Computers in Industry

Digital Twin Implementation in Additive Manufacturing: A comprehensive review

--Manuscript Draft--

Manuscript Number:	COMIND-D-24-00146
Article Type:	Research Paper
Keywords:	Digital Twin; Additive Manufacturing; Industry 4.0.
Corresponding Author:	Borhen Louhichi Imam Muhammad Ibn Saud Islamic University SAUDI ARABIA
First Author:	Sabrine Ben Amor
Order of Authors:	Sabrine Ben Amor
	Nessrine Elloumi
	Borhen Louhichi
Abstract:	The additive manufacturing (AM) field is rapidly expanding, attracting significant scientific attention. This family of processes will be widely used in the evolution of Industry 4.0, particularly in the production of customized components. However, as the complexity and variability of additive manufacturing processes increase, there is an increasing need for advanced techniques to ensure quality control, optimize performance, and reduce production costs. Multiple tests are required to optimize processing variables for specific equipment and processes, to achieve optimum processing conditions. The application of digital twin (DT) has significantly enhanced the field of additive manufacturing. A digital twin, abbreviated DT, refers to a computer-generated model that accurately depicts a real-world object, system, or process. A DT comprises the complete additive manufacturing process, from the initial conception phase to the final manufacturing phase. It enables the manufacturing process to be continuously monitored, studied, and optimized in real-time. DT has emerged as an important tool in the additive manufacturing industry. They allow manufacturers to enhance the process, improve product quality, decrease costs, and accelerate innovation. However, the development of DT in AM is an iterative and continuous process. It requires collaboration between domain experts, data scientists, engineers, and manufacturing teams to guarantee an accurate representation of the process by the digital twin. This paper aims to provide a comprehensive analysis of the current state of DT for additive manufacturing, examining their applications, benefits, challenges, and future directions.
Suggested Reviewers:	Yupiter Manurung yupiter.manurung@uitm.edu.my
	Antoine Tahan antoine.tahan@etsmtl.ca

Digital Twin for Manufacturing

Additive Manufacturing Process

virtual and physical model

Title Page (with Author Details)

Digital Twin Implementation in Additive Manufacturing: A comprehensive review

Sabrine Ben Amor[1], Nessrine Elloumi[2], Borhen Louhichi[3,1]

[1] University of Sousse, 4000 Sousse, Tunisia
[2] University of Sfax, 3000 Sfax, Tunisia

[3] Department of Mechanical Engineering, College of Engineering, Imam Mohammad ibn Saud Islamic University (IMSIU), Riyadh, 11432, Saudi Arabia

Correspondence: blouhichi@imamu.edu.sa; Tel.: +966- 55 355 6733

Digital Twin Implementation in Additive Manufacturing: A comprehensive review

Abstract

The additive manufacturing (AM) field is rapidly expanding, attracting significant scientific attention. This family of processes will be widely used in the evolution of Industry 4.0, particularly in the production of customized components. However, as the complexity and variability of additive manufacturing processes increase, there is an increasing need for advanced techniques to ensure quality control, optimize performance, and reduce production costs. Multiple tests are required to optimize processing variables for specific equipment and processes, to achieve optimum processing conditions. The application of digital twin (DT) has significantly enhanced the field of additive manufacturing. A digital twin, abbreviated DT, refers to a computer-generated model that accurately depicts a real-world object, system, or process. A DT comprises the complete additive manufacturing process, from the initial conception phase to the final manufacturing phase. It enables the manufacturing process to be continuously monitored, studied, and optimized in real-time. DT has emerged as an important tool in the additive manufacturing industry. They allow manufacturers to enhance the process, improve product quality, decrease costs, and accelerate innovation. However, the development of DT in AM is an iterative and continuous process. It requires collaboration between domain experts, data scientists, engineers, and manufacturing teams to guarantee an accurate representation of the process by the digital twin. This paper aims to provide a comprehensive analysis of the current state of DT for additive manufacturing, examining their applications, benefits, challenges, and future directions.

Keywords: Digital twin technology, Industry 4.0, Additive Manufacturing, Optimization of manufacturing processes.

1. Introduction

The term additive manufacturing (AM), or 3D printing as it's commonly known, refers to a production process that involves adding materials progressively to build parts layer by layer, using 3D model data, it contrasts with subtractive manufacturing techniques, where the final shape is obtained by removing material[1]. The AM process enables complex components using different materials, including polymers, metals, ceramics, and combinations [2] [3]. AM technology has completely changed the manufacturing industry, by creating complex geometries and customized products with greater efficiency and flexibility [4][5]. Industry 4.0 is a revolution in traditional manufacturing, using advanced technologies to create intelligent, interconnected systems [6]. The convergence of digital technology, including artificial intelligence (AI), big data analytics, the Internet of Things (IoT) [7], and cloud computing, with traditional manufacturing processes, is represented by Industry 4.0 [8][9]. Additive manufacturing is recognized as an innovative and powerful technology of Industry 4.0 which provides greater flexibility and personalization in the development and manufacture of complex parts, enhances manufacturing competitiveness, and reduces production time and waste of materials [10][11][12]. However, as the complexity and variability of additive manufacturing processes increase, there is a greater need for advanced techniques to ensure quality control, optimize performance, and reduce production costs [13]. Further investigations are currently carried out into digitalization, simulation [14], [15], [16], and machine learning technologies [17], [18], [19]. In this case, digital twin (DT) appeared as a powerful tool in the context of additive manufacturing [20][21]. A DT serves as a virtual depiction of the production process, providing a comprehensive perspective that encompasses the entire manufacturing workflow while capturing data in real-time [22] from sensors, machines, and further sources [23].

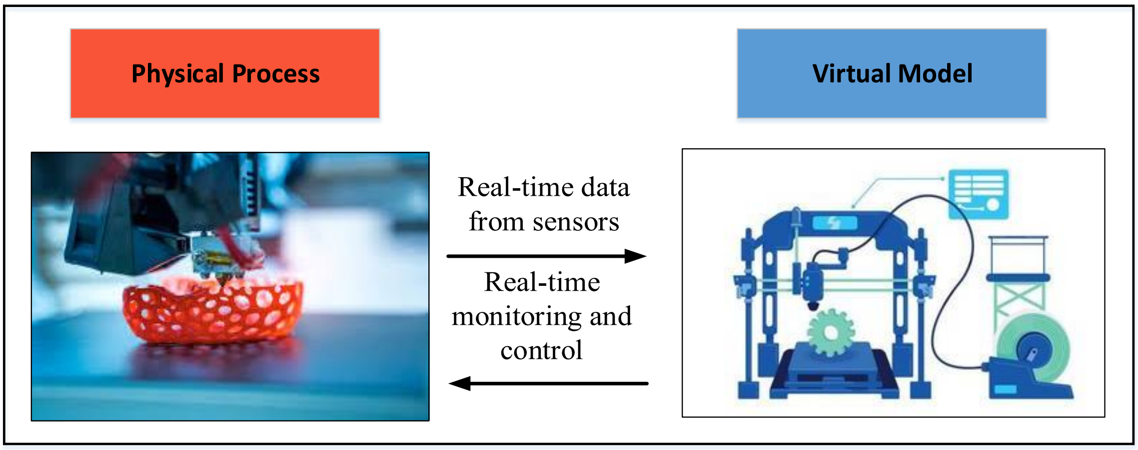

Figure 1: The interaction pathways between the physical and virtual models in the digital twin framework for additive manufacturing.

Digital twins enable monitoring and control of the additive manufacturing process in real-time [22][24] as shown in Figure 1. By integrating sensors and data acquisition systems with the digital twin, manufacturers can continuously capture data taken through the physical manufacturing environment and compare it with the virtual model [25]. This enables early detection of defects, predictive maintenance, and dynamic adjustment of process parameters to ensure consistent quality and performance [26][27]. The objective of this review paper is to present a succinct and thorough examination of the current state of the art, the challenges posed by DT applications in AM, and the building hierarchy of a DT for the additive manufacturing process. This will serve as a valuable resource for future research efforts focused on DT systems for the AM process. Through a critical investigation focused on the current state of knowledge, key challenges, and prospects, this study aims to contribute to the expanding knowledge body in the field of digital twins and additive manufacturing research. By highlighting the unique prospects and advances provided by the incorporation of digital twins with additive manufacturing, we aspire to offer researchers, practitioners, and industry professionals a valuable resource that goes beyond the scope of existing journals, providing a fresh perspective on the potential synergies between these transformative technologies. The present paper is o structured as shown below. After this introduction, section 2 presents the current state of the art in digital twins and additive manufacturing. Section 3 then describes the hierarchy of DT construction for the additive manufacturing process. Next, the current development of DT for the additive manufacturing process is examined in Section 3, with a conclusion and outlook in Section 5.

