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(Review Article)

Digital twins in additive manufacturing

Md. Hossain [1, 2, *] and Md. Bahar Uddin [3, 4]

[1] *College of Textile Technology, Bangladesh University of Textiles, Dhaka - 1208, Bangladesh.*
[2] *Department of Manufacturing System Engineering and Management, California State University, Northridge, CA 91330, USA.*
[3] *Pran RFL Group, Dhaka-1212, Bangladesh.*
[4] *Department of Mechanical Engineering, Khulna University of Engineering and Technology, Khulna, Bangladesh.*

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Abstract

Additive Manufacturing (AM), a transformative production method, is gaining momentum across industries due to its ability to fabricate complex geometries with minimal waste. However, challenges in optimizing process parameters and ensuring quality control hinder its full potential. Digital Twins (DTs), virtual replicas of physical systems, have emerged as a solution to enhance AM processes by enabling real-time monitoring, simulation, and predictive analysis. The paper highlights key advancements in combining DTs with Industry 4.0 and 5.0 technologies, such as machine learning, augmented reality, and high-performance computing, to improve efficiency, scalability, and sustainability in manufacturing. Challenges including data quality, system integration, and computational demands are discussed, with a vision for adaptive and intelligent DT systems.

Keywords: Additive Manufacturing; Digital Twin; Industry 4.0; Process Optimization; Smart Manufacturing; Real-Time Monitoring; Sustainability

1. Introduction

Additive manufacturing (AM), or 3D printing, is a process that uses computer-aided design (CAD) to create metal parts layer by layer. It offers advantages over traditional methods, such as the ability to produce complex shapes at a lower cost with minimal waste. AM is playing a key role in the ongoing industrial revolution, particularly in Industry 4.0. Since its introduction, AM has seen rapid growth and adoption across industries like aerospace, medicine, energy, and automotive, where it is used to turn digital models into finished products. AM is divided into seven main categories, each with its own unique processes, such as photopolymerization, powder bed fusion (PBF), direct energy deposition (DED), and thin plate lamination. In the last decade, AM has gained popularity and is expected to disrupt traditional manufacturing, changing how products are made and distributed [1-6].

Additive manufacturing (AM) process parameters, such as heat source power, powder/filament feeding velocity, hatch spacing, power distribution, and scanning velocity, greatly influence the structural integrity and mechanical properties of AM components [6]. While optimizing these parameters can improve the final product, the vast number of possible combinations makes trial-and-error methods costly and inefficient. Therefore, conducting experiments based on previous outcomes is essential for optimizing AM processes.

Digital twins (DTs) can address these challenges. A DT is a digital replica of a physical object or system, continuously updated to reflect production faults. It provides a virtual representation of a manufacturing process or product, allowing

* Corresponding author: Md. Hossain.

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real-time analysis and performance prediction [7][8]. Unlike traditional CAD systems, DTs integrate sensor data to model the physical world and help in improving manufacturing processes.

