rate, machine temperature and energy data	Accurate thermal and operational data are required	[25]
Predictive maintenance	Data driven prediction of equipment failure	Requires reliable real time equipment data	[26]
Cyber physical integration	Integration of CPS, IoT, AI, cloud and advanced manufacturing	Technical, computational, organizational and regulatory barriers	[27], [28]
Data quality	Sensor data acquisition, preprocessing, synchronization and calibration	Missing data, measurement errors, delays and inconsistencies	[29], [30]

7. Discussion

Smart manufacturing, digital twins, advanced additive manufacturing, and the enabling computational frameworks are a fundamental shift in the design, manufacture, monitoring and management of next generation engineering systems. The overall solution extends manufacturing beyond single-field automation and into the realm of inter-connected and data-rich production environments where physical assets, computational models, sensors, software platforms and human decision makers communicate and interact seamlessly [Tao, 2019]. The focus on technology provided in the previous sections suggests that the best value comes when multiple technologies are integrated into a digital ecosystem. The infrastructure that makes this convergence possible is what is known as smart manufacturing. The information can be gathered from machines and processes and can be shared between different levels of an organization, through Cyber physical systems, the Industrial Internet of Things, Cloud Computing, Edge Computing, Robotics, Automation, and Advanced Analytics [Hossain, 2022]. Production data can be linked to maintenance, quality systems, supply chain, and enterprise systems, thus increasing visibility across the traditionally separate functions. This connection allows manufacturing companies to detect process anomalies sooner, better co-ordinate production processes and make decisions based on real time data instead of just historical data or predetermined schedules. Digital twins serve as the computational bridge between physical manufacturing systems and digital systems [Zhou, 2018]. Their significance is that they can always add real world information to their virtual models. Component twins can be used to describe individual sensors, motors, valves or other components, and asset twins can be used to represent a machine. System and process twins are used to represent production lines, factories and manufacturing workflow. These various levels may be linked together in such a way that information can flow from the individual pieces of equipment to the larger systems [Kusiak, 2018]. This means that both the behavior of the component and the impact of that behavior on production performance and system level goals can be studied. This integration enables transition from post production quality inspection to continuous quality assurance. A conventional inspection might only detect a fault when the component is finished and fix it at a high cost or even be unfeasible. The in situ monitoring enables the discovery of abnormalities at

production [Negri, 2017]. If suitable control systems are in place, parameters can be altered during the manufacturing process. This closed loop operation can have a great potential to enhance the dimensional accuracy, surface quality, mechanical properties, and overall process consistency. This integration will need advanced computational models to be made feasible. Many manufacturing systems produce huge amounts of data, but data, by itself, is not useful for operational intelligence. The challenge is to convert measurements into reliable predictions and decisions, which requires data fusion, state estimation, simulation, machine learning, optimization and uncertainty quantification [Picone, 2023]. For instance, the state of a manufacturing system can be estimated using noisy measurements from sensors and predictions from models in a Kalman filter based approach. These estimated states can then be used to test energy usage, equipment condition, production efficiency and product quality. As AI and machine learning advance, there are more possibilities to enhance the digital twin. Nonlinear relationships that are not easily captured in conventional analytical models can be captured by data driven models [Schleich, 2017]. Multi step prediction, anomaly detection, process optimization, and quality forecasting are possible applications of deep learning. But the data-driven models can be inaccurate if the working conditions are very different from the conditions under which the data was obtained. Combine machine learning with physical models and uncertainty quantification is thus a more promising path to follow. It is possible to mix and match flexibility of learning based approaches and knowledge and physical constraints through physics informed and hybrid approaches [Sharma, 2022]. One use that surrogate modeling has in particular is in the context of high fidelity simulations that are computationally expensive. A validated surrogate model can be a good approximation to the physical model, but may need much less computational effort. This allows real-time predictions to be more readily achievable, and it can help in real-time optimization in digital twins. They are expected to become more vital for more complex additive processes associated with thermal behavior, material flow, residual stress, distortion and evolving geometry [Ceschin, 2016]. With these opportunities, there are some obstacles that prevent broad scale adoption. One of the basic questions still facing the data is how good is it? While digital twins rely on precise and up-to-date sensor data, industrial data can have noise, missing values, inconsistencies, sensor drift, and data synchronization issues. Data collected inaccurately can be carried forward in predictive models and control systems. This means that there is a need for continuous data validation, calibration, synchronisation and quality monitoring. More integration of AI, surrogate modeling, real-time sensing, predictive control and adaptive model updating will be needed [Hossain, 2025]. Multimodal sensing and closed loop control are unique aspects of additive manufacturing that should be given further consideration as they have the potential to detect and correct defects during manufacture. Common digital twin standards, open benchmark datasets, interoperability and robust validation processes will also be crucial for the wider industrial uptake. By leveraging reliable data, validated models and intelligent analytics, manufacturing systems can become more predictive, adaptive and efficient [Arnette, 2014]. Technological capability, however, will not ensure the successful implementation. Data reliability, computational efficiency, interoperability, cybersecurity, governance, workforce development, and human centered design must be built into the technology. All these related challenges will make or break the digital manufacturing from being pilot projects to stable, scalable, and intelligent industrial ecosystems.

8. Conclusion

The convergence of smart manufacturing, digital twins, advanced additive technologies, and computational intelligence is transforming next-generation engineering systems. These technologies enable real time monitoring, predictive maintenance, adaptive process control, intelligent quality management, and improved lifecycle optimization. Digital twins provide continuous connections between physical assets and virtual models, while additive manufacturing enables digitally integrated, flexible production. However, widespread implementation remains constrained by data quality, interoperability, computational complexity, cybersecurity, uncertainty, validation, and standardization challenges. Future progress will depend on scalable architectures, trustworthy artificial intelligence, robust data governance, standardized frameworks, and human-centered design. Their coordinated development can establish more efficient, resilient, sustainable, and adaptive manufacturing ecosystems.

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