2. The State of the Art

2.1 Additive Manufacturing

Additive manufacturing (AM) refers to the precise process of creating a tangible object in 3D based on digital data. This process involves adding successive layers of material, distinguishing it from traditional methods that involve subtracting material [28]. Additive manufacturing, layered manufacturing, 3D printing, rapid prototyping (RP), and freeform manufacturing are all technologies that fall within the scope of AM [11]. Numerous AM techniques are available [29], each one characterized by the materials used and the method of layer deposition.
The American Society for Testing and Materials (ASTM) subgroup F42, specifically dedicated to Additive Manufacturing, has categorized AM processes into seven categories [30] as shown in Figure 2. Some processes involve the melting or softening of materials to form components [31], as in technologies such as three-dimensional printing (3DP), sheet lamination (SL), fused filament fabrication (FFF), and powder bed fusion (PBF). Each additive manufacturing technique has its applications, constraints, and advantages in the field of part manufacturing and prototyping [32]. Material extrusion includes fused filament fabrication (FFF), which is a 3D printing technique that builds layered parts by depositing heated thermoplastic material in a computer-controlled printer [33]. Material-jetting technology, such as Polyjet-Multijet modeling, uses ink-jet processes [34]. In this method, components are generated using a print head accumulating photopolymers. In addition, almost all layers are Photocured by exposure to ultraviolet light, which complements spray head technology [35]. Binder jetting is a method of 3D printing that

involves selectively bonding layers of powdered materials together using a liquid binder [36]. The procedure entails applying a binding agent to the powder layer, which adheres the powder particles together to create the intended form. This process is sequentially repeated to construct the full object [37]. For directed energy deposition (DED) technology, the required 3D parts are produced by a metal deposition process based on a targeted energy source, using a laser source or electron beam [38][39]. The sheet lamination process builds objects layer by layer using sheets or rolls of material [40]. In this method, individual layers are cut from sheet materials (such as paper, polymer, or metal) and then bonded together to form the final 3D object [41]. For the powder bed fusion (PBF) process, a powder building material is uniformly spread in a thin, even layer. The heat generated by a laser or electron beam source causes partial melting or sintering of the powder material, resulting in the melting of adjacent powder grains [42][43]. The vat photopolymerization technologies employing liquid materials are categorized according to the type of source of light and the materials used [44]. The process of solidifying the liquid material within a chamber using a laser beam is termed stereolithography (SLA), while the curing process utilizing a lamp-style light source is referred to as digital light processing (DLP) [45][46].

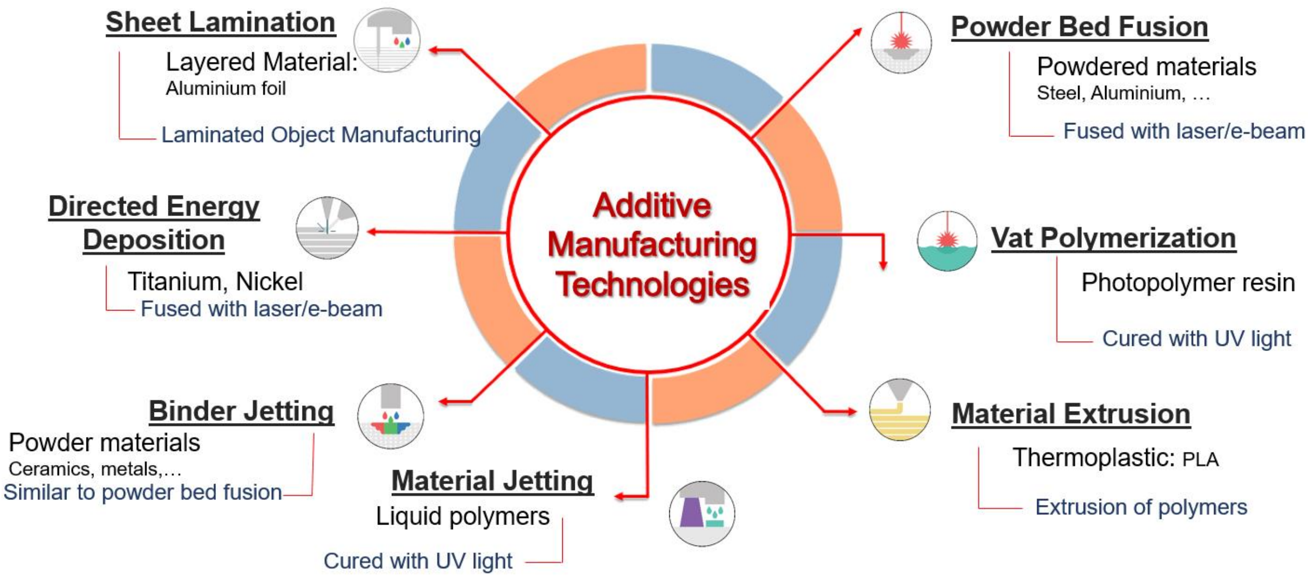

Figure 2: Classification of Additive Manufacturing process [47].

2.2 Digital Twin

The digital twin (DT) represents a virtual model that reflects the dynamics and behavior of physical objects, systems, or processes in real-time [48]. It captures not only the physical attributes but also the behavioral aspects of its physical counterpart throughout its entire lifecycle [49]. This virtual model is developed by collecting and integrating data from various sources, including IoT devices, sensors, simulations, and historical records [50]. The DT provides a real-time and accurate representation of the corresponding physical entity [51]. A substantial degree of integration occurs during the development of a DT between the virtual and real models via automated bidirectional data flow [3][52] as shown in Figure 3. The notion of DT may be traced back to its initial introduction by the National

Aeronautics and Space Administration (NASA), where it was employed to monitor satellite activity. This approach was also used to generate simulations of possible parameter changes [13]. NASA aimed to venture into space exploration using a DT, essentially a virtual model, simulating the physical satellite's behavior [53].

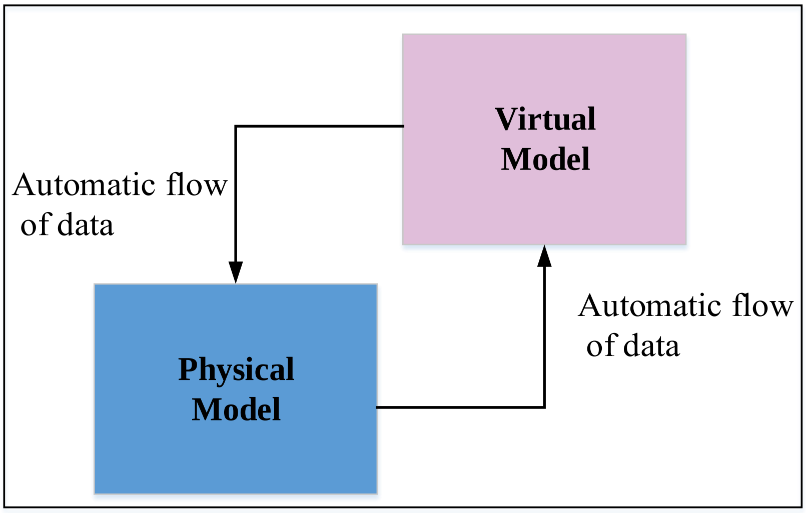

Figure 3: Digital twin data flow [3].

The DT technology is experiencing rapid growth as a core concept within Industry 4.0 [54][55], providing a powerful tool for enhancing productivity, efficiency, and innovation in manufacturing processes [49][56]. They enable manufacturers to leverage data, analytics, and simulation to optimize operations, improve product quality, and drive continuous improvement in an increasingly interconnected and digitized manufacturing landscape [23][57]. Based on a recent study, the DT market had a value of $6.9 billion in 2022. By 2027, it is expected to grow significantly, reaching a value of $73.5 billion[58]. This substantial increase reflects the growing adoption and recognition of the value and potential of DT technology across various industries. As more and more organizations recognize the potential offered by digital twins to enhance their efficiency, optimize processes, and enhance decision-making, the market will experience rapid growth over the coming years [59]. Research in the field of DT technology has garnered significant interest from both the academic community and industry. It has become an area of hot study, leading to the development of various tools, frameworks, and architectures aimed at accelerating the implementation of DT applications [12]. Nowadays, DT plays a critical and transformative role in industrial manufacturing [60][61], especially in the context of the AM process[62][63]. For hybrid manufacturing systems as well, digital twin systems are becoming essential to improve the efficiency, excellence, and environmental friendliness of hybrid subtractive and additive manufacturing processes [64]. They create a virtual model that can be used to optimize, control, and make decisions at every phase of the product lifecycle. Manufacturers can use them to improve the process, enhance product quality, reduce costs, and accelerate innovation [65].

