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

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Abstract: Smart manufacturing, digital twins and advanced additive technology are revolutionizing engineering systems by connecting the physical production environment with interconnected intelligence in the digital realm. This review focuses on the technological architecture, interoperability requirements, applications, and new opportunities of this convergence. Smart manufacturing is the convergence of Industrial Internet of Things devices, artificial intelligence, robotics, cloud and edge computing, manufacturing execution systems, real time analytics and manufacturing visibility. Digital twins are dynamic virtual copies of physical assets, processes, and systems that can be simulated, utilized for predictive maintenance, process optimization, quality management, and lifecycle decision making. Advanced additive manufacturing adds to this the ability to rapidly prototype, make complex shapes, provide individualized manufacturing, repair and digitally controlled manufacturing. The multi-protocol integration of OPC UA, MQTT, Asset Administration Shell, Functional Mock up Interface and ISA 95 ensures interoperability between disparate industrial systems and enhances the connection of the digital thread. Middleware, industrial data platforms and manufacturing intelligence layers enable the SCADA, MES, ERP, IIoT and digital twin environments to communicate with each other. Applications range from predictive maintenance to production planning, quality control, virtual commissioning, asset lifecycle management, process optimisation, and more, across automotive, aerospace, semiconductor, energy, healthcare and many other areas. Overall, a coordinated development of digital twins, smart manufacturing infrastructure, and additive technologies will create the basis for more adaptive, predictive, flexible, and data driven manufacturing systems that enable continuous optimization during the product lifecycle.

Keywords: Smart manufacturing; Digital twins; Additive manufacturing; Industrial Internet of Things; Manufacturing interoperability

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1. Introduction

Next generation engineering systems combine smart manufacturing, digital twins, additive manufacturing, industrial Internet of Things, robotics, artificial intelligence, and cloud based analytics in the form of highly connected and data driven manufacturing environments. At the very heart of Industry 4.0, these systems enable more agility, quality, efficiency, and coordination

throughout the product design, production, maintenance, and supply chain [1]. Smart manufacturing is the digitalization of manufacturing process from product development to production monitoring and optimization. Additive manufacturing, Artificial Intelligence, automation, sensing technologies, and advanced data analytics have all contributed to its development. These technologies have evolved manufacturing away from the traditional automation and towards cyber physical and interconnected production systems [2]. Real time information allows the manufacturers to keep track of operations, detect irregularities, work out the optimisation, minimise waste and make better decisions. Digital twins are an integral part of these systems. A digital twin is a virtual model of a physical asset, process or production system that integrates sensor data, historical information, simulation models and analytical tools into a dynamic model [3]. The seamless information flow between the physical and virtual worlds now opens the door for predictive maintenance, performance optimization, process monitoring, and improved decision-making at the operational level. Digital twins are no longer standalone technologies, but are combined with CAD, CAE, simulation, manufacturing execution and enterprise systems. Digital twin based production is complemented by Additive Manufacturing which can provide rapid prototyping, design flexibility, complex geometries, internal structures and decentralized production [4]. These are the principal AM families: Vat photopolymerization, Material extrusion, Powder bed fusion, Binder jetting, Material jetting, Directed energy deposition, and Sheet lamination. There are different process requirements for each process for material, dimensional accuracy, throughput, process control and inspection. Thus, the selection and design of the AM process should be part of digital engineering activities from the start of product development. Smart manufacturing is further enhanced by connected sensing and control infrastructures [5]. The information is continuously exchanged with production systems using IIoT devices, SCADA, MES, edge computing and cloud platforms. OPC UA, Asset Administration Shell, FMI, and ISA 95 are examples of interoperability standards and architectures that facilitate integration between machines, software platforms and enterprise operations. This digital thread allows for a coordinated approach to planning, monitoring, maintenance, and lifecycle management both within and across facilities and supply chains [6].

