Sustainable Manufacturing and Service Economics 2 (2023) 100017

Contents lists available at ScienceDirect

Sustainable Manufacturing and Service Economics

journal homepage: www.elsevier.com/locate/smse

Digital twin for smart manufacturing, A review

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ARTICLE INFO

Keywords:
Smart manufacturing
Digital twin
Manufacturing optimization

ABSTRACT

A virtual representation of a physical procedure or product is called digital twin which can enhance efficiency and reduce costs in manufacturing process. Utilizing the digital twin, production teams can examine various data sources and reduce the number of defective items to enhance production efficiency and decrease industrial downtime. Digital Twin can be utilized to visualize the asset, track changes, understand and optimize asset performance throughout the analysis of the product lifecycle. Also, the collected data from digital twin can provide the complete lifecycle of products and processes to optimize workflows of part production, manage supply chain, and manage product quality. The application of digital twin in smart manufacturing can reduce time to market by designing and evaluating the manufacturing processes in virtual environments before manufacture. Comprehensive simulation platforms can be presented using digital twins to simulate and evaluate product performances in terms of analysis and modification of produced parts. Commissioning time of a factory can also be significantly reduced by developing and optimizing the factory layout using the digital twin. Also, the productivity of part manufacturing can be enhanced by providing the predictive maintenance and data-driven root-cause analysis during part production process. In this paper, application of digital twin in smart manufacturing systems is reviewed to analyze and discuss the advantages and challenges of part production modification using the digital twin. So, the research field can advance by reading and evaluating previous papers in order to propose fresh concepts and approaches by using digital twins in smart manufacturing systems.

Introduction

A digital twin is a virtual representation of a physical system or process that allows for real-time monitoring, analysis, and optimization. In the context of smart manufacturing, a digital twin can be used to simulate and optimize the production process, predict and prevent equipment failures, and improve efficiency and quality of part production [1,2]. The digital twin can provide a detailed, accurate representation of the physical object or system, including its behavior, performance, and interactions with the environment [3]. Digital twins use machine learning, data analytics, and multi-physics simulation in order simulate and analyze different working conditions and other factors affect a system [4]. The creation of the digital twin is a critical component of future technology that will have an impact on several global sectors [5]. By analyzing data from the physical object, the Digital Twin can provide real-time feedback, monitor its performance, and identify potential issues before they occur [6]. A digital twin can be used in order to optimize the operation of a physical system, by simulating its behavior and identifying areas where improvements can be made. [7]. Furthermore, companies can utilize digital twins to model, anticipate, and improve products and manufacturing processes in different industries, including automotive, green energy, and aviation before organizations invest in actual prototypes and assets, [8]. As a result, digital twins can help businesses and manufacturing process in order to make better decisions, reduce costs, and improve performance across a range of industries and applications.

By creating a digital twin, engineers and designers can test various scenarios and make improvements, reducing the time and costs associated with physical testing and prototyping [9]. The use of digital twin technology is essential for product manufacturers in order to improve the productivity of their manufacturing processes and shorten time-to-market [10]. Digital twins in smart manufacturing are created by combining real-time data from physical sensors with computer-aided design (CAD) models and other simulation tools. This allows manufacturers to monitor and analyze the performance of equipment and processes in real time, identify potential issues before they occur, and make data-driven decisions to optimize production. [11]. By creating a digital twin of a part, engineers can analyze its performance under different conditions, such as changes in temperature, pressure, and load. This allows

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https://doi.org/10.1016/j.smse.2023.100017
Received 15 February 2023; Received in revised form 4 May 2023; Accepted 20 June 2023

them to predict how the part will perform in real-world situations, identify potential issues or failures, and optimize its design to improve its performance [12]. The digital twin provides several benefits to smart manufacturing. For one, it enables real-time monitoring of manufacturing processes, allowing for quick identification and resolution of issues. Additionally, it allows for the testing and optimization of products and processes before they are physically produced, which can save time and resources [13]. Moreover, production digital twins are employed to verify the effectiveness of a manufacturing process prior to component manufacture. A digital twin can be used to monitor the performance of individual machines or production lines, detect potential issues before they occur, and optimize the system's operations to minimize downtime and maximize output. It can also be used to simulate and test new production processes or equipment before they are implemented in the physical system in order to reduce the risk of costly errors or failures [3]. Performance digital twins enable the manufacturing managers to enhance models and system performance while generating new commercial prospects [14]. A digital twin, which spans the full engineering lifecycle, makes it possible to test and apply continuous improvements at any point in the manufacturing process in a digital setting that is far less expensive to run than the real world. Some businesses utilize digital twins to simulate whole manufacturing lines and identify more effective ways in order to enhance productivity in part production process [15].

Smart manufacturing is a manufacturing approach that incorporates advanced technologies such as artificial intelligence, the Internet of Things (IoT), robotics, and big data analytics to optimize production processes and increase efficiency. The complexity of the production environment is rising, and the tasks involved in manufacturing are getting more customized [16]. As a result, the production system requires a high degree of cognitive and learning skills in terms of analysis and modification of manufacturing process. Smart manufacturing also provides opportunities for product customization and personalization, as well as real-time supply chain management. It enables manufacturers to respond quickly to changes in demand, market trends, and customer preferences, and to create products that are tailored to individual customers' needs [17]. It involves the use of connected devices, automation, and real-time data to improve efficiency, productivity, and quality in manufacturing operations [18]. Smart manufacturing aims to create a more agile, flexible, and responsive manufacturing environment that can quickly adapt to changing market demands and provide high-quality products at lower costs. [19]. Thus, it uses and integrates digital software tools and data throughout the product lifecycle. In a smart manufacturing process, every resource is digitalized in order to be nalyzed and modified in virtual environments [20]. The transition from conventional MSD to digital twins-based SMSD approach is shown in the Fig. 1 [21].

Status monitoring, simulation, and visualization make up the majority of the present uses of digital twins in smart manufacturing. Machines are continually monitored utilizing internet of things for status monitoring, and the most recent state of a machine may be evaluated by querying its digital twin [22]. Also, digital twins of physical assets (such as machines) are generated in order to analyze and modify the mechanism and process of machines in part production [23]. Digital twins of products, systems, and equipment are developed for simulation in order to simulate actual working environments. Using the proposed digital twins, new products and processes can be designed, developed, and modified using virtual simulation before being implemented on genuine physical assets in order to enhance the performances of products and production process [24]. Real-time dashboards and alarm systems can be integrated into digital twins for display in order to track and troubleshoot an operational environment [25]. Digital twins are now only thought of as an identical clone of physical assets without any value-added services placed on top that would allow physical assets to become autonomous intelligent agents [26].

Digital twins in predictive maintenance can increase productivity, identify issues early, and continue to provide fresh perspectives in addition to process optimization [27]. The company can identify the main source of the issue with the aid of a contextual model of your machines created by the digital twin during the production process [28]. Additionally, testing operating conditions and receiving anticipated results digitally, identifying new revenue streams, cutting down on waste, costs, and energy use, performing predictive maintenance on manufacturing processes, improving quality and customer satisfaction, tracking each product from production to finish, enabling new business models, cutting down on time to market, and finally enhancing productivity of part manufacturing are all important [29]. A big advantage of this upgraded digital twin design is the potential to give much more than just a perfect duplicate in order to provide value-added services on top of digital twins which are not accessible on physical assets [30]. Fig. 2 depicts the architecture of the Digital Twin for digital production [31].

The use of digital twins in a manufacturing system could be categorized into three phases. In the system design phase, digital twin could be used to conduct validation and test that can quickly locate the inefficiency reason, and test the practicability of physical manufacturing solution in execution. In this phase, a digital twin can be used to monitor and analyze the performance of manufacturing system in real-time. This can help in order to identify issues before they become critical, predict failures, and optimize the operation of system [20,32].

In the system configuration/reconfiguration phase, the digital twin-based configuration is supposed to enable the validating of manufacturing system performance in a semi-physical simulation manner. This phase typically involves designing the digital twin based on the physical system's specifications, such as its geometry, material properties, and operating conditions. Once the digital twin is created, it can be used to simulate the behavior of system under various conditions, such as changes to the input parameters or the introduction of new components. During this phase, the digital twin can also be used to identify potential failures and vulnerabilities in the physical system before they occur [33].

In the system operation, how to update the online parallel controlling in the cyber model and feedback on the adjustment instructions to the physical manufacturing system is a key enabling technology. In this phase, digital twins can be used to monitor and optimize the performance of manufacturing systems in real-time. This can help manufacturers to identify and resolve issues before they cause downtime, reduce waste, and improve efficiency of part production [34,35].