3. The hierarchy for building a DT system for the AM process

The process for creating a DT for AM process follows a hierarchical structure consisting of several essential steps and components as presented in Figure 4. Although the specific hierarchy may differ according to the context and specific objectives of the DT system, the following provides a general overview:

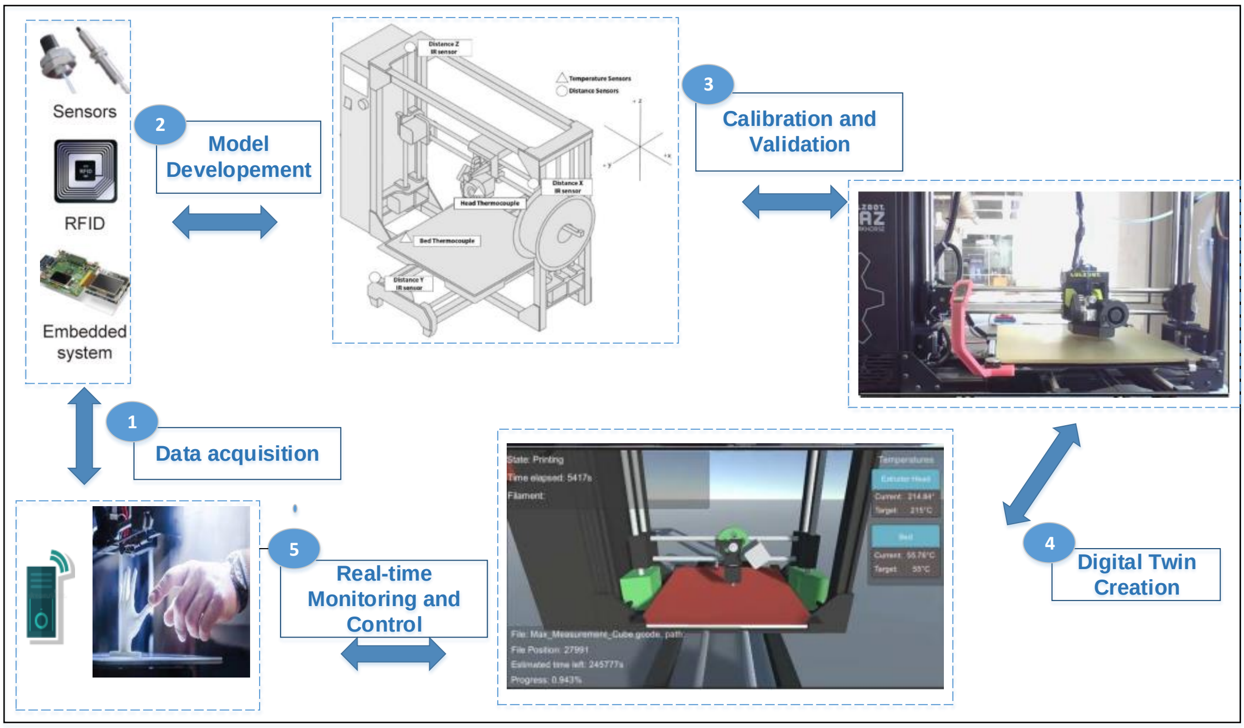

Figure 4: The different steps for building a DT system for the AM process [12] [66].

3.1 Data acquisition

The initial step is to collect relevant data from different sources including sensors, monitoring systems, and simulation tools [67]. This includes data on process parameters, material properties, environmental conditions, and machine performance. The real-time aspect is typically included in the data acquisition step of building a DT for the 3D printing process [12][68]. Data acquisition involves the collection and control of data in real-time throughout the AM process [69]. This may be achieved using in-situ sensors [70] or other monitoring devices that provide instantaneous measurements of process parameters, machine performance, and environmental conditions [22]. By integrating real-time data with historical data and simulation models, the DT can comprehensively understand the process and enable predictive capabilities to optimize process parameters, detect defects, and improve overall performance [71]. Training the digital twin of an AM process requires a substantial amount of data to enhance its accuracy. This data can be sourced from experiments, academic literature, sensors, and numerical simulations [72]. However, digital twins in additive manufacturing face various obstacles in collecting data. These limitations include the need to accurately model material behaviors, guarantee sensor accuracy, and mitigate potential biases. The accuracy of simulations is affected by these limitations, which in turn affect the accuracy of predictions of additive manufacturing processes.

3.2 Model Development

The model describes system behavior according to the physical process. Both mathematical and numerical models are developed to represent the AM process. These models encompass the physical behavior of materials, process dynamics, and interactions among different components of the system [73][74]. There is a wide variety of additive manufacturing processes, each employing a distinct material composed of filaments and powders of varying dimensions [71]. Numerous models become necessary when once the environmental conditions during the printing process are incorporated into the model due to the many possible combinations.

3.3 Calibration and Validation

This step represents a fundamental part of the development and deployment of the DT framework. It involves assuring the accuracy and reliability of DT models and simulations in representing the real-world AM process. AM requires extensive experimentation and destructive testing to examine microstructures and mechanical properties. Prediction of thermal evolution, microstructure, mechanical properties, and deformation of components is essential. Moreover, it is one of the most important elements of a DT for the AM procedure [75].

3.4 Digital Twin Creation

The calibrated and validated models are integrated into a DT framework. The digital twin integrates mathematical models with real-time data from the AM process to generate a digital representation of the physical system [76]. The widely used 3D real-time development platform known as Unity is utilized in a diverse range of applications, including the creation of virtual human beings. The software offers a sophisticated hardware motor, a powerful system of events, an animated system, enhanced parameters for lighting, and the possibility of incorporating customized software logic using a programming language. Pantelidakis et al. [12] used this platform to build the DT ecosystem through a virtual illustration.

3.5 Real-time surveillance and management

The DT ensures continuous monitoring in real-time of the AM process, where sensor data is continuously fed into the system to update and refine the digital twin's predictions and simulations [77]. This enables proactive identification of potential issues, process optimization, and control of the AM process in real-time. Machine learning and the Internet of Things (IoT) [78][79] are crucial in the hierarchy of building a DT for the AM process [80][81]. IoT devices and sensors collect real-time data from the AM process, capturing parameters, performance, and environmental conditions [82][71], [82]. This data is then integrated into the DT system, where machine learning algorithms [83] can identify patterns, detect anomalies, and optimize process parameters, leading to improved efficiency and quality in the AM process [84]. The use of Artificial Intelligence (AI) in digital twin technology for additive manufacturing (AM) is becoming more prevalent, offering numerous advantages in terms of efficiency, optimization, and quality control [85]. Sampedro et al. [86] developed a digital twin-driven system using the 3D-AmplifAI algorithm to detect defects within a 3D printer. Real-time monitoring and control constraints in digital twins for AM encompass the difficulties of recording rapid process changes, synchronizing between digital and physical systems, and managing possible time lags.

4. The development of digital twins for the AM process

The research on digital twin for AM aims to advance the understanding and capabilities of this technology. It focuses on optimizing processes, improving control quality, and driving creativity in the field of 3D printing [44][87]. The findings from this research have the potential to revolutionize additive manufacturing and further unlock its benefits in a variety of industries [3]. Different digital twins for the AM process were developed in the current literature. Zhang et al. [88] provide a concise survey of the current status, challenges, and prospective potential of DT in additive manufacturing. Kantaros et al. [44] presented a mechanistic approach model for 3D printing processes. This approach involves the use of models and equations based on physics to generate simulations and predictions of production process performance, as illustrated in Figure 5.