2. Materials and Methods

This study employed a narrative-integrative review approach to synthesize the technological foundations, interoperability mechanisms, industrial applications, and emerging engineering implications of smart manufacturing, digital twins, and advanced additive manufacturing. The review corpus consisted of the scholarly works cited in this manuscript, including journal articles, conference proceedings, and book chapters addressing Industry 4.0, cyber-physical production systems, the Industrial Internet of Things (IIoT), digital twins, artificial intelligence, edge and cloud computing, interoperability standards, predictive maintenance, and additive manufacturing. The analysis was conducted through thematic synthesis. Relevant evidence was organized into four analytical domains: connectivity, interoperability, and standards; digital twins and advanced additive technologies; software platforms and middleware; and business and industrial use cases. The reviewed studies were compared according to their reported technological functions, integration requirements, operational benefits, and implementation challenges. The synthesis was then used to identify recurring patterns concerning data integration, model fidelity, real-time monitoring, predictive analytics, lifecycle management, production flexibility, and cross-platform interoperability. Because this study is literature-based rather than experimental, the findings represent a structured synthesis of published evidence and conceptual relationships rather than

primary measurements.

Next Generation Smart Manufacturing Engineering Systems: Connectivity, Interoperability, and Standards

Next generation smart manufacturing engineering systems integrate the use of next generation hardware, software, automation, additive manufacturing, real time data acquisition, artificial intelligence, digital twin, and industrial connectivity to optimize product design, manufacturing, maintenance and supply chain operations. The benefits of additive manufacturing are to increase the design space by providing rapid prototyping, reducing production time and creating complex geometries and internal structures that are hard to make with traditional manufacturing methods [7]. These capacities are complimentary to conventional automation and facilitate quicker design iterations and more adaptable manufacturing. Data acquisition is a key element of these systems that is done in real time. Equipment performance, material motion, inventory, and process conditions are tracked and reported by SCADA and other industrial data platforms and alerts are issued when unusual behavior is detected. Smart sensors, barcode readers, vision systems, energy meters, environmental probes, and other types of IIoT devices, send operational data to controllers and edge gateways (Table 1) [8]. Edge computing supports protocol conversion, buffering, preprocessing and fast local analytics, and cloud and plant level platforms offer time series data, historians, statistical process control, overall equipment effectiveness, analytics and manufacturing execution systems. The combination of IIoT, Cyber Physical Systems, Robotics, AI, Machine Learning, Simulation, Cloud Computing and Digital Twins brings together a whole manufacturing environment that can help in predictive maintenance, process optimization, quality control and production planning based on operational data [9]. Manufacturing operations management also links manufacturing execution systems to maintenance, laboratory information management, warehouse operations, and other site level functions. This architecture will enhance the visibility of production activities and provide interoperability and synchronicity between shop floor and enterprise systems. The key to this integration is connectivity and interoperability. OPC UA offers structured, model based communication with standardized information, metadata, units and semantic relationships, while MQTT offers light weight event driven communication between edge and cloud [10]. They can be used in conjunction with each other to enable scalable publish and subscribe architectures, efficient data exchange, traceability and lower integration complexity. Also, Sparkplug B can offer consistent naming, contextual information and state awareness across MQTT based industrial networks.

Table 1. Core technologies, functions, and contributions in next generation engineering systems

Technology	Primary Function	Contribution to Engineering Systems	References
Smart manufacturing	Integrates connected equipment, automation, AI, analytics, and manufacturing systems	Improves production visibility, efficiency, coordination, and adaptive decision making	[26, [13]
Industrial Internet of Things (IIoT)	Collects real time operational data through sensors and connected devices	Enables continuous monitoring of equipment, materials, energy, and process conditions	[10], [8]
Digital twins	Creates dynamic virtual representations of physical assets, processes, or systems	Supports simulation, predictive maintenance, process optimization, and lifecycle management	[25]

Technology	Primary Function	Contribution to Engineering Systems	References
Artificial intelligence and machine learning	Performs prediction, pattern recognition, optimization, and intelligent decision support	Enables predictive maintenance, quality control, production planning, and process optimization	[33]
Edge and cloud computing	Provides distributed data processing, storage, and analytics	Reduces latency for time sensitive operations while supporting large scale data management	[32]