The benefit of a digital twin is that it can provide a virtual replica of a physical system, allowing for testing and analysis without disrupting the actual system. A digital twin for smart manufacturing can provide significant benefits in terms of efficiency, cost reduction, and product quality. As manufacturing becomes increasingly complex and interconnected, digital twins are likely to become an essential tool for manufacturers looking to stay competitive in the global marketplace. However, the disadvantage is that creating and maintaining a digital twin can be expensive and time-consuming, and may require specialized knowledge and expertise. To develop a digital twin in the modern production systems, there are significant obstacles, nevertheless. Low-quality data collected during part manufacture can reduce a digital twin's ability to modify a manufacturing process. All of these endpoints contribute to a massive amount of data collection, and each one is a potential security vulnerability. Therefore, firms should examine and update current security procedures before deploying digital twin technology. Advanced Internet of Things (IoT) algorithms should be developed in terms of analysis and adjustment of component manufacture to manage a huge amount of data that are acquired from the sensors in the machines. Digital twin models are powered by data from hundreds of remote sensors connected via shaky networks. Businesses who want to deploy digital twin technology need to be able to manage data stream gaps and eliminate inaccurate data. Building digital twins also requires real-time data communication. Because for digital twins to be effective, they must accurately mirror the condition of real devices. Privacy and security of data is also another challenge of part manufacturing modification using

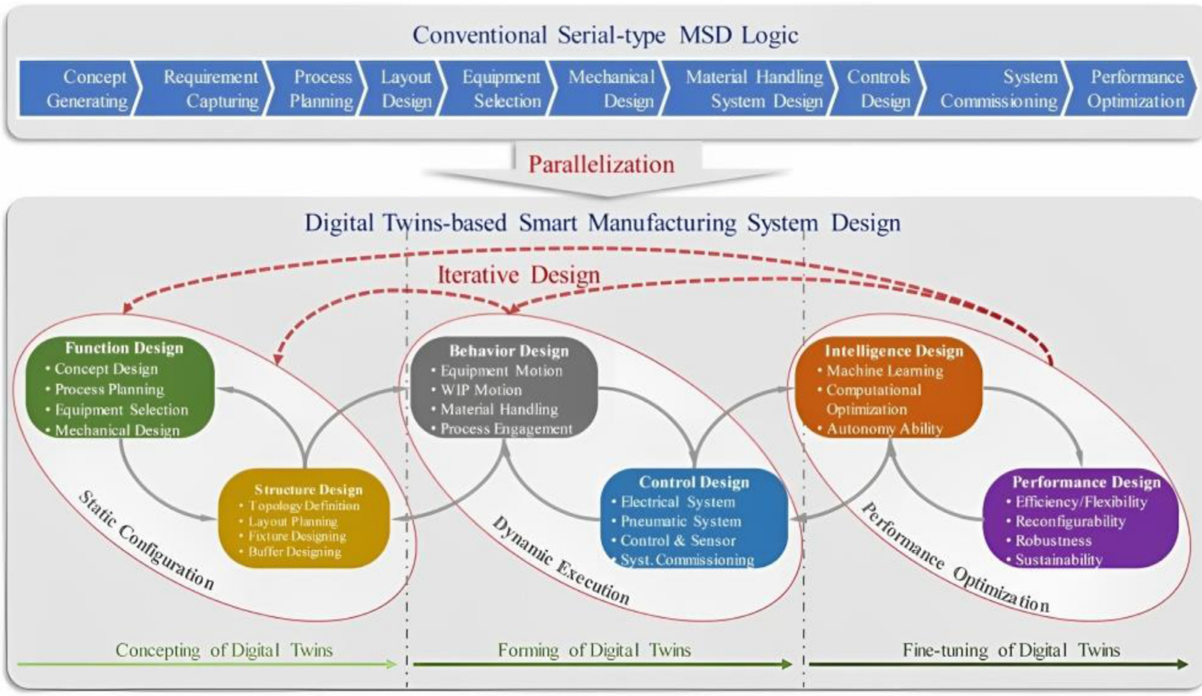

Fig. 1. The switch from the traditional MSD strategy to the SMSD approach based on digital twins [21].

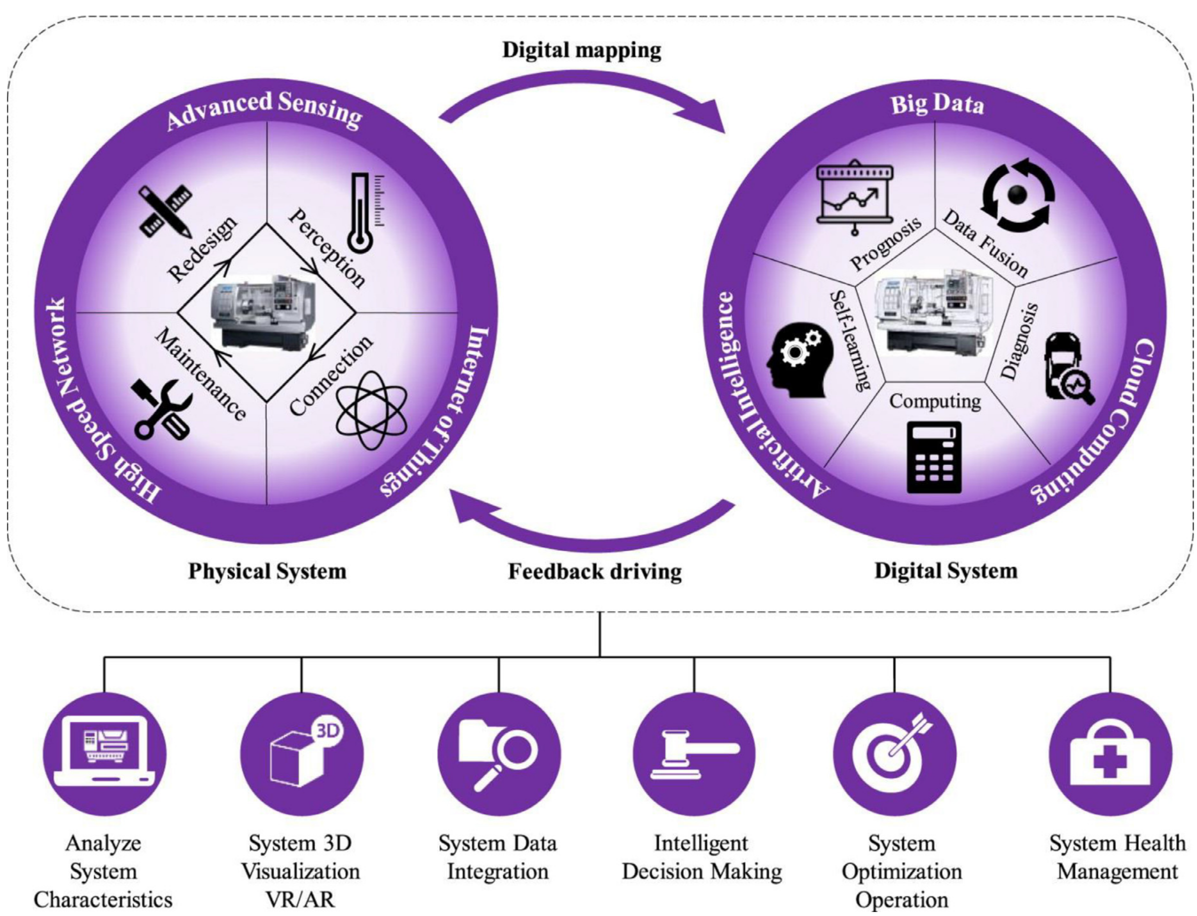

Fig. 2. The design of the digital twin for manufacturing [31].

digital twin. Moreover, the lack of stable and sustainable technologies stands in developing a concrete end-to-end collaborative digital twin system for smart distributed manufacturing.

To improve the green performance of smart manufacturing systems, Li et al. [36]developed the concept of the digital twin. Lu et al. [37] described the status and development of digital twin-driven smart manufacturing in order to create applications for this technology. Lattanzi et al. [38] presented a review of concepts for a practical industrial implementation of the twin in smart manufacturing in order to assess and modify the current state-of-the-art on Digital Twin concepts and to draw their most recent state for use and deployment in actual industrial processes. To improve the impact of the digital twin on the energy consumption of component production, Wang et al. [39] provide an overview of digital twin approaches in smart manufacturing and management of energy applications.

Regrading the presented review papers in application of digital twin in part manufacturing process [19,36-40], more published papers in different topics of part manufacturing such as continues improvement and production monitoring system, optimization of part production process, quality enhancement of produced part, safety enhancement of working conditions, virtual commissioning, and predictive maintenance of production machines are discussed. Moreover, application of digital twin in different industries such as automotive industry, aeronautical industry, renewable energy industry and telecom industry are studied in order to enhance the performances of digital twin in productivity enhancement of part production.