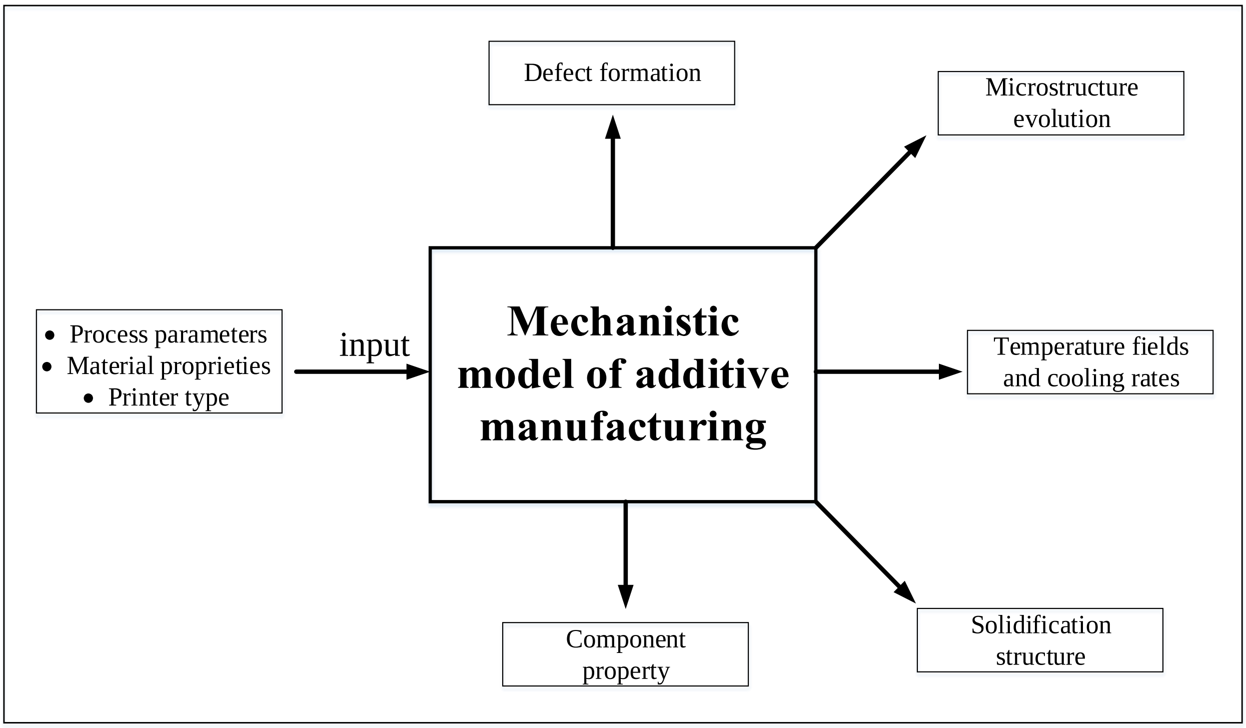

Figure 5: Mechanistic model of 3D printing processes [13].

Mukherjee et al. [75] demonstrated that a DT of a 3D printer reduces trial and error, achieves desired product features, and makes printed components cost-effective. The digital twin for 3D printing comprises the mechanical model, the detection and monitoring model, and the statistical model, along with machine learning and big data, as illustrated in Figure 6. In their research, they showed that by using a comprehensive digital twin, it's possible to minimize testing, defaults, and the time from conception to production. In the same context, Knapp et al. [89] introduced an innovative framework of a mechanistic model for forecasting the processes occurring at the melt pool level.

Kabaldin et al. [90] created a system to enable 3D printing using arc welding within CNC machines. This system offers the possibility of connecting high-speed computing modules and training neural networks with feedback. These improve the preparation of inspection programs and components for CNC machines. Additionally, the integration of a DT enhances the capabilities of computer-aided manufacturing systems, allowing for improved preparation of inspection programs and devices for CNC machines. This innovative approach enables advanced control and optimization in 3D printing using arc welding, leading to enhanced productivity and superior output quality.

Haw et al. [91] proposed a potential application of DT for the design of additively manufactured biomedical scaffolding products. DT offers significant benefits during all three stages in the process of product development: design, development, and virtual validation. The application of DT in the design of additively produced biomedical scaffolds increases efficiency, reduces costs, and improves the global quality and safety of the final products. In the same context, Scime et al. [92] introduced a cyber-physical infrastructure aimed to facilitate the production of Instance-Qualified AM components. The proposed methodology emphasizes scalability and leverages the power of artificial intelligence (AI). A further methodology has been proposed by Arden et al. [93] to analyze, optimize, and manage the spreading of powder in the AM process. The authors used the discrete element method (DEM) to simulate the PBF coating, which serves as a virtual environment for training and testing their framework. The approach investigates the compromises inherent in the spreading of powder, such as the roughness of the layer, the overlap time, and the addition height of the fused layer. They use a multi-objective Bayesian optimization technique to explore these trade-offs. This optimization process investigates the space of parameters defined by the recoated speed, recoated angle, and platen displacement, thereby revealing new recoating techniques that promote specific desired results. By integrating the DT approach and DEM simulation, the proposed methodology is designed to enhance the performance and reliability of AM powder spreading processes.

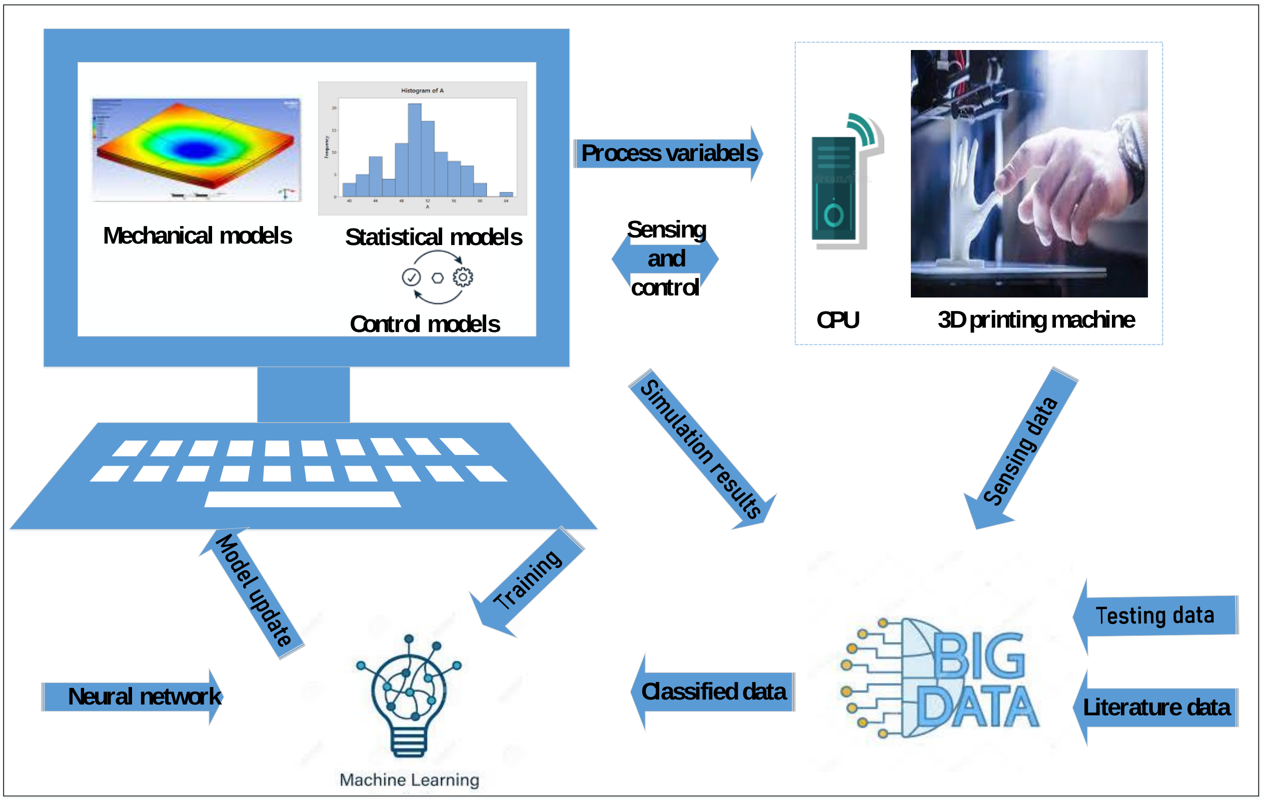

Figure 6: The approach of a digital twin for the AM process [71].