Digital Twins and Advanced Additive Technologies in Twin Driven Manufacturing

Digital twins are virtual replicas of physical objects, processes or systems that are built using real time data, analytics and simulation, to replicate and analyse their physical counterparts. The virtual model can adjust to the physical changing conditions by continuously acquiring data from the sensors, operational systems, environment and user interactions. Digital twins can help optimize operations, reduce costs, enable predictive maintenance, and enhance decision-making during the entire lifespan of the product [11]. Digital twins can be organized according to their scope and functional purpose. Process Digital Twins are oriented towards manufacturing or logistics processes, enabling the evaluation of changes in processes without interrupting production (Figure 1). System digital twins are composed of several product and process models that can be used to represent larger system environments like production lines, or even factories [12]. There are specific types of twins such as performance twins (for equipment health and failure prediction), operational twins (for real-time resource and process management), and environmental twins (for energy consumption, emissions and sustainability performance analysis). These combined forms offer varying levels of visibility throughout industrial processes. A digital twin is effective only when it can be continually monitored, have good data management, good simulation models, and analytical functions [13]. Digital twins can help increase productivity, minimize downtime, optimize resources, and make strategic decisions. They are integrated with product lifecycle management, bringing these advantages from product design and manufacturing into operation, maintenance and end-of-life management. Digital twins are now growing to become integrated into CAD, CAE and simulation, manufacturing and enterprise software systems rather than applications. Predictive maintenance is one of the key use cases. Maintenance focused twins regularly monitor equipment performance and condition to detect deterioration and predict equipment abnormalities [14]. This enables maintenance tasks to be planned ahead of potential failures which helps to minimize downtime and maximize asset utilization. Another benefit of cloud based digital twin is the ability to assess remaining useful life of assets in large fleet, showcasing the power of data driven maintenance.

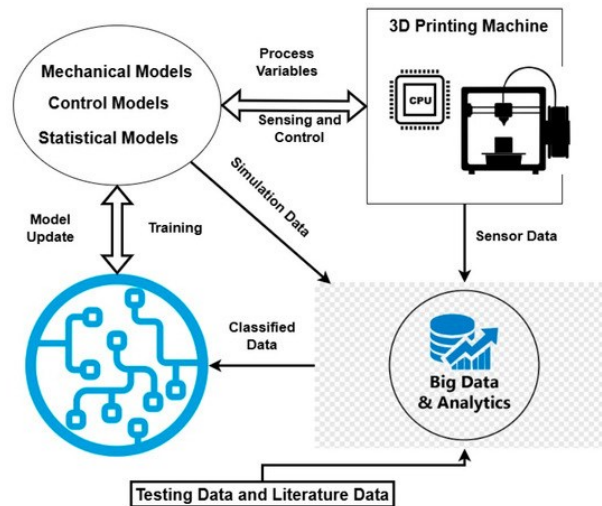


Figure 1. Digital Twins, AI, and Cybersecurity in Additive Manufacturing [36]

Software Platforms and Middleware for Smart Manufacturing and Digital Twins

Industrial manufacturing has a wide range of machines, sensors, controllers, software platforms, and communication standards, making it an ideal use case for a middleware that can offer uniform connectivity and data exchange. Middleware provides an intermediate software layer that helps SCADA, MES, IIoT platforms and enterprise applications communicate without having to connect directly to each individual device [15]. Flexible connectivity can be achieved by using configurable libraries and plugins, and even direct connections can be left for some legacy systems or systems for safety reasons. Contextual data management provides another layer of value to industrial data. Metadata can be attached to SCADA and operational technology data to support the identification of components, subassemblies, production stages, equipment states and process conditions [16]. This contextualization makes it easier to trace back and better enables production information to be understood in its operational meaning, instead of as single data points. It can assist in quickly identifying bottlenecks, investigating defects, implementing quality management, and adherence to regulatory standards. Manufacturing intelligence platforms add another essential software layer by bridging a gap between ERP, MES, SCADA and IIoT environments with a common data format. These systems can integrate information from various sources, and create a continuous loop between production priorities, process conditions, and operational constraints, without replacing existing IT and OT systems (Figure 2) [17]. This information on high speed equipment data can be then integrated with enterprise requirements and manufacturing execution data, which can assist in automated optimization and production control. Visualization tools also enable engineers, operators, managers and other stakeholders to look at production conditions and assess the impact of different scenarios using what if analyses. Middleware, manufacturing intelligence platforms, simulation environments and digital twins (DT) are thus the software foundation for next generation smart manufacturing [18]. These components join together heterogeneous industrial systems, structure the information of operation, facilitate real time analysis, and allow the intelligent decision making. In addition, if applied with AI and visualization tools like augmented reality, they can enhance predictive maintenance, production optimization, engineering analysis, and factory floor decision-making even further.