Soori et al. suggested virtual machining techniques to evaluate and enhance CNC machining in virtual environments [41–44]. To investigate and enhance performance in the component production process employing welding procedures, Soori et al. [45] suggested an overview of current developments in friction stir welding techniques. Soori and Asamel [46] examined the implementation of virtual machining technology to minimize residual stress and displacement error throughout turbine blade five-axis milling procedures. Soori and Asmael [47] explored applications of virtualized machining techniques to assess and reduce the cutting temperature throughout milling operations of difficult-to-cut objects. Soori et al. [48] indicated an advanced virtual machining approach to improve surface characteristics throughout five-axis milling procedures for turbine blades. Soori and Asmael [49] created virtual milling processes to reduce displacement error throughout five-axis milling operations of impeller blades. In order to analyze and develop the process of part production in virtual environments, virtual product development is presented by Soori [50]. Soori and Asmael [51] proposed an overview of current advancements from published research to review and enhance the parameter technique for machining process optimization. In order to improve the efficiency of energy consumption, the quality and availability of data across the supply chain, and the accuracy and dependability of component manufacture, Dastres et al. [52] proposed a review of RFID-based wireless manufacturing systems. Soori et al. [53] explored machine learning and artificial intelligence in CNC machine tools to boost productivity and improve profitability in production processes of component employing CNC machining operations. To improve the performance of machined components, Soori and Arezoo [54] reviewed the topic of measuring and reducing residual stress in machining operations. To improve surface integrity and decrease residual stress during Inconel 718 grinding operations, Soori and Arezoo [55] proposed the optimum machining parameters employing the Taguchi optimization method. In order to increase the life of cutting tools during machining operations, Soori and Arezoo [56] examined different method of tool wear prediction algorithms. Soori and Asmael [57] investigated computer assisted process planning to boost productivity in the part manufacturing procedure. Dastres and Soori [58] addressed improvements in web-based decision support systems to give solutions for data warehouse management using decision-making assistance. Dastres and Soori [59] reviewed applications of artificial neural networks in different sections, such as analysis systems of risk, drone navigation, evaluation of welding, and evaluation of computer simulation quality, to explore the execution of artificial neural networks for improving the effectiveness of products. Dastres and Soori [60] proposed employing communication system in environmental concerns to minimize the negative effects of technological advancement on natural catastrophes. To enhance network and data online security, Dastres and Soori [61] suggested the secure socket layer. Dastres and Soori [62] studied the developments in web-based decision support systems to develop the methodology of decision support systems by evaluating and suggesting the gaps between proposed approaches. To strengthen network security measures, Dastres and Soori [63] discussed an analysis of recent advancements in network threats. To increase the potential of image processing systems in several applications, Dastres and Soori [64] evaluated image processing and analysis systems. Dimensional, geometrical, tool deflection, and thermal defects have been modified by Soori and Arezoo [65] to improve accuracy in 5-axis CNC milling processes. Recent developments in published articles are examined by Soori et al. [66] in order to assess and improve the impacts of artificial intelligence, machine learning, and deep learning in advanced robotics. Soori and Arezoo [67] developed a virtual machining system application to examine whether cutting parameters affect tool life and cutting temperature during milling operations. Soori and Arezoo [68] studied the impact of coolant on the cutting temperature, roughness of the surface, and tool wear during turning operations with Ti6Al4V alloy. Recent developments from published papers are reviewed by Soori [69] in order to examine and alter composite materials and structures. Soori et al. [70] examined the Internet of things application for smart factories in industry 4.0 to increase quality control and optimize part manufacturing processes To minimize cutting tool wear during drilling operations, Soori and Arezoo [71] designed a virtual machining system. Soori and Arezoo [72] decreased residual stress and surface roughness to improve the quality of items produced utilizing abrasive water jet machining.

In order to provide the most recent developments from the published papers in the analysis and modification of smart manufacturing systems, a review of recent developments in smart manufacturing by intelligent digital twin is presented in the study work. The review paper is novel as new aspects of application of digital twin in smart manufacturing such as continuous improvement of manufacturing systems, process and product performance optimization using the digital twin, downtime reduction in process of part production, virtual commissioning and assembly simulation are studied and recent achievement from published papers are also discussed. Moreover, the implementation of digital twins in a variety of industries, including the automotive, aerospace, renewable energy, and telecom sectors, has also been investigated in order to improve their productivity enhancement of part manufacturing. As a result, the gaps between the proposed ideas and methodologies are obtained by analyzing the previous published papers in the research field and ideas and directions of future research works are also presented. So, the productivity of the production process can be increased, modern smart manufacturing methodologies can be introduced.

Applications of digital twin in smart manufacturing

The performance of a product can be analyzed and modified using the applications of digital twin in part manufacturing. A digital twin can be used to model the entire manufacturing process, from raw materials to finished products. It can be used to simulate different scenarios and predict how the system will behave under different conditions. This allows manufacturers to identify potential issues and optimize the system for better performance [73]. In smart manufacturing, the digital twin can be connected to real-world sensors and other devices, allowing it to be updated in real-time based on the data collected from the manufacturing process. This allows manufacturers to monitor and control the system more effectively, and to make adjustments to optimize performance [74]. A digital twin can simulate the actual performances of produced parts regarding to the different working conditions in virtual environments. Testing is a critical step of designing component in order to evaluate the performance targets of produced parts in working conditions and industry compliances. By creating a digital twin and using the digital simulation and analysis, the need for developing physical prototypes can be removed [75]. This leads to a shorter development period and better final quality of product or process. The use of digital twins at a manufacturing site can also be used to monitor and enhance a whole production line or even the complete manufacturing process from product conception and development to production [76]. By using the digital twins in analysis and modification of parts, optimization process of part designing can be enhanced. As a consequence, companies can use this technology to evaluate product design in a virtual environments in order to enhance accuracy and quality of produced parts [77].

Digital twin for continuous improvement of manufacturing systems

Digital twins offer a powerful tool for continuous improvement of manufacturing systems, enabling manufacturers to reduce costs, improve quality, and increase productivity [78]. In the context of continuous improvement of manufacturing systems, a digital twin can be used to simulate and optimize the performance of the actual system. Manufacturers can now track machine performance in real time and compare it to expectations thanks to the usage of digital twins. After then, the knowledge may be used to improve machine performance and extend its usable life. Hitachi, a pioneer in the industry, is helping to advance things. This allows manufacturers to identify and address potential issues before they occur, reducing downtime and improving overall efficiency [79]. In addition to simulation and optimization, digital twins can also be used for monitoring and analysis of manufacturing systems in real time. By collecting data from sensors and other sources, manufacturers can use digital twins to identify patterns, trends, and anomalies in their systems. This information can then be used to make data-driven decisions about how to optimize production and improve overall performance [80]. Digital twins can also be used to test and validate new manufacturing processes or equipment before they are implemented in the real world. This can help to reduce the risk of costly errors or failures, and accelerate the time to market for new products [81]. The utilization of digital twins generates a lot of information on anticipated performance outcomes, enabling more effective product research and development. Businesses can utilize this data to get insights that will help them make the required product adjustments before they start production [82].

Part production monitoring and modification using digital twin

The digital-twin strategy can be used to improve quality of products, production methods, or even whole value chains. In the context of part production, a digital twin can be created for a specific machine or production line, allowing for real-time monitoring of production processes. This includes tracking variables such as temperature, pressure, and flow rate, which can impact the quality of the final product [83]. By analyzing data from the digital twin, manufacturers can identify areas where production processes can be optimized or modified to improve efficiency and product quality. For example, if the digital twin detects that a certain machine is producing parts with higher defect rates than others, adjustments can be made to the production process to improve quality [84]. Digital twins can also be used to track energy consumption in process of part manufacturing and find areas where money can be saved. Continuous Improvement at manufacturing sites can also implemented by using digital twins [85]. Manufacturers can now track machine performance in real time and compare it to expectations thanks to the usage of digital twins [86]. A hypothetical shop floor for a digital twin is shown in Fig. 3 [87].

Process and product performance optimization using digital twin

Industrial processes can be optimized by using digital twins without losing time or resources. To increase productivity in the part production process, manufacturing industry operations can be optimized using a digital twin [40]. The use of digital twins can help companies to optimize the performance of their processes and products by providing a virtual replica that can be used for simulation and analysis. By leveraging the power of advanced analytics and machine learning, companies can make data-driven decisions to improve their performance, reduce costs, and increase efficiency [88]. For manufacturers in all industries, the process can be very valuable, from forecasting quality in real time to doing away with the need for costly physical testing [89]. By using sophisticated simulations based on actual data collected by Internet of Things sensors, digital twins can contribute to the improvement of current industrial processes [90]. A digital twin of a production line can be used to simulate how changes in the manufacturing process, such as adjusting machine settings or modifying the assembly line layout, would affect production output and efficiency. This can help companies identify the most effective process changes before implementing them in the real world, saving time and money [91]. Utilizing the digital twin, production teams may examine various data sources and reduce the number of defective items to increase efficiency and save money in process of part production. Industries are able to boost production and decrease industrial downtime. The concept is also used to predict maintenance concerns more quickly [92].

Smart manufacturers can predict the final product's quality by utilizing a digital twin in order to enable them to make more informed decisions about things like material and process changes [93]. Digital twins can be used in industrial manufacturing to ensure consistency during mass production [94]. Fig. 4 illustrates a digital twin mapping strategy through model update and optimization procedure [31].