In the literature, various researchers have discussed collectively the conception and testing of a DT for quality control and evaluation in different categories of the AM process. Fabio et al. [76] presented the design, implementation, and verification of a novel DT solution for the material extrusion process. The solution is based on three major elements: a central module that contains the simulation motor, an interface to manage incoming data, and a graphic interface for remote control by the user. The developed DT takes the input of process data obtained from different sensors and the G-Code file employed by the actual printer, to provide a range of functions to control the process, monitor condition, and check geometric accuracy in real-time. In the same context, Pantelidakis et al. [12] implemented a new digital twin ecosystem designed to test, monitor processes, and remotely manage the fused deposition modeling (FDM) printer using a virtual simulation platform. The DT ecosystem developed consists of two methods. The first is a data-driven method that uses an open-source 3D printer control application for capturing machine status and relevant settings. The second method uses external sensors that approach the real behavior of the 3D printer, ensuring precise harmonization between the virtual and physical printers. This implementation improves the control and monitoring of the AM process, facilitating improved efficiency and accuracy. Castelló et al. [94] emphasize an innovative digital twin for modeling materials which simplifies the composite part creation process using large-format additive manufacturing (LFAM). For the same category of process, an in-depth analysis was carried out by Reddy et al. [95] to examine the application of DT in 3D printers, and to present the recommended framework and method. For example, the process

of updating the digital model is time-consuming, and there is a noticeable delay in results at the interaction layer level.
Concerning the directed energy deposition (DED) process, Reisch et al. [96] explored the concept of context awareness within process control applications for the wire arc additive manufacturing (WAAM) process. They integrated three types of contexts, including the machine context, the time context, and the spatial context, using a digital twin as an illustration of the real WAAM part during the manufacturing process. Exception detection is performed using both the machine and temporal environments. In the same context, Haochen et al. [97] presented a comprehensive overview of current advances in the application of DT to AM processes. The objective is to gather comprehensive insights into the existing developments and identify key areas for improvement. The research aims to propose a suitable DT for the WAAM system. Another digital twin for the DED process was developed by Noh et al.[98]. Initially, a digital representation of the DED equipment was created, which included a three-dimensional model of the DED machine. An inertial measurement unit (IMU) was incorporated into the DED machine to coordinate in real-time the movements of digital components with the corresponding physical counterparts of the machine. Subsequently, the DT of the process is created by categorizing items according to the precise geometry of the deposited components. Ultimately, the DT of both the DED equipment and process are merged to accurately recreate the identical system as the physical one.

For the powder bed fusion category, a new DT or the manufacturing process using metal powder bed fusion was presented in [99]. This advanced numerical model can simulate the dynamic temperature profile at individual points in the process, enabling the detection of potential problems such as superheating. The approach is supported by a machine learning algorithm that has been developed on experimental confirmation of synthesized data derived from finite element analysis (FEA). This algorithm takes into account various factors, including scanning strategy, laser settings, material characteristics, and part geometry. Gaikwad et al. [22] presented the concept of DT applied to AM, to improve the detection of process anomalies. The concept involves integrating physics-based predictions, real-time sensor data, and machine learning techniques. The suggested DT technique, which integrates insights of a theoretical model with sensor data, exhibits enhanced accuracy in identifying process faults as compared to employing either the theoretical model or sensor data independently. The efficacy of this digital twin methodology was confirmed using empirical results derived from metal additive AM processes. For the same category of AM process, Yeung et al. [100] have developed a DT system for monitoring and optimizing the laser powder bed fusion. The framework is constructed using the recently invented state-of-the-art point-wise scan control approach.
In conclusion, this section has presented the development of DT approaches for AM. The studies and research discussed have highlighted the immense power of DT in enhancing various aspects of the AM process. Although digital twins for AM provide useful information and efficiency gains, they are not without limitations. Challenges include the complexity of accurately simulating material behavior, effectively representing process dynamics in real-time, and the sensitivity of results to the quality of input data. Restrictions

are further exacerbated by the complexity of multi-physics modeling, post-processing considerations, and the need for considerable computing resources. The dynamic nature of additive manufacturing technology and the absence of standardized data formats pose ongoing problems. To overcome these restrictions, it is necessary to constantly improve models, guarantee data confidentiality, and enhance operator expertise. Ongoing research is striving to overcome these difficulties and unleash the full capabilities of DT in additive manufacturing.

5. Conclusions and future work

In summary, our examination of the synergy between additive manufacturing and digital twin technology has highlighted key findings that underscore the transformative potential of this integration. Additive manufacturing, with its unrivaled flexibility, facilitates the development of complex customized parts, significantly improving manufacturing competitiveness and simultaneously addressing concerns about manufacturing time and wasted materials. The advent of DT as a robust solution in this sector enables manufacturers to optimize operations, enhance product quality, reduce costs, and accelerate innovation. However, as our study shows, tapping the full potential of digital twins in AM is not without its complexities. Developing a digital twin requires meticulous attention to nuances such as model accuracy, data integration, and scalability. Following a comprehensive analysis of existing research literature, we have identified persistent challenges and focal points in the research field. There is an urgent need for standardized frameworks that consider the continuous technological progress and increasing complexity of AM processes.

Our research underscores the necessity of collaboration between researchers, software developers, and industry experts. Such partnerships are essential to navigate the twists and turns of successfully implementing and deploying digital twin solutions in real manufacturing environments. Going forward, the trajectory of research should be guided by a commitment to refining the digital twin framework, integrating advanced analysis techniques, and exploring innovative avenues for process optimization and control. By addressing these challenges, the field can lead the way to a more robust, efficient, and adaptive future in additive manufacturing, fulfilling the full potential of digital twin technology.

6. References

[1] Y. Qin, Q. Qi, P. Shi, P. J. Scott, and X. Jiang, "Status, issues, and future of computer-aided part orientation for additive manufacturing," *International Journal of Advanced Manufacturing Technology*, vol. 115, no. 5–6, pp. 1295–1328, 2021, doi: 10.1007/s00170-021-06996-6.

[2] S. Ben Amor, A. Tahan, and B. Louhichi, "Proposition of a Geometric Complexity Model for Additive Manufacturing Process Based on CAD," in *2019 23rd International Conference Information Visualisation (IV)*, IEEE, Jul. 2019, pp. 442–448. doi: 10.1109/IV.2019.00080.

[3] T. O. R. F. Shimamura and D. Timper, "A feasibility study of Digital Twin for additive manufacturing From the perspective of resource efficiency ," 2021.

[4] S. Ben Amor, A. Tahan, and B. Louhichi, “The Impact of Geometric Complexity on Printing Time and Cost for Additive Manufacturing (AM) Process,” 2022, pp. 203–210. doi: 10.1007/978-3-030-86446-0_27.

[5] M. Pant, P. Pidge, L. Nagdeve, and H. Kumar, “A Review of Additive Manufacturing in Aerospace Application,” *Revue des composites et des matériaux avancés*, vol. 31, no. 2, pp. 109–115, Apr. 2021, doi: 10.18280/rcma.310206.

[6] S. Vaidya, P. Ambad, and S. Bhosle, “Industry 4.0 – A Glimpse,” *Procedia Manuf*, vol. 20, pp. 233–238, 2018, doi: 10.1016/j.promfg.2018.02.034.

[7] M. Jacoby and T. Usländer, “Digital Twin and Internet of Things—Current Standards Landscape,” *Applied Sciences*, vol. 10, no. 18, p. 6519, Sep. 2020, doi: 10.3390/app10186519.

[8] P. Stavropoulos and D. Mourtzis, “Digital twins in industry 4.0,” in *Design and Operation of Production Networks for Mass Personalization in the Era of Cloud Technology*, Elsevier, 2022, pp. 277–316. doi: 10.1016/B978-0-12-823657-4.00010-5.

[9] H. Ahuett-Garza and T. Kurfess, “A brief discussion on the trends of habilitating technologies for Industry 4.0 and Smart manufacturing,” *Manuf Lett*, vol. 15, pp. 60–63, Jan. 2018, doi: 10.1016/j.mfglet.2018.02.011.

[10] U. M. Dilberoglu, B. Gharehpapagh, U. Yaman, and M. Dolen, “The Role of Additive Manufacturing in the Era of Industry 4.0,” *Procedia Manuf*, vol. 11, pp. 545–554, 2017, doi: 10.1016/j.promfg.2017.07.148.

[11] B. DUMAN and A. A. SÜZEN, “MODELING OF IOT-BASED ADDITIVE MANUFACTURING MACHINE’S DIGITAL TWIN FOR ERROR DETECTION,” *Mühendislik Bilimleri ve Tasarım Dergisi*, vol. 11, no. 2, pp. 486–497, Jun. 2023, doi: 10.21923/jesd.1251972.

[12] M. Pantelidakis, K. Mykoniatis, J. Liu, and G. Harris, “A digital twin ecosystem for additive manufacturing using a real-time development platform,” *The International Journal of Advanced Manufacturing Technology*, vol. 120, no. 9–10, pp. 6547–6563, Jun. 2022, doi: 10.1007/s00170-022-09164-6.