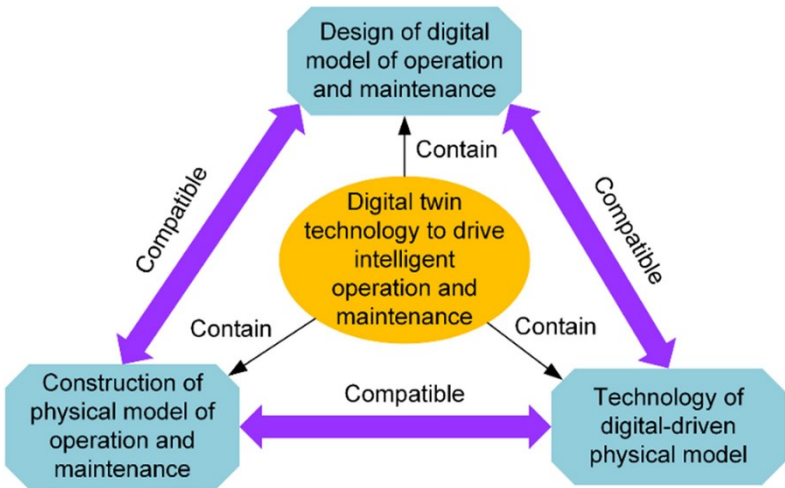


Figure 2. Digital Twin for Integration of Design-Manufacturing [37]

Business and Industry Use Cases of Smart Manufacturing and Digital Twins

Consistent exchange of information between machines, software platforms, and enterprise systems is the basis of modern smart manufacturing, and is achieved through industrial standards and interoperability. These standardized interfaces eliminate fragmentation and enable data from production to flow between different systems. Architectures in manufacturing are increasingly shifting away from traditional point-to-point exchanges to AI powered, workflow oriented environments where data, analytics, automation and operations are synced and orchestrated across integrated platforms [19]. Operational value can come from digital twins and manufacturing intelligence platforms. They integrate real-time data on equipment with virtual equipment models and analytical tools to facilitate predictive maintenance, proactive quality management, and prescriptive decision making (Table 2). Predictive maintenance is the ability to detect equipment condition changes and make predictions of equipment failures prior to production interruptions [20]. This helps plan maintenance activities based on true asset conditions and helps increase the reliability of equipment and decrease unplanned downtime. Prescriptive analytics adds to this by suggesting specific actions that can be taken depending on the operational results that can be predicted. The Predictive Maintenance & Asset Health Management solution integrates digital twin models with live data on equipment signatures to evaluate the health of assets and detect degradation. Thus, maintenance can be scheduled based on real-time operational data instead of specified time periods [21]. This technique can minimize unplanned failures, maximize equipment life, improve equipment availability, and decrease maintenance costs, especially those associated with high dollar equipment where downtime can mean a significant loss of money. In general, these applications reflect a general shift to smarter and more autonomous production systems. Backed by standardized communication interfaces, digital twins, AI, real time analytics, and manufacturing intelligence platforms are creating a foundation for connectivity, and turning operational data into decision makers [22].

Table 2. Applications, benefits, challenges, and enabling requirements of integrated smart manufacturing

Application	Integrated Technologies	Major Benefits	Key Challenges	References
Predictive maintenance	Digital twins, IIoT, AI, sensor data, analytics	Early failure detection, reduced	High quality data, accurate models,	[21]

Application	Integrated Technologies	Major Benefits	Key Challenges	References
Process optimization	Digital twins, simulation, AI, real time analytics	downtime, improved asset utilization Improved process efficiency, resource utilization, and operational performance	continuous monitoring Model fidelity, data contextualization, computational requirements	[34]
Quality management	IIoT, digital twins, machine learning, manufacturing intelligence	Early defect detection, improved traceability, proactive quality control	Data integration, sensor reliability, process specific models	[33]
Production planning	AI, digital twins, MES, real time data	Better scheduling, resource allocation, and production coordination	Interoperability and synchronization between shop floor and enterprise systems	[23]