Downtime reduction in process of part production using digital twin

To reduce downtime in the process of part production, the digital twin can be used to simulate different scenarios and identify potential problems before they occur [95]. The digital twin can be used to simulate the effects of changing the parameters of the production process, such as the speed of the machines or the temperature of the environment. By simulating these conditions, it is possible to identify potential issues and make adjustments to the process to prevent downtime [96]. Another way that a digital twin can help reduce downtime is by providing real-time monitoring of the production process. By monitoring the production process in real time, it is possible to identify potential issues as they arise and take corrective action before they lead to downtime [97]. By connecting the digital twin to sensors in the real production environment, it is possible to monitor the process in real-time and identify any issues that may lead to downtime. This allows for quick corrective action to be taken before downtime occurs [98]. By connecting the digital twin to sensors in the real production environment, it is possible to monitor the process in real-time and identify any issues that may lead to downtime. This allows for quick corrective action to be taken before downtime occurs [99]. The digital twin can be used to train operators and test different scenarios before they are implemented in the real world. This can help to reduce human error and improve the efficiency of the production process, ultimately leading to less downtime [100]. The digital twin can also be used to simulate different production methods and identify the most efficient process for producing the part. By optimizing the production process, it is possible to reduce the risk of downtime caused by process inefficiencies [101]. By analyzing sensor data and other information from the digital twin, it is possible to identify patterns and trends that may indicate potential issues with equipment. This can allow maintenance teams to schedule repairs or replacements before a breakdown occurs, reducing the risk of downtime [102]. Overall, the use of a digital twin in the process of part produc-

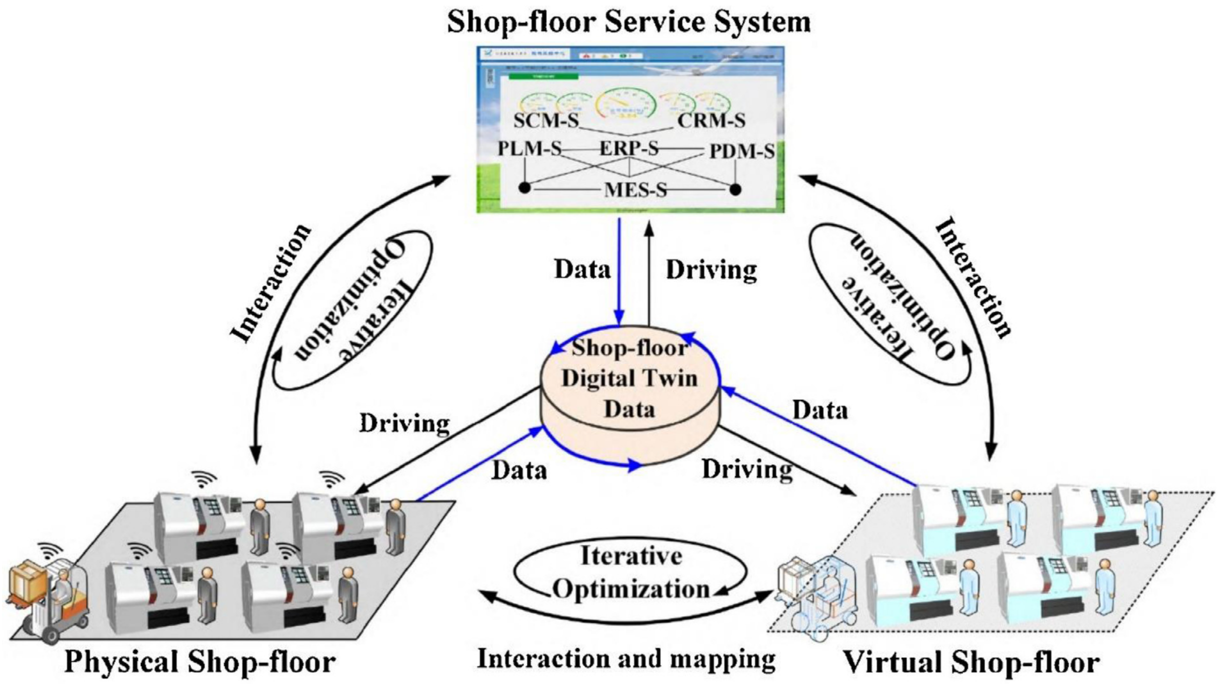

Fig. 3. Conceptual model of digital twin shop-floor [87].

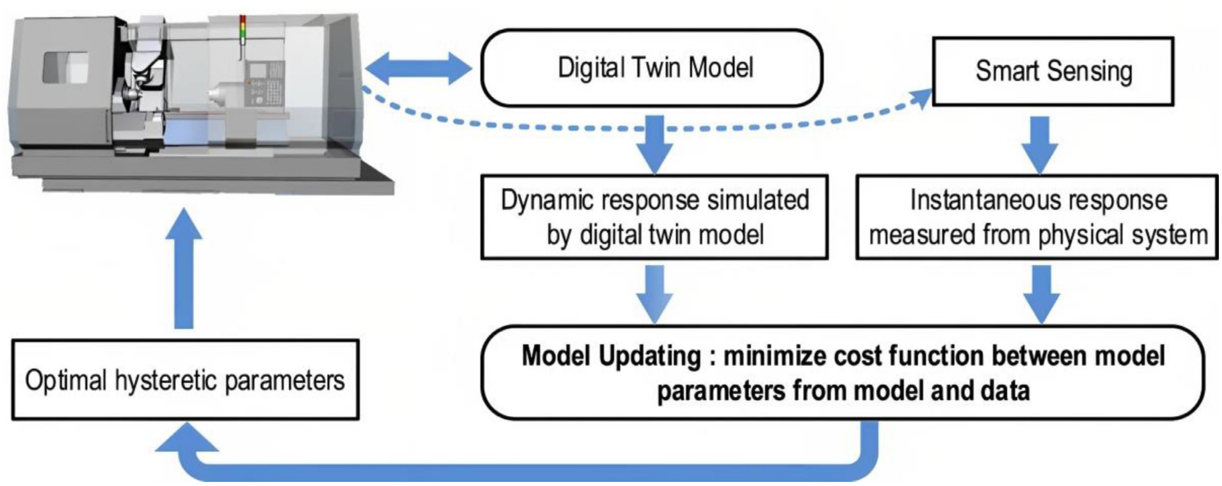

Fig. 4. Digital Twin mapping scheme by model updating and optimization process [31].

tion can be an effective way to reduce downtime. By simulating different failure conditions and providing real-time monitoring, it is possible to identify potential risk and make adjustments to the process to prevent downtime [103].

Safety enhancement by identifying hazards and risks of manufacturing process

Identifying hazards and risks is a critical step in enhancing safety in the manufacturing process. By recognizing dangers and risks through preventative maintenance, digital twins can increase safety in prat production process. Machine health and operational conditions are evaluated using digital twin data [104]. In the context of a manufacturing process, a digital twin can be used to identify hazards and risks and enhance safety [105]. A digital twin can be used to identify hazards in the manufacturing process by simulating the behavior of the system under different conditions. Once hazards have been identified, a digital twin can be used to assess the risks associated with them. This can be done by simulating the consequences of a hazard under different scenarios and quantifying the likelihood and severity of those consequences [106]. Based on the results of hazard identification and risk assessment, a digital twin can be used to optimize safety measures. A digital twin can also be used for training and education purposes in process of part production. By simulating hazardous scenarios, workers can be trained on how to respond to them in a safe and effective manner. Additionally, preventative maintenance using digital twins cuts down on time spent in the field, which lessens the danger of mishaps and injuries. Instead of doing actual testing, it is safer and less expensive to train and validate algorithms using digital twins [107]. Overall, a digital twin can be a valuable tool for enhancing the safety of a manufacturing process by identifying hazards, assessing risks, optimizing safety measures, and providing training and education.

Digital twin in predictive maintenance

Predictive maintenance is an approach that uses data analysis tools and techniques to monitor equipment and predict when maintenance is required, with the goal of minimizing downtime and reducing mainte-

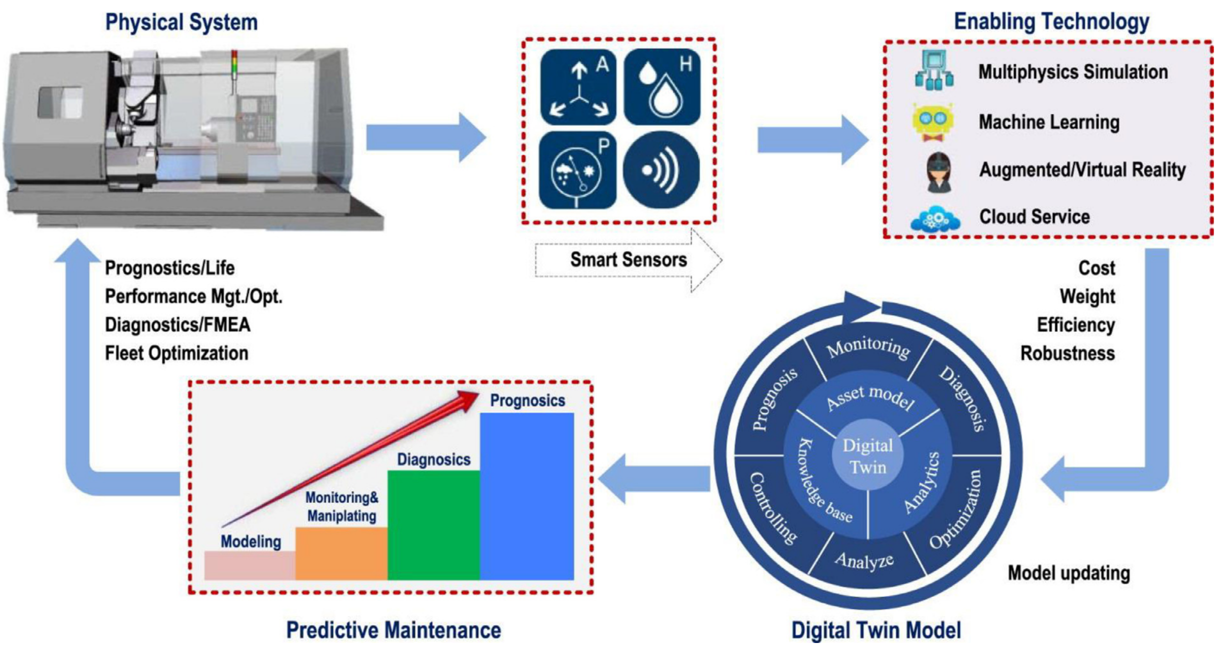

Fig. 5. Framework for problem diagnostics using Digital Twin [31].