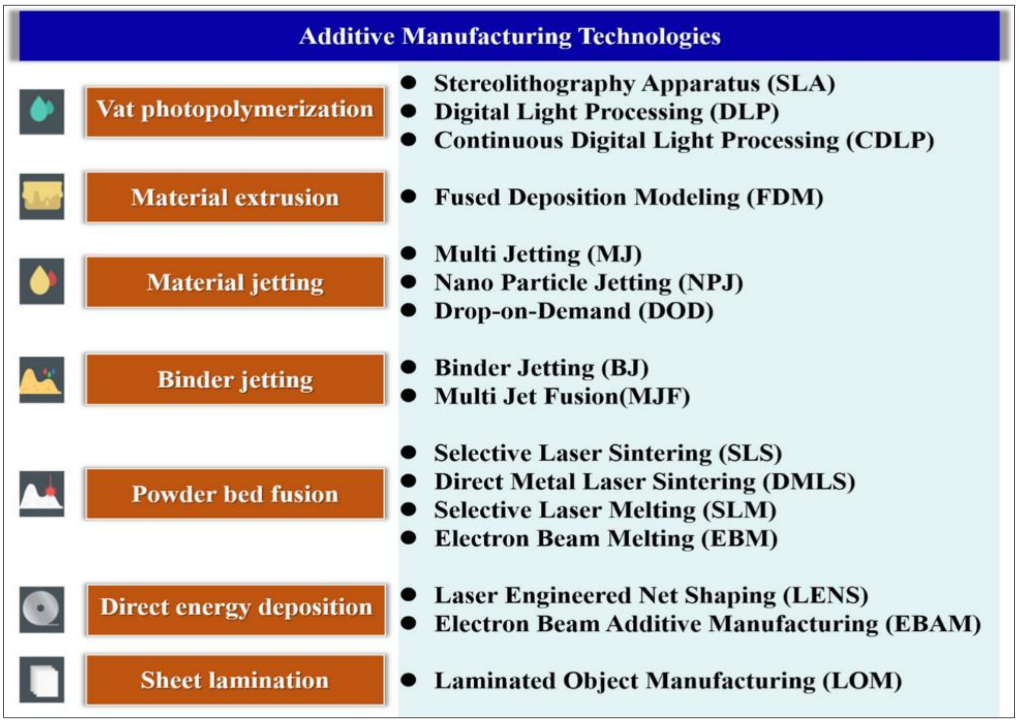

Figure 1 Categories of AM [5]

In the context of Industry 4.0, technologies like digitization, big data, simulation, and machine learning (ML) are being explored to optimize DTs in AM. By leveraging data from physical models and operational histories, DTs can simulate manufacturing processes, predict equipment status, and optimize process parameters [9, 10]. This leads to better quality control, process optimization, and reduced product validation times. Additionally, integrating multi-physics simulation with data analysis and ML can further enhance the AM process by adjusting parameters based on real-time conditions [11, 12].

DTs are also being explored in other sectors like maintenance and repair, with companies like Decision Lab Ltd. and Siemens creating models for production operations. However, the full integration of DTs in AM is still under development, and further research is needed to overcome technical challenges. The combination of AM and DT holds great potential for revolutionizing manufacturing processes and driving digital transformation [4].

2. Additive manufacturing processes and equipment for metals

Currently, AM of metallic materials is an important theme under discussion. Its usage is moving from research to commercialization, because metal parts have many applications in industry. The processing of metals by AM is often more complicated than other materials. Vat polymerization cannot be used for metals, and some of the other processes that are suitable for metal fabrication, such as material extrusion [14] and material jetting [23], [24], are still in the development stage. Metal AM processes are classified as (1) powder bed fusion (PBF), (2) directed energy deposition (DED), (3) binder jetting (BJ), and (4) sheet lamination (SL).

The currently available commercial AM systems for metallic material applications, along with their manufacturer, are listed in table 1. The systems are classified on the basis of the ASTM standard definitions. The processing information, including layer thickness range and laser focus diameter, along with system energy sources are also listed. Laser-based PBF is the most frequently applied process, and the laser power is in the range of 100–1000 W, depending on the manufacturer. The thickness of each build layer of laser PBF can be as small as 20 μm, which shows its advantage in terms of resolution in comparison to the other processes. Arcam (acquired by GE in 2017) is the only currently available manufacturer for electron beam melting (EBM)-based PBF. The power of e-beam is much larger than lasers, and a thicker layer can be built with each scan. The other metal AM processes are also included. Trumpf provides both powder-fed DED and laser PBF at the same time. ExOne and Fabrisonic are manufacturers of BJ and SL systems that are suitable for metal AM.

Table 1 Currently available commercialized additive manufacturing systems for metallic materials application

Manufacturer	System	Process	Layer thickness (µm)	Laser focus diameter (µm)	Energy source
Concept laser [15]	M1 cusing	Laser PBF	20–80	50	Fiber laser 200–400 W
Sisma [16]	MYSINT300	Laser PBF	20–50	100–500	Fiber laser 500 W
SLM solutions [17]	SLM500	Laser PBF	20–74	80–115	Quad fiber lasers 4 × 700 W
Realizer [18]	SLM300i	Laser PBF	20–100	N/A	Fiber laser 400–1000 W
Renishaw	AM 400	Laser PBF	N/A	N/A	Optical fiber, 400 W
Farsoon [19]	FS271M	Laser PBF	20–80	40–100	Yb-fiber laser, 200 W
EOS [20]	M 400	Laser PBF	N/A	90	Yb-fiber laser, 1000 W
Arcam AB [21]	Arcam Q20plus	EBM PBF	140	–	Electron beam 3000 W
Optomec [22]	LENS print engine	DED (LENS)	25	–	IPG fiber laser 1–2 kW
Sciaky [23]	EBAM 300	DED (wire fed)	N/A	–	Electron beam
Trumpf [24]	TruPrintTru TruLaser	Laser PBF	–	–	–
DED (powder fed)	N/A	–	YAG laser (6600 W)		
ExOne [25]	M print	BJ	150	–	–