3. Results

The review identified a convergent engineering architecture in which smart manufacturing, digital twins, IIoT, artificial intelligence, edge and cloud computing, and additive manufacturing operate as complementary rather than isolated technologies. Across the reviewed literature, real-time sensing and industrial connectivity provide the operational data layer, while middleware, SCADA, MES, ERP, and manufacturing intelligence platforms contextualize and exchange information between shop-floor and enterprise systems. Interoperability mechanisms such as OPC UA, MQTT, Asset Administration Shell, Functional Mock-up Interface, and ISA-95 repeatedly emerge as key enablers of the digital thread because they reduce fragmentation between heterogeneous machines, software environments, and organizational levels.

A second major result concerns the role of digital twins as the analytical and simulation layer of next-generation engineering systems. The reviewed studies consistently associate digital twins with continuous monitoring, predictive maintenance, process optimization, virtual evaluation, production planning, and lifecycle management. Their effectiveness, however, depends on reliable sensor data, appropriate contextualization, synchronization between physical and virtual assets, and sufficiently accurate models. Advanced additive manufacturing extends this architecture by connecting digital design directly with flexible physical production, supporting rapid prototyping, complex geometries, customized components, repair, and digitally controlled manufacturing. The synthesis also indicates that digital-twin configurations must be adapted to the characteristics of individual additive manufacturing processes rather than applied as a single universal model.

The industrial application evidence was concentrated in four recurring areas: predictive maintenance, process optimization, quality management, and production planning. Predictive maintenance was linked to earlier failure detection, lower unplanned downtime, and improved asset utilization; process optimization to improved efficiency and resource use; quality management to earlier defect detection and stronger traceability; and production planning to improved scheduling,

allocation, and coordination. At the same time, the reviewed evidence identified persistent implementation constraints, particularly data quality, model fidelity, sensor reliability, computational requirements, cybersecurity, legacy-system integration, interoperability, and workforce readiness. Overall, the results show that the greatest engineering value is produced when these technologies are integrated through a coordinated digital thread and deployed around measurable operational use cases rather than implemented as stand-alone tools.

4. Discussion

Smart manufacturing, digital twin, and advanced additive technologies are a fundamental transformation in the organization and operation of modern engineering systems. The new paradigm in manufacturing is not a linear sequence of design, production, maintenance and supply chain functions, but one that links them together via the continuous exchange of data, computational models, intelligent analytics and automated decision support [23]. The evidence in the previous sections suggests that the primary value that this convergence brings is not in a single technology. Rather, value is generated by the interplay of various interdependent physical systems, digital representations, communication standards, simulation environments and analytical platforms. The integration helps manufacturing companies transition from isolated automation to constantly monitored, adaptive and increasingly predictive production environments [24]. Digital twins are one of the most pivotal aspects of this change. They can keep a dynamic picture of physical assets and processes, which offers a means for real time operational information to be understood in the larger engineering context. Most monitoring systems provide up-to-the-minute information, while a digital twin can include not only the current data but also historical data, simulation models, equipment attributes, and operational constraints [25]. The distinction is significant because production decisions often have to be made not just on what is occurring at a specific point in time, but also on how present conditions are expected to impact future performance. Therefore, digital twins offer great opportunities for predictive maintenance, process optimization, virtual commissioning, production planning and lifecycle management. Quality and availability of data is a major factor in the effectiveness of digital twins [26]. A big pile of sensor data doesn't necessarily translate to a coherent digital model. Data needs to be properly contextualized, synced, validated and linked to the right asset and process models. This is why IIoT infrastructure, industrial data platforms, historians, edge computing, and middleware are key elements in the development of twin based manufacturing. Edge systems can analyze time-sensitive data near the equipment to minimize latency and transmission of unnecessary data; cloud systems and plant level systems can offer enhanced data storage and analytics capabilities [27]. A layered architecture is thus a more suitable approach than a purely centralized or decentralized approach due to the varying needs for latency, computational intensity, availability and security of different classes of manufacturing data. Another critical element in determining the ability of these architectures to work is interoperability. Modern factories consist of a variety of equipment from various vendors and generations, with different communication protocols and data structures. In the absence of common interfaces, the integration of SCADA, MES, ERP, IIoT devices, digital twins and additive manufacturing equipment becomes costly and challenging [28]. Advanced Additive Manufacturing (AAM) provides another layer of value to this transformation. The Digital Model to Physical Production relationship is changed by AM, since the manufacturing process can be directly controlled by the digital model. Many conventional manufacturing processes would require a long lead-time for the tools and components required to produce complex geometries, internal channels, customized components, rapid prototypes, and repair structures [29]. This flexibility is crucial for AM, as it fits well with digital twins that allow for the simulation of alternative designs and process parameters before production. Production data can then be fed into the digital twin to check if the actual production result matches the desired result. The various AM process families require different needs for digital monitoring and control. Powder condition, thermal behavior, layer formation, surface characteristics and dimensional stability are all considerations for powder bed fusion [30]. Layer adhesion, anisotropy, support and surface quality