nance costs. Digital twin technology is an approach that involves creating a virtual model of a physical asset or system, which can be used for simulations and testing [108]. Early problem identification aids in avoiding failures that might lower production quality. Manufacturers can forecast when problems will arise and address maintenance issues before they stop production by utilizing digital twins to examine the internal workings of their complicated machines [109]. In predictive maintenance, digital twins can increase productivity, identify issues early on, and keep providing fresh perspectives [110]. Understanding the core cause of the problems can be aided by using a contextual model of machining processes through the digital twin in the production process. A proactive method of equipment maintenance is predictive maintenance [111]. It enables real-time monitoring of equipment performance and failure prediction. This forecast aids in preventing circumstances where a machine malfunction can result in production halts. Early defect analysis and identification also aid in upholding safety standards and regulations in an industrial setting. Condition monitoring is one of the key components of predictive maintenance [112]. Additionally, predictive maintenance aids in the early identification of faults that may later develop into more serious ones. Real-time equipment monitoring should lead to better decision-making for executives in the manufacturing industry [113]. Additionally, the equipment will operate more effectively overall and last longer. The success that manufacturing companies have had is one of the factors contributing to the increased success of predictive maintenance. A part of manufacturing's predictive analytics is predictive maintenance [114]. Manufacturers need predictive maintenance solutions because they may improve product quality, optimize preventive or corrective measures taken on assets, eliminate production delays caused by unscheduled machine downtime, and ultimately keep company expenses low [115]. Fig. 5 depicts a defect diagnostic framework with a digital twin [31].

Reduction of product time to market using the digital twin

Digital twin technology can help reduce the time to market for a product by providing a virtual model of the product that can be tested and optimized before the physical product is built. This can help to identify potential problems early on in the design process and make necessary changes before production begins [116]. In addition, By creating a digital twin of the product, designers can test different configurations and optimize the design for performance and efficiency. This can help to reduce the number of physical prototypes needed and speed up the design process [117]. Operators can accelerate all phases of the manufacturing process, including design, development, testing, and maintenance, as a result of the removal of the delays associated with physical goods in terms of hardware, labor, and materials [118]. Digital twins can be used to simulate the product in a virtual environment, allowing for testing and validation of different scenarios. This can help to identify potential problems and make necessary changes before the physical product is built [119]. Digital twins can be shared among different teams and stakeholders, allowing for better collaboration and communication throughout the product development process. This can help to speed up decision-making and reduce the time to market [120]. Digital twins can be also used to monitor the performance of the product in real-time, allowing for early detection of potential problems and maintenance needs. This process can help to reduce downtime and improve overall product reliability. Overall, digital twin technology can help to reduce the time to market for a product by providing a virtual model that can be optimized and tested before the physical product is built, as well as by enabling better collaboration and communication among different teams and stakeholders.

Digital twin in virtual commissioning

A digital twin can be used as a tool for virtual commissioning, as it allows engineers and technicians to simulate and test the control system and automation system in a virtual environment, before it is installed in the real world. Early system design validation through virtual commissioning enables the prediction and resolution of problems and errors that arise during the first integration of equipment and processes [121]. By using a digital twin, it is possible to identify and resolve potential issues and problems in the control system or automation system, before it is deployed in the field. This can help reduce the time and cost of commissioning, as well as improve the performance and reliability of the system. Contrary to physical commissioning, virtual commissioning has the substantial benefit that no one has to wait for the arrival of all hardware before beginning [122].

The use of a digital twin for virtual commissioning is becoming increasingly common in industries such as manufacturing, aerospace, and automotive, where complex automation systems and control systems are used [123]. Manufacturers can save time, money, decrease risk, and promote concurrent engineering by predicting the expensive future problems in process of part production. Virtual commissioning is perhaps the most crucial step in the simulation process because it creates a risk-free testing environment [124]. It is also advantageous to system builders and integrators since it can accelerate project timelines. The digital twin can be integrated with other simulation tools, such as finite element analysis and computational fluid dynamics, to provide a comprehensive virtual testing environment for the system [125].

A virtual commissioning digital twin provides a platform for engineers to design, test, and optimize systems and processes in a digital environment, reducing the risks and costs associated with physical commissioning. [126]. It is increasingly being used in a range of industries, including manufacturing, energy, and transportation, to improve efficiency, reduce costs, and enhance performance [127].

Collaboration improvement between teams using digital twins for manufacturing

Digital twins are virtual replicas of physical assets or processes that can be used to simulate and optimize performance. They can be particularly useful in manufacturing, where they can help teams collaborate more effectively and improve efficiency [128]. Digital twins can strengthen engineering specialties and product design teams in addition to enhancing cooperation and workflow among various production teams [129]. Here are some ways that digital twins can be used to improve collaboration between teams in manufacturing:

1 Shared understanding: Digital twins can provide a shared understanding of the manufacturing process, allowing teams to work together more effectively. By creating a digital twin of a machine or process, teams can collaborate on a single model and avoid misunderstandings or miscommunications. This shared understanding can also help teams identify potential issues and make improvements more quickly.
2 Real-time monitoring: Digital twins can be used to monitor the performance of machines or processes in real-time. This can help teams identify issues as they arise and make adjustments quickly. By sharing this real-time data with other teams, such as maintenance or quality control, teams can collaborate more effectively and avoid downtime.
3 Simulation and optimization: Digital twins can be used to simulate different scenarios and optimize performance. By running simulations, teams can identify potential issues and test solutions before implementing them in the real world. This can help teams collaborate more effectively by giving them a common platform to test ideas and make decisions.
4 Remote collaboration: Digital twins can be accessed from anywhere, allowing teams to collaborate remotely. This can be particularly useful for global teams or teams that are working from home. By using digital twins, teams can collaborate in real-time, even if they are in different locations.

Fig. 6 illustrates a digital twin in production.

Overall, digital twins can be a powerful tool for improving collaboration between teams in manufacturing. By providing a shared understanding, real-time monitoring, simulation and optimization, and remote collaboration, digital twins can help teams work together more effectively and improve efficiency.

Assembly simulation using digital twin

Assembly simulation using a digital twin is a powerful tool for optimizing the manufacturing process. A digital twin is a virtual replica of a physical object or system that can be used to simulate and analyze its behavior in real-time. In the case of assembly simulation, a digital twin can be used to model the assembly process and identify potential issues before they occur in the physical world. It is useful for digital prototyping in order to design and analyze new ideas and concepts in utilizing the new devices and methods [131]. A Digital Twin of the manufacturing and assembly system can visualize the entire process, and enable the assembly line designers in order to identify bottlenecks and throughput before the operation phase. Performance and flexibility analysis and verification for decision-making is another application of digital twin in the assembly of manufacturing process [132]. Moreover, assembly simulation using a digital twin can help reduce costs and improve efficiency by identifying potential issues before they occur in the physical world. It can also help reduce the time and resources required for physical prototyping and testing, as the digital twin can be used to test various scenarios and identify the optimal assembly process [133]. Fig. 7 illustrates the operation of the virtual environment for the creation of a smart assembly process based on DT [131].

Overall, assembly simulation using a digital twin is a powerful tool for optimizing the manufacturing process and improving product quality. It can help reduce costs, improve efficiency, and ensure that products are manufactured to the highest standards.

Applications of digital twin in the different industries

There are different applications for the digital twin in the different industries such as aeronautical industries, automotive industry, power-generation equipment and the telecom industry. In this section, applications of digital twin in the different industries is reviewed and discussed.

Aeronautical industries

The application of digital twins in aeronautical industries can lead to improved safety, efficiency, and sustainability, as well as cost savings and increased innovation. Digital twins provide a variety of advantages to businesses in the aerospace industry, including the capacity to extend the life of machinery and parts and use data to improve next versions [134]. Aerospace businesses can utilize digital twins in R&D to enhance the engineering of new parts by simulating their performance under a wide range of circumstances. A digital twin can be used to simulate and analyze the behavior of aircraft and their components, from design and manufacturing to maintenance and operations [135]. By creating a virtual model of an aircraft or its components, engineers can simulate different scenarios and test various design options before committing to a physical prototype. This can reduce the time and cost associated with traditional design and testing methods [136]. Moreover, digital twins can be used to monitor and optimize the performance of aircraft in real-time. By integrating data from sensors and other sources, operators can detect and diagnose potential issues before they become critical, and make informed decisions about maintenance and repairs. Fig. 8 displays a mapping diagram between digital twin models and the manufacturing entity of a jet engine fan blade [137].