3. Types of AM

There are several types of AM technologies, each with its unique process and applications [26]. The most common types include

- Stereolithography (SLA): SLA employs a laser to cure liquid resin into hardened plastic through a layerby-layer process. This method is renowned for creating parts with high resolution and smooth surface finishes [8].
- Fused Deposition Modeling (FDM): FDM extrudes thermoplastic filament through a heated nozzle, which is deposited layer by layer to create a part. It is widely used due to its simplicity and cost-effectiveness [9].
- Selective Laser Sintering (SLS): SLS uses a laser to sinter powdered material, typically nylon or other polymers, into a solid structure. This method is known for its ability to create strong and durable parts without the need for support structures [10].
- Digital Light Processing (DLP): This method is similar to SLA but uses a digital light projector to cure photopolymer resin. It can quickly produce high-resolution parts [11]
- Binder Jetting: In this process, a liquid binding agent is deposited over a powder bed to bond the material and form a solid part. It's suitable for metals, ceramics, and even sand [12].
- Material Jetting: This technique involves depositing droplets of build material layer by layer, which are then cured by UV light. It allows for high precision and can print multiple materials at once [13].

- Powder Bed Fusion (PBF): PBF includes technologies like Selective Laser Melting (SLM) and Electron Beam Melting (EBM). These use a laser or electron beam to melt and fuse powder particles together [14].
- Direct Energy Deposition (DED): DED uses thermal energy, such as a laser or electron beam, to fuse materials by melting them as they are deposited. This method is used for repairing and adding material to existing components [15].
- Sheet Lamination: This method involves stacking and bonding sheets of material, which are then cut to shape using a laser or another cutting tool. It is known for its speed and ability to use a wide range of materials [16].

4. Digital Twin (DT)

A Digital Twin (DT) is a virtual model of a physical entity or system that simulates, analyzes, and optimizes its real-world counterpart. It involves creating an accurate digital model that mirrors the characteristics, conditions, and behaviors of the physical object, allowing for ongoing monitoring and predictive analysis. Digital Twins (DTs) use data from sensors and Internet of Things (IoT) devices to update the virtual model in real time, providing insights to improve performance, reduce downtime, and optimize operations [26].

Table 2 Different types of DTs in AM [26]

Types of DTs	Applications	Advantages	Challenges
Product DTs	Product design enhancement Lifecycle management Performance forecasting	- Enhanced product quality - Accelerated time-to-market	- High initial investment - Integration complexity
Process DTs	Process optimization Real-time performance monitoring Predictive maintenance	- Improved operational efficiency - Minimized downtime	- Dependence on high-quality data - Cybersecurity vulnerabilities
System DTs	System-level performance evaluation Resource optimization Integrated system management	- Comprehensive system visibility - Informed decision-making	- Complex system modeling - High computational demand
Service DTs	Real-time service tracking Predictive maintenance Lifecycle optimization	- Prolonged component life - Reduced service interruptions	- Need for accurate sensor data - Implementation challenges
Hybrid DTs	Integrated product and process intelligence End-to-end system optimization	- Holistic insights - Peak operational efficiency	- High implementation complexity - Advanced technical expertise required