are factors that influence material extrusion. The potential to deposit material on to existing components is particularly important for repair and life extension applications, which is where directed energy deposition becomes relevant. The different aspects reveal that a universal digital twin architecture cannot simply approach all AM processes as the same. Models, sensors, quality indicators and control strategies specific for the process must be developed in order to accurately capture the physics of the manufacturing process [31]. Product lifecycle management is also evolving with the bringing together of AM and digital twins. Product information can be stored from product design to manufacture, use, maintenance and in the end, retire. For higher value parts, it is possible to offer opportunities for condition based maintenance and extension of parts life. The characteristics of a component manufactured by AM can be linked to its manufacturing parameters, inspection data, material data, operating history and repair history. In industries like aerospace, energy, healthcare, and defense, where component reliability and regulatory requirements are paramount, such traceability is of special significance [32]. One of the most obvious benefits of the combined architecture is predictive maintenance. The traditional methods for maintenance are usually based on a programmed maintenance schedule or a fault-based approach after failure. Digital twins enable the real-time assessment of equipment condition based on sensor measurements, past behaviour, and model-based predictions. If degradation patterns are identified, maintenance can be done before failure. This can help minimise downtime, maximise asset availability and optimise maintenance resources. The business value of these systems is also important [33]. Many digital transformation initiatives fall short when the advantages of technologies don't lead to tangible business results. The best case scenario is when digital twin and smart manufacturing are used to solve high dollar issues like unplanned downtime, poor quality, inefficient scheduling, excessive energy consumption, or long development cycles. Adopting technology for a specific operational goal can be more advantageous than predictive maintenance of more-costly assets, virtual commissioning of complex production lines, or digital optimization of the AM processes [34]. This indicates that one should start implementing with measurable use-cases and gradually scale-up as the technical maturity and organizational confidence grows. In general, the integration of smart manufacture, digital twins and advanced additive technologies can offer excellent support for next generation engineering systems. The foundation for communication is the interoperable standards, the flow of information is managed by middleware and IoT platforms, dynamic representation and simulation is possible with digital twins, prediction and optimization is possible with AI, and flexible digital production is made possible with additive manufacturing [35].

5. Conclusion

The convergence of smart manufacturing, digital twins, and advanced additive technologies is reshaping modern engineering systems by connecting physical production with real time digital intelligence. Digital twins enable continuous monitoring, simulation, predictive maintenance, and lifecycle optimization, while additive manufacturing provides flexible and digitally driven production capabilities. IIoT, middleware, cloud platforms, and interoperability standards strengthen communication across heterogeneous industrial environments. Despite challenges related to data quality, cybersecurity, model fidelity, integration, and workforce readiness, these technologies provide substantial opportunities for improving quality, efficiency, flexibility, and sustainability. Their coordinated development will support increasingly adaptive, predictive, and intelligent manufacturing ecosystems.

Author Contributions

S.M.A. conceived the review topic, conducted the literature search, analyzed and synthesized the relevant literature, and drafted the manuscript. S.M.A. critically revised the manuscript, developed the conceptual framework, and approved the final version for publication.

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