Overall, the use of digital twins in aeronautical industries can lead to improved safety, efficiency, and sustainability, as well as cost savings and increased innovation.

Automotive industry

In the automotive industry, digital twins are used to simulate and test various aspects of a vehicle, from design and development to manufacturing and maintenance [138]. By creating a digital twin of a car, engineers and designers can analyze its performance and behavior in various scenarios, identify potential issues, and optimize its design and features before the actual production begins. This can save time and costs while improving quality and safety of car production process [139]. Digital twins are also used in predictive maintenance, where they can monitor the condition of a vehicle in real-time and detect potential problems before they become critical. This process can

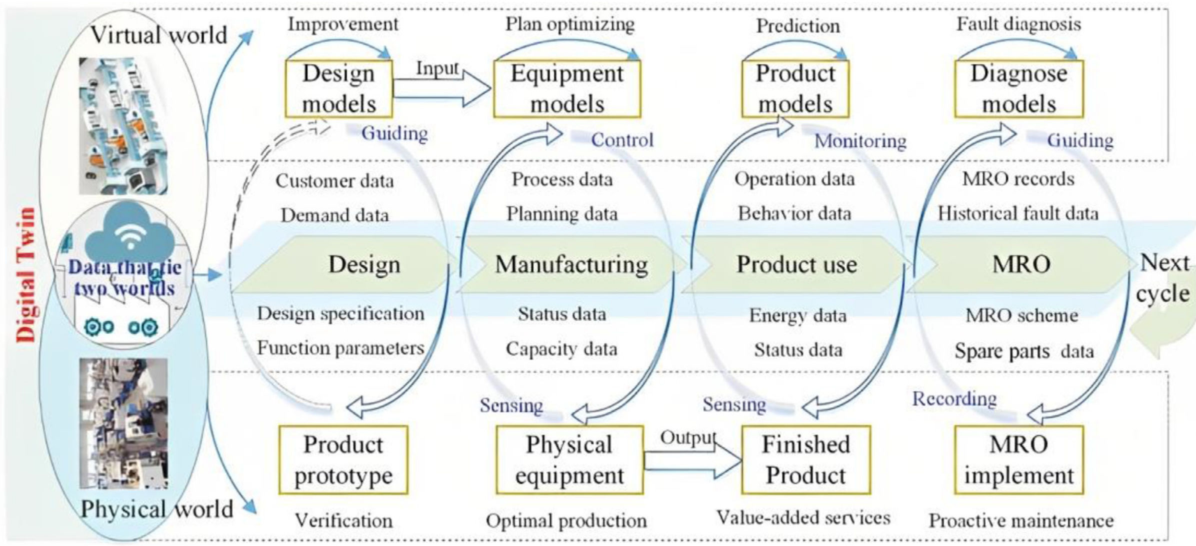

Fig. 6. Digital twin in manufacturing [130].

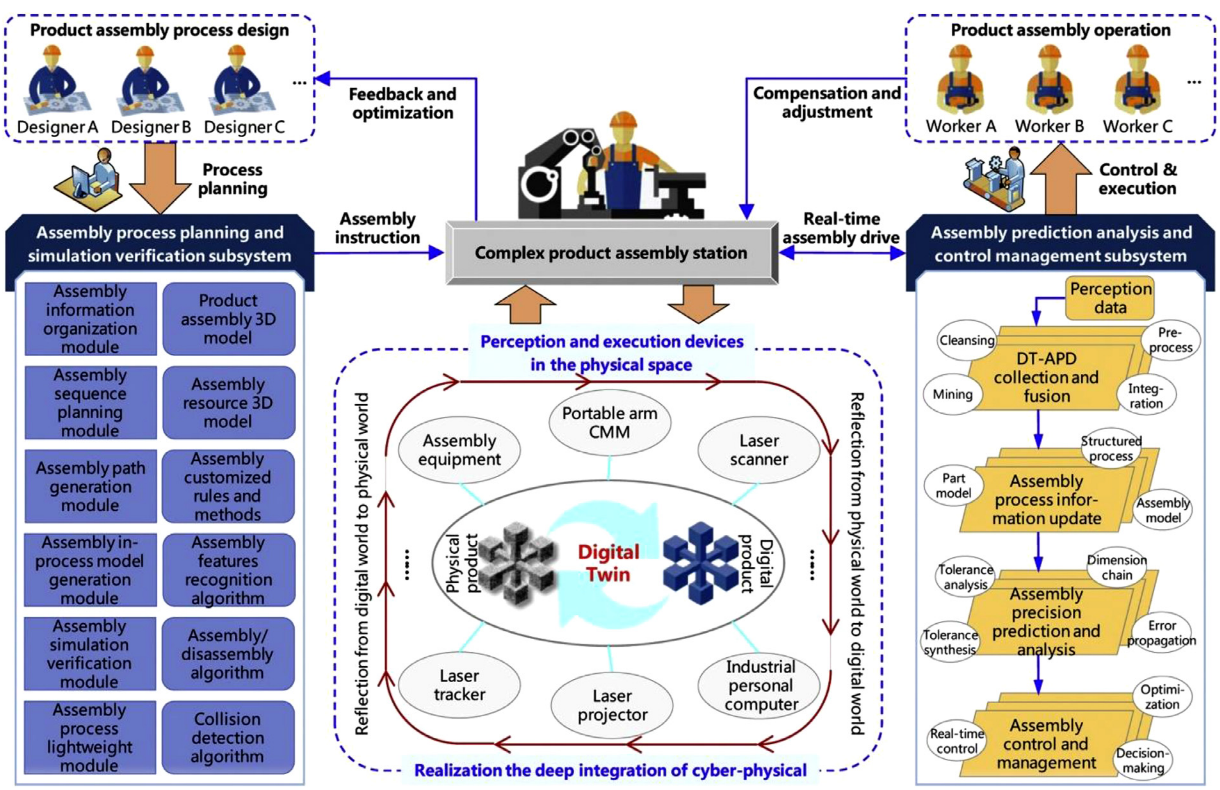

Fig. 7. Mechanism of DT-based smart assembly process design in virtual space [131].

help to reduce downtime, prevent breakdowns, and extend the lifespan of the vehicle [140]. Access to real-time data of part production can also speed up car manufacturing by reducing data processing time and enhancing communication between automotive development teams [141]. By establishing a clever link between the automaker and the driver, this technology can help Maintenance Repair Operations (MROs) [142]. Fig. 9 illustrates the MRO's incorporated Digital Twin technology [138].

In the system design phase, digital twins in the automotive sector can be used to a variety of things, including automobiles and robotic arms. Digital twins make vehicle design and development more dependable from a vehicle standpoint [143]. By accelerating simulations and executing them concurrently, it is possible to create thousands of hours of driving while retaining a realistic simulation environment with applied gravity, weight, and physical collision prediction [144]. A digital twin of an EV could be used to simulate various scenarios, such as different driving conditions, battery usage, and charging patterns. This can help the manufacturer optimize the design of the EV for maximum efficiency and performance, as well as identify potential issues before they arise [145]. Overall, digital twins have the potential to revolutionize the automotive industry by enabling more efficient and effective design, development, manufacturing, and maintenance processes.