[13] L. Zhang *et al.*, “Digital Twins for Additive Manufacturing: A State-of-the-Art Review,” *Applied Sciences*, vol. 10, no. 23, p. 8350, Nov. 2020, doi: 10.3390/app10238350.

[14] J. Song, Y. Chew, L. Jiao, X. Yao, S. K. Moon, and G. Bi, “Numerical study of temperature and cooling rate in selective laser melting with functionally graded support structures,” *Addit Manuf*, vol. 24, pp. 543–551, Dec. 2018, doi: 10.1016/j.addma.2018.10.039.

[15] L.-E. Loh, J. Song, F. Guo, and G. Bi, “Analytical Solution of Temperature Distribution in a Nonuniform Medium Due to a Moving Laser Beam and a Double Beam Scanning Strategy in the Selective Laser Melting Process,” *J Heat Transfer*, vol. 140, no. 8, Aug. 2018, doi: 10.1115/1.4040256.

[16] J. Song *et al.*, “Numerical and experimental study of laser aided additive manufacturing for melt-pool profile and grain orientation analysis,” *Mater Des*, vol. 137, pp. 286–297, Jan. 2018, doi: 10.1016/j.matdes.2017.10.033.

[17] K. Ren, Y. Chew, Y. F. Zhang, J. Y. H. Fuh, and G. J. Bi, “Thermal field prediction for laser scanning paths in laser aided additive manufacturing by physics-based machine learning,” *Comput Methods Appl Mech Eng*, vol. 362, p. 112734, Apr. 2020, doi: 10.1016/j.cma.2019.112734.

[18] K. Ren, Y. Chew, Y. F. Zhang, G. J. Bi, and J. Y. H. Fuh, “Thermal analyses for optimal scanning pattern evaluation in laser aided additive manufacturing,” *J Mater Process Technol*, vol. 271, pp. 178–188, Sep. 2019, doi: 10.1016/j.jmatprotec.2019.03.029.

[19] K. Ren, Y. Chew, J. Y. H. Fuh, Y. F. Zhang, and G. J. Bi, “Thermo-mechanical analyses for optimized path planning in laser aided additive manufacturing processes,” *Mater Des*, vol. 162, pp. 80–93, Jan. 2019, doi: 10.1016/j.matdes.2018.11.014.

[20] M. Soori, B. Arezoo, and R. Dastres, “Digital twin for smart manufacturing, A review,” *Sustainable Manufacturing and Service Economics*, vol. 2, p. 100017, Apr. 2023, doi: 10.1016/j.smse.2023.100017.

[21] N. Jyeniskhan, K. Shaimergenova, Md. H. Ali, and E. Shehab, “Digital Twin for Additive Manufacturing: Challenges and Future Research Direction,” in *2023 IEEE International Conference on Smart Information Systems and Technologies (SIST)*, IEEE, May 2023, pp. 337–342. doi: 10.1109/SIST58284.2023.10223556.

[22] A. Gaikwad, R. Yavari, M. Montazeri, K. Cole, L. Bian, and P. Rao, “Toward the digital twin of additive manufacturing: Integrating thermal simulations, sensing, and analytics to detect process faults,” *IISE Trans*, vol. 52, no. 11, pp. 1204–1217, Nov. 2020, doi: 10.1080/24725854.2019.1701753.

[23] J. Leng, D. Wang, W. Shen, X. Li, Q. Liu, and X. Chen, “Digital twins-based smart manufacturing system design in Industry 4.0: A review,” *J Manuf Syst*, vol. 60, pp. 119–137, Jul. 2021, doi: 10.1016/j.jmsy.2021.05.011.

[24] R. M. Scheffel, A. A. Fröhlich, and M. Silvestri, “Automated fault detection for additive manufacturing using vibration sensors,” *Int J Comput Integr Manuf*, vol. 34, no. 5, pp. 500–514, May 2021, doi: 10.1080/0951192X.2021.1901316.

[25] T. DebRoy, W. Zhang, J. Turner, and S. S. Babu, “Building digital twins of 3D printing machines,” *Scr Mater*, vol. 135, pp. 119–124, Jul. 2017, doi: 10.1016/j.scriptamat.2016.12.005.

[26] B. Schleich, N. Anwer, L. Mathieu, and S. Wartzack, “Shaping the digital twin for design and production engineering,” *CIRP Annals*, vol. 66, no. 1, pp. 141–144, 2017, doi: 10.1016/j.cirp.2017.04.040.

[27] K. Paraskevoudis, P. Karayannis, and E. P. Koumoulos, “Real-Time 3D Printing Remote Defect Detection (Stringing) with Computer Vision and Artificial Intelligence,” *Processes*, vol. 8, no. 11, p. 1464, Nov. 2020, doi: 10.3390/pr8111464.

[28] S. Ben Amor, F. Zongo, A. Eltaief, A. Maatki, B. Louhichi, and A. Tahan, "A new method to select optimal part building orientation for additive manufacturing processes based on geometric complexity and heat shrinkage," *Progress in Additive Manufacturing*, vol. 8, no. 2, pp. 211–222, Apr. 2023, doi: 10.1007/s40964-022-00324-4.

[29] H. Bikas, P. Stavropoulos, and G. Chryssolouris, "Additive manufacturing methods and modelling approaches: a critical review," *The International Journal of Advanced Manufacturing Technology*, vol. 83, no. 1–4, pp. 389–405, Mar. 2016, doi: 10.1007/s00170-015-7576-2.

[30] ISO/ASTM, "Additive Manufacturing - General Principles Terminology (ASTM52900)," *Rapid Manufacturing Association*, pp. 10–12, 2013, doi: 10.1520/F2792-12A.2.

[31] B. N. Lee, E. Pei, and J. Um, "An overview of information technology standardization activities related to additive manufacturing," *Progress in Additive Manufacturing*, vol. 4, no. 3, pp. 345–354, Sep. 2019, doi: 10.1007/s40964-019-00087-5.

[32] H.-J. Steenhuis and L. Pretorius, "The additive manufacturing innovation: a range of implications," *Journal of Manufacturing Technology Management*, vol. 28, no. 1, pp. 122–143, Feb. 2017, doi: 10.1108/JMTM-06-2016-0081.

[33] M. Montez *et al.*, "Fused deposition modeling (FDM): processes, material properties, and applications," in *Tribology of Additively Manufactured Materials*, Elsevier, 2022, pp. 137–163. doi: 10.1016/B978-0-12-821328-5.00005-6.

[34] A. Elkaseer, K. J. Chen, J. C. Janhsen, O. Refle, V. Hagenmeyer, and S. G. Scholz, "Material jetting for advanced applications: A state-of-the-art review, gaps and future directions," *Addit Manuf*, vol. 60, p. 103270, Dec. 2022, doi: 10.1016/j.addma.2022.103270.

[35] Y. L. Yap, C. Wang, S. L. Sing, V. Dikshit, W. Y. Yeong, and J. Wei, "Material jetting additive manufacturing: An experimental study using designed metrological benchmarks," *Precis Eng*, vol. 50, pp. 275–285, Oct. 2017, doi: 10.1016/j.precisioneng.2017.05.015.

[36] P. Shakor, S. H. Chu, A. Puzatova, and E. Dini, "Review of binder jetting 3D printing in the construction industry," *Progress in Additive Manufacturing*, vol. 7, no. 4, pp. 643–669, Aug. 2022, doi: 10.1007/s40964-021-00252-9.

[37] M. Li, W. Du, A. Elwany, Z. Pei, and C. Ma, "Metal Binder Jetting Additive Manufacturing: A Literature Review," *J Manuf Sci Eng*, vol. 142, no. 9, Sep. 2020, doi: 10.1115/1.4047430.

[38] D. Svetlizky *et al.*, "Directed energy deposition (DED) additive manufacturing: Physical characteristics, defects, challenges and applications," *Materials Today*, vol. 49, pp. 271–295, Oct. 2021, doi: 10.1016/j.mattod.2021.03.020.

[39] S.-H. Li, P. Kumar, S. Chandra, and U. Ramamurty, "Directed energy deposition of metals: processing, microstructures, and mechanical properties," *International Materials Reviews*, vol. 68, no. 6, pp. 605–647, Aug. 2023, doi: 10.1080/09506608.2022.2097411.

[40] A. Pilipović, "Sheet lamination," in *Polymers for 3D Printing*, Elsevier, 2022, pp. 127–136. doi: 10.1016/B978-0-12-818311-3.00008-2.