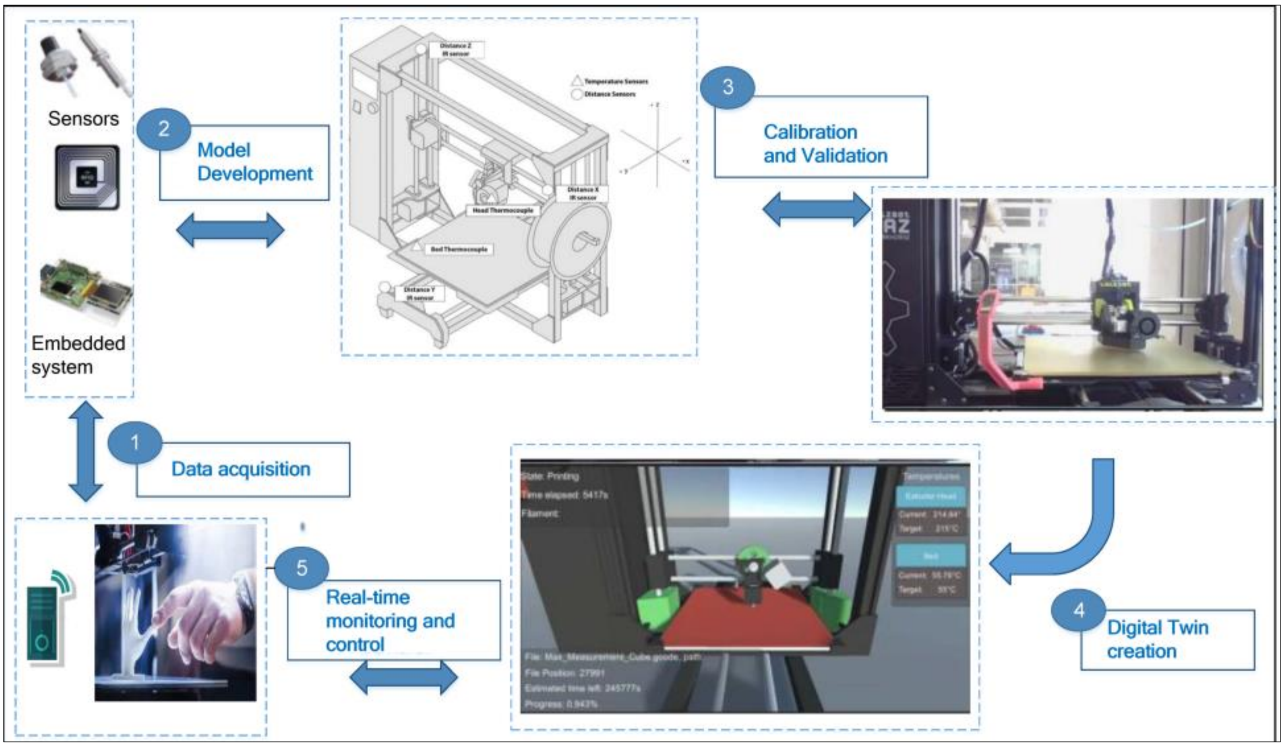

Figure 2 Different stages of a Digital Twin system in the additive manufacturing process [27-29]

Figure 2 shows the different stages of a Digital Twin system in the additive manufacturing process

5. DT and hybrid manufacturing

Papacharalampopoulos et al. (2023) integrated DT capabilities with Industry 5.0 (I5.0) criteria, focusing on sustainability and human inclusion. The study demonstrated improvements in worker well-being and production efficiency but was limited to a small case study with AM and laser welding [30].

Montoya et al. (2021) examined the influence of laser intensity distribution and process speed in laser-based AM. They found that these parameters affected the thermal history of substrates, though the study was limited by linear simulations and assumptions of constant substrate properties [32].

Hartmann et al. (2024) studied a multiscale DT for L-DED to reduce time and costs in AM. The DT showed errors in clad dimensions and temperatures, but its validation was restricted to specific materials and geometries [31].

Beckman et al. (2021) created DT replicas of nonwoven fibrous air filtration media, demonstrating the utility of computational models for filtration efficiency. However, improvements were needed in the geometry creation algorithm and Computational Fluid Dynamics analysis [33].

Sofic et al. (2022) investigated the transformation of manufacturing firms using digital technologies, demonstrating that AM and DTs contributed to higher turnover and resilience, especially during the COVID-19 pandemic. However, the study was limited to a single dataset and focused mainly on financial resilience [34].

Reisch et al. (2023) proposed a smart manufacturing system using DTs to compensate for defects in the Wire Arc Additive Manufacturing (WAAM) process. The system showed high success in correcting defects, but WAAM struggled with precision, requiring additional reworking for surface quality [35].

Turazza et al. (2020) explored the use of DTs in polymer extrusion die fabrication using continuous liquid interface production. They achieved successful production but noted that the quality of extruded products did not match the reference samples, requiring further improvements in the simulation model [36].