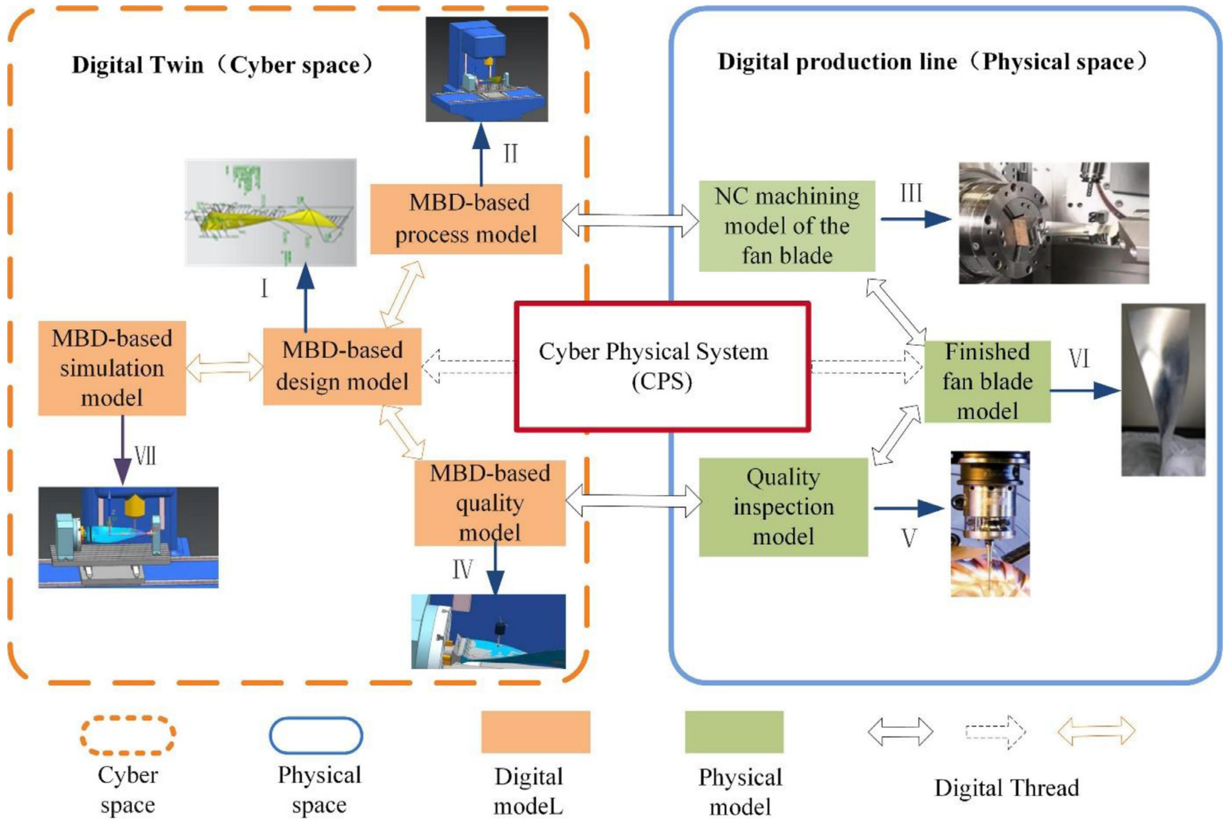

Fig. 8. Mapping diagram between digital twin models and manufacturing entity of jet engine fan blade [137].

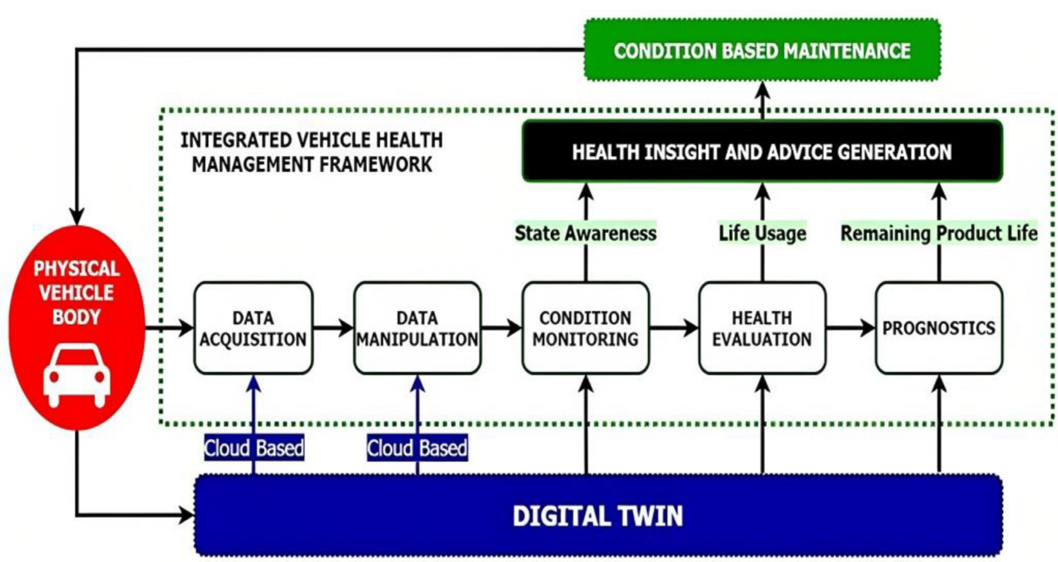

Fig. 9. Digital Twin technology embedded within the MRO [138].

The renewable energy industry

The market for renewable energy is expanding in light of the present climate change situation. Owners of renewable energy companies must increase the effectiveness of their power grids and cut costs in order to maintain growth in a fiercely competitive industry [146]. In the renewable energy industry, digital twins can be used to model and simulate various components and systems, such as wind turbines, solar panels, batteries, and power grids [147]. Additionally, the digital twin aids in life cycle management and behavior prediction for the solar power plant's system. Digital twins can also be used to monitor and predict the performance of renewable energy systems in real-time. By combining data from sensors, weather forecasts, and other sources, a digital twin can provide accurate predictions of power generation, maintenance needs, and potential failures. By creating a digital twin of a renewable energy system, engineers and operators can examine and optimize different designing procedures, identify potential problems, and improve performance and efficiency of final produced parts. For example, a digital twin of a wind turbine can simulate different wind speeds and directions to determine the optimal angle of the blades and the most efficient

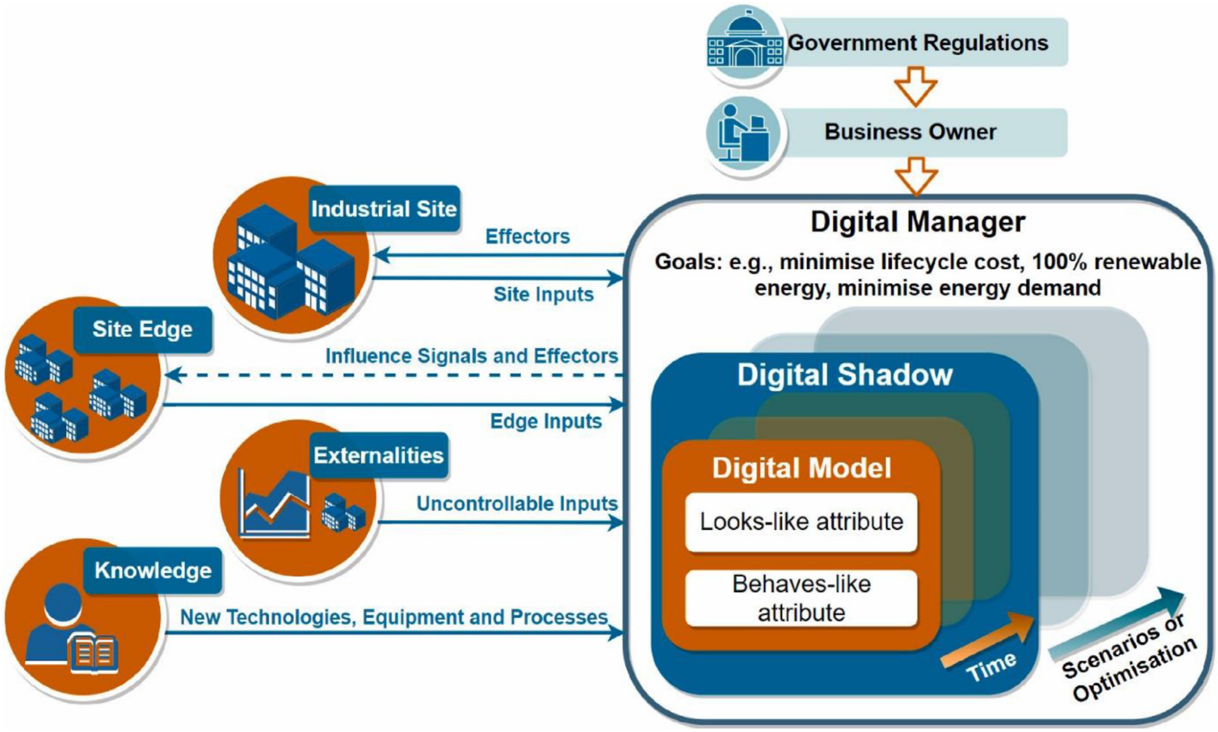

Fig. 10. A framework for utilizing Energy Digital Twin technologies in the process and energy sectors, encompassing Digital Model, Digital Shadow, and Digital Manager [149].

power output [148]. Fig. 10 depicts a framework for applying Energy Digital Twin technology to the process and energy sectors. This technology includes Digital Model, Digital Shadow, and Digital Manager [149].

Overall, the application of digital twins in the renewable energy industry is expected to grow as renewable energy sources become more prevalent and complex. With the help of advanced analytics and machine learning algorithms, digital twins can help to maximize the value of renewable energy systems, reduce costs, and minimize downtime.

The telecom industry

The telecom industry digital twin is used to improve the efficiency, reliability, and performance of telecom networks by providing a platform for testing and optimizing new technologies, identifying potential problems before they occur, and improving overall network operations. By removing the silos, digital twins can provide a comprehensive end-to-end network picture that offers accurate real-time data and allows quick anomaly detection [150]. It can also be used to train network engineers and technicians, as well as to provide insights to customers on network performance. Telcos can guarantee flawless network operation and immediately alert customers of impending maintenance tasks. Digital twin technology is used by Neural Technologies to identify those who would be impacted by rising network latency [151]. Some potential applications of the telecom industry digital twin include:

1 Predictive Maintenance: By analyzing real-time data from sensors and other sources, the digital twin can predict when a piece of network equipment may fail, allowing for proactive maintenance to prevent downtime [152].
2 Network Optimization: The digital twin can be used to test and optimize new network configurations, such as routing protocols or equipment upgrades, before they are implemented in the physical network.
3 Performance Monitoring: By simulating the behavior of the physical network, the digital twin can provide real-time insights into network performance, allowing for quick identification and resolution of issues [153].
4 Customer Insights: The digital twin can be used to provide customers with insights into network performance, allowing them to better understand the quality of service they are receiving and to make informed decisions about their telecom services [154].