[41] I. Gibson, D. Rosen, B. Stucker, and M. Khorasani, "Sheet Lamination," in *Additive Manufacturing Technologies*, Cham: Springer International Publishing, 2021, pp. 253–283. doi: 10.1007/978-3-030-56127-7_9.

[42] Y. Zhang *et al.*, "Additive Manufacturing of Metallic Materials: A Review," *J Mater Eng Perform*, vol. 27, no. 1, pp. 1–13, Jan. 2018, doi: 10.1007/s11665-017-2747-y.

[43] W. Abd-Elaziem *et al.*, "On the current research progress of metallic materials fabricated by laser powder bed fusion process: a review," *Journal of Materials Research and Technology*, vol. 20, pp. 681–707, Sep. 2022, doi: 10.1016/j.jmrt.2022.07.085.

[44] A. Kantaros, D. Piromalis, G. Tsaramirsis, P. Papageorgas, and H. Tamimi, "3D Printing and Implementation of Digital Twins: Current Trends and Limitations," *Applied System Innovation*, vol. 5, no. 1, p. 7, Dec. 2021, doi: 10.3390/asi5010007.

[45] U. Shaukat, E. Rossegger, and S. Schlögl, "A Review of Multi-Material 3D Printing of Functional Materials via Vat Photopolymerization," *Polymers (Basel)*, vol. 14, no. 12, p. 2449, Jun. 2022, doi: 10.3390/polym14122449.

[46] R. V. Pazhamannil and P. Govindan, "Current state and future scope of additive manufacturing technologies via vat photopolymerization," *Mater Today Proc*, vol. 43, pp. 130–136, 2021, doi: 10.1016/j.matpr.2020.11.225.

[47] M. Rafiee, R. D. Farahani, and D. Therriault, "Multi□Material 3D and 4D Printing: A Survey," *Advanced Science*, vol. 7, no. 12, Jun. 2020, doi: 10.1002/advs.201902307.

[48] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital Twin in manufacturing: A categorical literature review and classification," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018, doi: 10.1016/j.ifacol.2018.08.474.

[49] R. Parvanda and P. Kala, "Trends, opportunities, and challenges in the integration of the additive manufacturing with Industry 4.0," *Progress in Additive Manufacturing*, vol. 8, no. 3, pp. 587–614, Jun. 2023, doi: 10.1007/s40964-022-00351-1.

[50] X. Liu *et al.*, "A systematic review of digital twin about physical entities, virtual models, twin data, and applications," *Advanced Engineering Informatics*, vol. 55, p. 101876, Jan. 2023, doi: 10.1016/j.aei.2023.101876.

[51] Y. Lu, C. Liu, K. I.-K. Wang, H. Huang, and X. Xu, "Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues," *Robot Comput Integr Manuf*, vol. 61, p. 101837, Feb. 2020, doi: 10.1016/j.rcim.2019.101837.

[52] R. Stark, C. Fresemann, and K. Lindow, "Development and operation of Digital Twins for technical systems and services," *CIRP Annals*, vol. 68, no. 1, pp. 129–132, 2019, doi: 10.1016/j.cirp.2019.04.024.

[53] E. J. Tuegel, A. R. Ingraffea, T. G. Eason, and S. M. Spottswood, "Reengineering Aircraft Structural Life Prediction Using a Digital Twin," *International Journal of Aerospace Engineering*, vol. 2011, pp. 1–14, 2011, doi: 10.1155/2011/154798.

[54] R. Sahal, S. H. Alsamhi, and K. N. Brown, “Digital Twins Collaboration in Industrial Manufacturing,” in *Digital Twins: Basics and Applications*, Cham: Springer International Publishing, 2022, pp. 59–72. doi: 10.1007/978-3-031-11401-4_7.

[55] M. Javaid, A. Haleem, and R. Suman, “Digital Twin applications toward Industry 4.0: A Review,” *Cognitive Robotics*, vol. 3, pp. 71–92, 2023, doi: 10.1016/j.cogr.2023.04.003.

[56] R. Wagner, B. Schleich, B. Haefner, A. Kuhnle, S. Wartzack, and G. Lanza, “Challenges and Potentials of Digital Twins and Industry 4.0 in Product Design and Production for High Performance Products,” *Procedia CIRP*, vol. 84, pp. 88–93, 2019, doi: 10.1016/j.procir.2019.04.219.

[57] M. Perno, L. Hvam, and A. Haug, “Implementation of digital twins in the process industry: A systematic literature review of enablers and barriers,” *Comput Ind*, vol. 134, p. 103558, Jan. 2022, doi: 10.1016/j.compind.2021.103558.

[58] “Digital Twin Market by Enterprise, Application (Predictive Maintenance, Business optimization), Industry (Aerospace, Automotive & Transportation, Healthcare, Infrastructure, Energy & Utilities) and Geography - Global Forecast to 2027.”

[59] F. Pires, A. Cachada, J. Barbosa, A. P. Moreira, and P. Leitao, “Digital Twin in Industry 4.0: Technologies, Applications and Challenges,” in *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)*, IEEE, Jul. 2019, pp. 721–726. doi: 10.1109/INDIN41052.2019.8972134.

[60] T. Böttjer *et al.*, “A review of unit level digital twin applications in the manufacturing industry,” *CIRP J Manuf Sci Technol*, vol. 45, pp. 162–189, Oct. 2023, doi: 10.1016/j.cirpj.2023.06.011.

[61] C. Cimino, E. Negri, and L. Fumagalli, “Review of digital twin applications in manufacturing,” *Comput Ind*, vol. 113, p. 103130, Dec. 2019, doi: 10.1016/j.compind.2019.103130.

[62] R. K. Phanden, S. V. Aditya, A. Sheokand, K. K. Goyal, P. Gahlot, and A. Jacso, “A state-of-the-art review on implementation of digital twin in additive manufacturing to monitor and control parts quality,” *Mater Today Proc*, vol. 56, pp. 88–93, 2022, doi: 10.1016/j.matpr.2021.12.217.

[63] T. Mukherjee, “Recent progress in process, structure, properties, and performance in additive manufacturing,” *Science and Technology of Welding and Joining*, pp. 1–5, Sep. 2023, doi: 10.1080/13621718.2023.2253588.

[64] R. Jain, N. Bharat, and P. S. C. Bose, “Digital Twins of Hybrid Additive and Subtractive Manufacturing Systems–A Review,” 2024, pp. 173–183. doi: 10.1007/978-981-99-6094-1_18.

[65] S. M. Rachmawati, M. A. P. Putra, J. M. Lee, and D. S. Kim, “Digital twin-enabled 3D printer fault detection for smart additive manufacturing,” *Eng Appl Artif Intell*, vol. 124, p. 106430, Sep. 2023, doi: 10.1016/j.engappai.2023.106430.

[66] D. R. Gunasegaram, A. B. Murphy, M. J. Matthews, and T. DebRoy, “The case for digital twins in metal additive manufacturing,” *Journal of Physics: Materials*, vol. 4, no. 4, p. 040401, Oct. 2021, doi: 10.1088/2515-7639/ac09fb.

[67] T. H.-J. Uhlemann, C. Schock, C. Lehmann, S. Freiberger, and R. Steinhilper, “The Digital Twin: Demonstrating the Potential of Real Time Data Acquisition in Production Systems,” *Procedia Manuf*, vol. 9, pp. 113–120, 2017, doi: 10.1016/j.promfg.2017.04.043.

[68] S. Krückemeier and R. Anderl, “Concept for Digital Twin Based Virtual Part Inspection for Additive Manufacturing,” *Procedia CIRP*, vol. 107, pp. 458–462, 2022, doi: 10.1016/j.procir.2022.05.008.

[69] A. Phua, C. H. J. Davies, and G. W. Delaney, “A digital twin hierarchy for metal additive manufacturing,” *Comput Ind*, vol. 140, p. 103667, Sep. 2022, doi: 10.1016/j.compind.2022.103667.

[70] Y. Cai, B. Starly, P. Cohen, and Y.-S. Lee, “Sensor Data and Information Fusion to Construct Digital-twins Virtual Machine Tools for Cyber-physical Manufacturing,” *Procedia Manuf*, vol. 10, pp. 1031–1042, 2017, doi: 10.1016/j.promfg.2017.07.094.

[71] L. Zhang *et al.*, “Digital twins for additive manufacturing: A state□of□the□art review,” *Applied Sciences (Switzerland)*, vol. 10, no. 23. pp. 1–10, 2020. doi: 10.3390/app10238350.