Table 3 Literature Reviews of DT and hybrid manufacturing

Ref.	Approach	Application	Evaluation	Limitations
[30]	DT with Industry 5.0 criteria	Process selection, AM and laser welding	Improved worker well-being, production efficiency	Limited to a case study of two parts; economic implications not fully explored; lack of quality assessment
[32]	Linear isotropic numerical model	Thermal history in laser-based AM	Parameters affect temperature and heat-affected zone	Limited to linear simulations, neglected heat transfer in the z-direction, and assumed constant properties
[31]	Multiscale DT for L-DED	AM process optimization	Predicted clad dimensions with acceptable errors	Limited to specific conditions, materials, and geometries; computational efficiency issues
[33]	DT replica creation for air filters	Nonwoven fibrous air filtration	Good agreement with SEM imagery, predicted filtration efficiency	Needed refinement in DT geometry creation and CFD analysis; limited scope for other models
[34]	Data analysis and social network	Digital transformation of manufacturing firms	Higher turnover in firms using AM, big data, and DTs	Based on a single dataset; focused on financial resilience only
[35]	Smart manufacturing system with DT	Wire Arc Additive Manufacturing (WAAM)	93.4% success in compensating for defects in WAAM	WAAM struggles with surface quality and precision; requires additional reworking
[36]	DT in polymer extrusion production	Fabrication of polymer extrusion dies	Successfully produced up to 1000 meters of conformal products	Quality of extruded products did not match reference samples; requires further validation of simulations

6. Challenges of DT

- DTs require high-quality data to replicate systems accurately. Poor data can lead to inaccurate models and predictions, reducing their effectiveness in real-time applications [35].
- Integrating DTs with existing manufacturing systems can be complex and resource-intensive, requiring significant investment in technology and expertise [38].
- Scalability remains a concern, especially when using low-cost sensors. Scaling up DTs for larger systems without performance loss is a critical challenge [35].
- Techniques like Augmented Reality (AR) and adaptive simulations demand significant computational power, which can hinder their use in resource-limited environments [37].
- DT models must be continuously validated against real-world data. This is challenging in complex systems where discrepancies may arise [40-47].
- Creating multiscale models and linking processes across scales is technically difficult. Non-technical issues like standardization and international collaboration also complicate DT implementation [48-52].
- Real-time data processing requires efficient algorithms that balance accuracy and speed, a significant challenge in fast-paced manufacturing [34].
- Incorporating sustainability into DTs requires further development of lifecycle data exchange and cost estimation methods [36].
- DT frameworks relying on advanced technologies like High-Performance Computing (HPC) and AM require costly tech integrations.
- Physics-based models improve accuracy but are complex and resource-intensive, limiting their practical use in some contexts [35].

7. Future Scope

- Future DTs could use better data integration, combining IoT sensor data, historical data, and real-time monitoring to improve accuracy and reliability.
- DTs could use advanced algorithms like PINNs and ML models to perform real-time simulations with higher computational power.
- Research could focus on using DTs to optimize resources, reduce environmental impact, and promote recycling in AM.
- Future DTs could use AR/VR to create more user-friendly interfaces for monitoring and optimizing AM processes.
- DTs could improve worker well-being, safety, and human-machine interaction in AM environments, helping shape the next generation of smart manufacturing.
- DTs could be more adaptive, enabling real-time changes based on live data with the help of AI and ML algorithms.
- Better cost models could help forecast and budget more accurately by considering all production and lifecycle costs.
- DTs could be extended to new AM applications involving complex geometries, multi-material parts, and new materials.
- Integrating models that simulate different physical phenomena could improve DTs' accuracy and applicability in AM processes.

8. Conclusion

DTs in AM offer a great opportunity to develop optimal real-time monitoring systems for defect detection and process optimization. By providing a detailed understanding of melt pool behavior and defect formation, DTs surpass traditional single-sensor approaches, such as those used in the robotic Laser-Directed Energy Deposition (L-DED) process. This capability allows for on-the-fly corrections of defects by generating auto-tuned process parameters and adjusting robot toolpaths, thus improving the efficiency and sustainability of AM processes. DTs in AM face several challenges. These include the need for high-quality input data to create accurate models, the complexity of integrating various technologies, and the substantial computational power required for real-time applications. Scalability remains a key concern, especially when adapting DTs for larger and more complex systems, and the reliance on physics-based models to enhance accuracy presents further obstacles. Future advancements could focus on better data integration, employing advanced computational methods to enhance simulation accuracy, and incorporating sustainable manufacturing practices into DT-based systems. The integration of Augmented Reality (AR), Virtual Reality (VR), and Industry 5.0 (I5.0) principles could also contribute to the evolution of DTs in AM. Additionally, real-time adaptive systems, improved cost models, and expanded use cases for DTs in diverse applications could significantly increase their effectiveness. Furthermore, multi-scale and multi-physics modeling capabilities can enhance the accuracy of DT simulations. DTs have the potential to revolutionize AM by improving efficiency, sustainability, and innovation. Addressing the current challenges and leveraging emerging technologies will be key to fully realizing their benefits.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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