Fig. 11 illustrates the justification for commissioning a system controlled by digital twins [155].

Overall, the telecom industry digital twin is a powerful tool for improving the efficiency, reliability, and performance of telecom networks, and is likely to play an increasingly important role as the telecom industry continues to evolve and expand.

Conclusion and future research work directions

A digital twin for smart manufacturing typically involves the use of sensors and other data collection tools to gather real-time data about the physical system or process, such as machine performance, temperature, pressure, and other parameters. This data is then fed into a digital model, which simulates the behavior of the physical system and allows manufacturers to visualize and analyze their operations in real-time. Digital twin is a virtual simulation of a physical system or process, which is used to monitor, control, and optimize its real-world counterpart. In the context of smart manufacturing, a digital twin can be used to create a virtual representation of a factory or production line, allowing manufacturers to simulate and optimize their manufacturing processes, identify potential problems and opportunities for improvement, and make informed decisions about production planning and resource allocation. The implementation of digital twins can significantly boost a company's added value by improving time and cost efficiency, ensuring seamless product or process functioning, and encouraging operational excellence. Digital twins can aid organizations in achieving improved efficiency, better decision-making, and operational optimization by utilizing data and sophisticated analytics. They can assist in detecting product problems before they cause damages and failure to the process of part production.

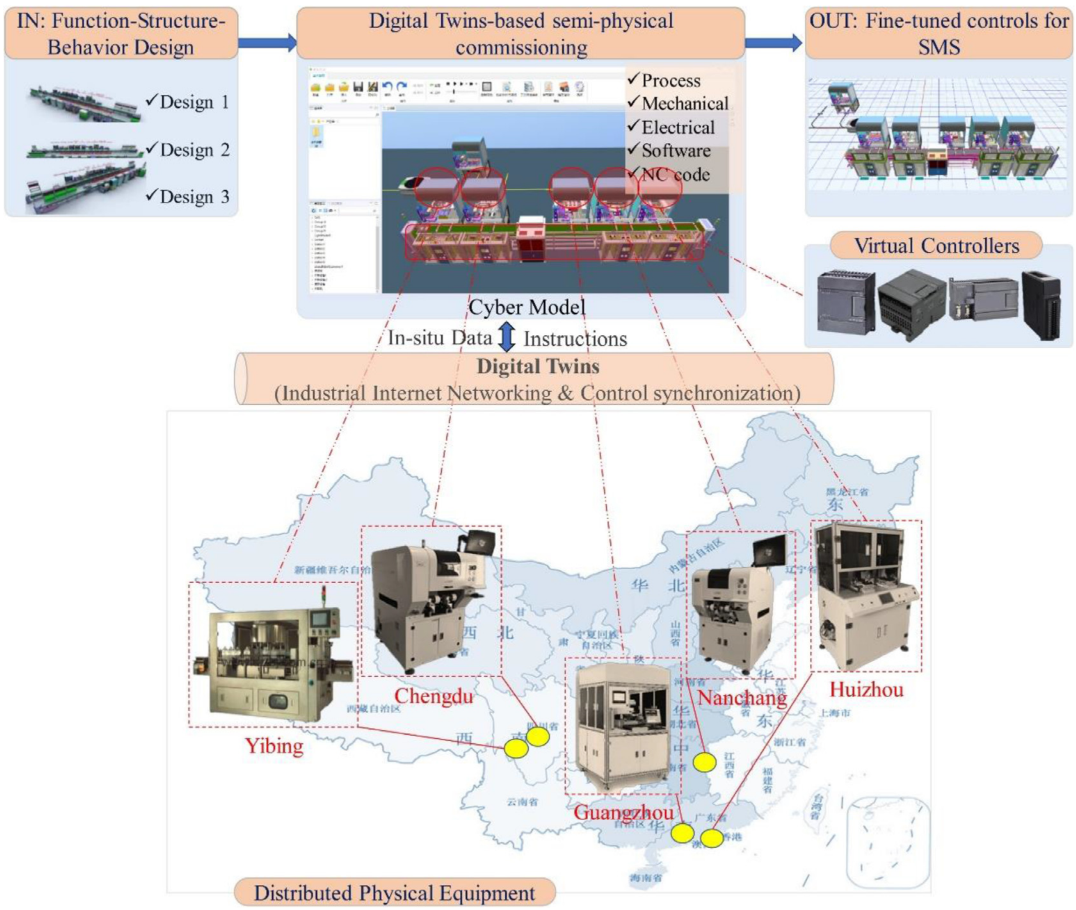

Fig. 11. The purpose of commissioning controls for digital twin-based systems [155].

So, manufacturers can extend the life of their physical assets and machines using the application of digital twin in predicting and analyzing the problems and errors of manufacturing process and products. The application of digital twin can also be applied to streamline of production procedures and save downtime in terms of productivity enhancement of part production. Some benefits of using digital twins in smart manufacturing include:

1 Improved productivity and efficiency: By simulating manufacturing processes and identifying potential bottlenecks and inefficiencies, manufacturers can optimize their operations to increase productivity and reduce waste.
2 Predictive maintenance: Digital twins can be used to monitor machine performance and detect potential problems before they lead to downtime or costly repairs, enabling manufacturers to schedule maintenance activities proactively.
3 Enhanced quality control: By monitoring the performance of machines and production processes in real-time, manufacturers can detect defects and anomalies early in the production process, reducing the likelihood of defects in finished products.
4 Reduced costs: By identifying opportunities for optimization and reducing waste, manufacturers can save money on materials, energy, and labor costs.

Overall, the use of digital twins in smart manufacturing can help manufacturers achieve greater efficiency, reduce costs, and improve the quality of their products. The potential of digital twins in smart manufacturing is limitless since more and more cognitive resources are continuously being allocated to their exploitation. Since digital twins are always learning new skills, they can keep producing the insights needed to improve products and expedite processes. Digital twin technology is increasingly being adopted in smart manufacturing to improve efficiency, reduce costs, and enhance product quality. Here are some areas for future research in digital twin technology for smart manufacturing:

1 Integration with the Internet of Things (IoT): The IoT is a network of physical devices that are embedded with sensors, software, and connectivity to enable data exchange. The integration of digital twin technology with IoT can enable real-time monitoring, analysis, and control of manufacturing processes.
2 Integration with Industry 4.0 technologies: The integration of digital twin technology with other Industry 4.0 technologies such as the Internet of Things (IoT), artificial intelligence (AI), and machine learning can enhance the functionality and effectiveness of digital twins for smart manufacturing.
3 Multi-scale digital twins: Multi-scale digital twins can provide a more comprehensive and detailed understanding of the manufacturing process by incorporating multiple levels of detail, from the microscopic to the macroscopic. This approach can help identify and solve problems at different scales, leading to better process optimization.
4 Integration with advanced analytics: Digital twin technology can provide a wealth of data on manufacturing processes and equipment performance. By integrating digital twin technology with advanced analytics tools such as machine learning and artificial intelligence, manufacturers can gain deeper insights into their operations and make more informed decisions
5 Machine learning and artificial intelligence: Digital twin technology can be enhanced with machine learning and artificial intelligence algorithms to enable predictive maintenance, real-time optimization, and anomaly detection. This can help to reduce downtime and increase efficiency.

6 Real-time optimization: Real-time optimization using digital twins can enable manufacturers to quickly adjust their processes to changing conditions, such as fluctuations in demand or supply chain disruptions. This can improve process efficiency, reduce downtime, and increase overall productivity.
7 Collaboration and communication: Digital twins can facilitate collaboration and communication between different stakeholders in the manufacturing process, including designers, engineers, operators, and managers. Future research can focus on developing tools and platforms that enable seamless communication and collaboration.
8 Optimization of supply chain processes: Digital twin technology can be used to create virtual representations of supply chain networks, enabling manufacturers to optimize their logistics and inventory management processes. Future research could focus on developing more sophisticated models for supply chain optimization using digital twin technology.
9 Human-machine collaboration: As manufacturing processes become increasingly automated, it will be important to consider the role of human workers in these environments. Future research could explore ways to integrate digital twin technology with human-machine interfaces to improve collaboration and decision-making.
10 Cybersecurity: With the increasing use of digital twins in manufacturing, it is important to ensure that these virtual replicas are secure from cyber attacks. Future research can focus on developing cybersecurity protocols and technologies to protect digital twins from malicious attacks.
11 Scalability: As concerns about environmental sustainability become more pressing, manufacturers are looking for ways to reduce their carbon footprint and minimize waste. Digital twin technology can be used to model the environmental impact of manufacturing processes and identify opportunities for improvement. Digital twin technology is being used in various industries, including aerospace, automotive, and healthcare. Future research can focus on developing scalable digital twin solutions that can be easily customized and deployed across different manufacturing environments.

Overall, digital twin technology has the potential to revolutionize smart manufacturing by enabling real-time monitoring, optimization, and collaboration. Future research can focus on addressing the challenges and limitations of digital twin technology to realize its full potential in smart manufacturing.

Declaration of Competing Interest

Digital Twin for Smart Manufacturing, A Review. There is no Conflict of Interest

Data availability

No data was used for the research described in the article.

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