[72] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, “Digital twin-driven product design, manufacturing and service with big data,” *The International Journal of Advanced Manufacturing Technology*, vol. 94, no. 9–12, pp. 3563–3576, Feb. 2018, doi: 10.1007/s00170-017-0233-1.

[73] M. Segovia and J. Garcia-Alfaro, “Design, Modeling and Implementation of Digital Twins,” *Sensors*, vol. 22, no. 14, p. 5396, Jul. 2022, doi: 10.3390/s22145396.

[74] M. M. Francois *et al.*, “Modeling of additive manufacturing processes for metals: Challenges and opportunities,” *Curr Opin Solid State Mater Sci*, vol. 21, no. 4, pp. 198–206, Aug. 2017, doi: 10.1016/j.cossms.2016.12.001.

[75] T. Mukherjee and T. DebRoy, “A digital twin for rapid qualification of 3D printed metallic components,” *Appl Mater Today*, vol. 14, pp. 59–65, Mar. 2019, doi: 10.1016/j.apmt.2018.11.003.

[76] F. Corradini and M. Silvestri, “Design and testing of a digital twin for monitoring and quality assessment of material extrusion process,” *Addit Manuf*, vol. 51, p. 102633, Mar. 2022, doi: 10.1016/j.addma.2022.102633.

[77] D. Mourtzis, T. Togias, J. Angelopoulos, and P. Stavropoulos, “A Digital Twin architecture for monitoring and optimization of Fused Deposition Modeling processes,” *Procedia CIRP*, vol. 103, pp. 97–102, 2021, doi: 10.1016/j.procir.2021.10.015.

[78] N. Jyeniskhan, A. Keutayeva, G. Kazbek, M. H. Ali, and E. Shehab, “Integrating Machine Learning Model and Digital Twin System for Additive Manufacturing,” *IEEE Access*, vol. 11, pp. 71113–71126, 2023, doi: 10.1109/ACCESS.2023.3294486.

[79] C. B. Toprak and C. U. Dogruer, "A Critical Review of Machine Learning Methods Used in Metal Powder Bed Fusion Process to Predict Part Properties," *International Journal of Precision Engineering and Manufacturing*, Oct. 2023, doi: 10.1007/s12541-023-00905-5.

[80] H. Xu, J. Wu, Q. Pan, X. Guan, and M. Guizani, "A Survey on Digital Twin for Industrial Internet of Things: Applications, Technologies and Tools," *IEEE Communications Surveys & Tutorials*, pp. 1–1, 2023, doi: 10.1109/COMST.2023.3297395.

[81] M. J. Kaur, V. P. Mishra, and P. Maheshwari, "The Convergence of Digital Twin, IoT, and Machine Learning: Transforming Data into Action," 2020, pp. 3–17. doi: 10.1007/978-3-030-18732-3_1.

[82] M. Machado, E. Oliveira, L. Silva, J. Silva, and J. Sousa, "Development of a Digital Twin for Additive Manufacturing," in *Volume 2B: Advanced Manufacturing*, American Society of Mechanical Engineers, Nov. 2021. doi: 10.1115/IMECE2021-68002.

[83] S. V. Nagar, A. C. Chandrashekar, and M. Suvarna, "Optimized Additive Manufacturing Technology Using Digital Twins and Cyber Physical Systems," 2020, pp. 65–73. doi: 10.1007/978-3-030-23162-0_7.

[84] J. Butt and V. Mohaghegh, "Combining Digital Twin and Machine Learning for the Fused Filament Fabrication Process," *Metals (Basel)*, vol. 13, no. 1, p. 24, Dec. 2022, doi: 10.3390/met13010024.

[85] D. R. Gunasegaram *et al.*, "Towards developing multiscale-multiphysics models and their surrogates for digital twins of metal additive manufacturing," *Addit Manuf*, vol. 46, p. 102089, Oct. 2021, doi: 10.1016/j.addma.2021.102089.

[86] G. A. R. Sampedro, M. A. P. Putra, and M. Abisado, "3D-AmplifAI: An Ensemble Machine Learning Approach to Digital Twin Fault Monitoring for Additive Manufacturing in Smart Factories," *IEEE Access*, vol. 11, pp. 64128–64140, 2023, doi: 10.1109/ACCESS.2023.3289536.

[87] P. M. Abhilash, J. Boban, A. Ahmed, and X. Luo, "Digital twin-driven additive manufacturing," in *Hybrid Metal Additive Manufacturing*, Boca Raton: CRC Press, 2023, pp. 196–221. doi: 10.1201/9781003406488-12.

[88] L. Zhang, W. Zhou, and X. Chen, "Digital Twins and Additive Manufacturing," in *Digital Twins: Basics and Applications*, Cham: Springer International Publishing, 2022, pp. 27–35. doi: 10.1007/978-3-031-11401-4_4.

[89] G. L. Knapp *et al.*, "Building blocks for a digital twin of additive manufacturing," *Acta Mater*, vol. 135, pp. 390–399, Aug. 2017, doi: 10.1016/j.actamat.2017.06.039.

[90] Yu. G. Kabaldin, P. V. Kolchin, D. A. Shatagin, M. S. Anosov, and A. A. Chursin, "Digital Twin for 3D Printing on CNC Machines," *Russian Engineering Research*, vol. 39, no. 10, pp. 848–851, Oct. 2019, doi: 10.3103/S1068798X19100101.

[91] J. Haw, S. L. Sing, and Z. H. Liu, "Digital twins in design for additive manufacturing," *Mater Today Proc*, vol. 70, pp. 352–357, 2022, doi: 10.1016/j.matpr.2022.09.268.

[92] L. Scime, A. Singh, and V. Paquit, “A scalable digital platform for the use of digital twins in additive manufacturing,” *Manuf Lett*, vol. 31, pp. 28–32, Jan. 2022, doi: 10.1016/j.mfglet.2021.05.007.

[93] A. Phua, P. S. Cook, C. H. J. Davies, and G. W. Delaney, “Smart recoating: A digital twin framework for optimisation and control of powder spreading in metal additive manufacturing,” *J Manuf Process*, vol. 99, pp. 382–391, Aug. 2023, doi: 10.1016/j.jmapro.2023.04.062.

[94] P. Castelló-Pedrero, C. García-Gascón, J. Bas-Bolufer, and J. A. García-Manrique, “Integrated computational modeling of large format additive manufacturing: Developing a digital twin for material extrusion with carbon fiber-reinforced acrylonitrile butadiene styrene,” *Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications*, vol. 238, no. 2, pp. 332–346, Feb. 2024, doi: 10.1177/14644207231219856.

[95] K. S. S. Reddy, R. Rajesh, P. A. C. Raj, N. Arya, R. Bhaskaran, and J. L. Prasad, “Implementation and Manufacturing of DT Sensor Ecosystem for Real-Time Monitoring of Virtual 3D Printers,” *SN Comput Sci*, vol. 4, no. 5, p. 556, Jul. 2023, doi: 10.1007/s42979-023-01969-w.

[96] R. T. Reisch *et al.*, “Context awareness in process monitoring of additive manufacturing using a digital twin,” *The International Journal of Advanced Manufacturing Technology*, vol. 119, no. 5–6, pp. 3483–3500, Mar. 2022, doi: 10.1007/s00170-021-08636-5.

[97] H. Mu, F. He, L. Yuan, P. Commins, H. Wang, and Z. Pan, “Toward a smart wire arc additive manufacturing system: A review on current developments and a framework of digital twin,” *J Manuf Syst*, vol. 67, pp. 174–189, Apr. 2023, doi: 10.1016/j.jmsy.2023.01.012.

[98] I. Noh, H. Shin, Y. Choi, Y. Lee, Y. Jeon, and S. W. Lee, “Development of an Interactive Digital Twin for Directed Energy Deposition (DED) Process,” in *Volume 2: Manufacturing Processes; Manufacturing Systems*, American Society of Mechanical Engineers, Jun. 2022. doi: 10.1115/MSEC2022-85513.

[99] O. Fergani and K. Eissing, “A machine learning-based digital twin of the manufacturing process: metal powder-bed fusion case,” no. February, pp. 1–8, 2020, doi: 10.31224/osf.io/736a5.

[100] H. Yeung, F. Kim, and A. Donmez, “Application of Digital Twins to Laser Powder Bed Fusion Additive Manufacturing Process Control,” in *Volume 1: Additive Manufacturing; Advanced Materials Manufacturing; Biomanufacturing; Life Cycle Engineering*, American Society of Mechanical Engineers, Jun. 2023. doi: 10.1115/MSEC2023-105627.

We have no conflicts of interest to disclose