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Adoption of Digital Twin and Artificial Intelligence in Metal Additive Manufacturing: Current Status and Vision for Future

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Abstract: The transformation of artificial intelligence (AI) and machine learning (ML) from computer science theory into real-world technologies is a primary driver of the fourth industrial revolution (Industry 4.0). Industry 4.0 has shifted manufacturing operations away from mechanical technologies and toward digitalization. In this era of Industry 4.0, intelligent tools and techniques are opening new dimensions to optimize manufacturing processes and systems. Metal Additive manufacturing (MAM) as a highly digitalized manufacturing technology can apply the concept of the digital twin (DT) and AI, which promises highly automated and optimized part production. However, adoption of DT and AI requiring a wide framework of various technologies, it is not state of the art yet. This paper presents a comprehensive review of AI and DT enabled models in Metal Additive Manufacturing. This paper also identifies challenges and opportunities to not only further leverage emerging technologies, artificial intelligence (AI) and digital twin (DT) for metal additive manufacturing, but also influence of future development of DT and AI to better meet the needs of additive manufacturing. These insights significantly contribute to the understanding and further development of AI and DTs in metal additive manufacturing within the context of Industry 4.0, offering a fresh perspective that aligns with the evolution of the smart manufacturing industry. These advanced technologies have radically transformed advanced manufacturing and are essential to modern economic prosperity.

Introduction

Industry 4.0 and smart manufacturing are crucial fundamentals of modern manufacturing industries and the national economy. The Fourth Industrial Revolution is blurring the boundaries between the physical, digital, and biological worlds. Technologies like the Internet of Things (IoT), artificial intelligence, augmented/virtual/mixed reality, robotics, and Additive manufacturing are transforming the Aerospace and Advanced Manufacturing industries. With the profound research and development of Industry 4.0 and artificial intelligence (AI), digital twin (DT) has drawn growing research attention [1–2]. Deep research is in progress on digitization through various smart algorithms of Machine Learning (ML), Artificial Intelligence (AI), Big Data Analytics (BDA), high fidelity simulation in addition to various other cutting-edge tools and technologies [3-4]. In this direction, Digital Twin (DT) and AI are turn out to be the most popular tool to improve the AM processes performance with respect to the defects, porosity, roughness, deformation and many more. Digital twins enable real-time monitoring and optimization of the manufacturing process, leading to improved quality control, reduced downtime, and enhanced productivity. In its original form, the DT is defined as a digital informational construct about a physical system, which should include all information regarding the system asset that could be obtained from its thorough inspection of the physical system. A DT model comprises three main parts: a) the real world, b) the virtual world and c) the connections of information associating the virtual with the real world, with the digital twin serving as a digital controller of the real-world manufacturing system [5]. Besides DT, another key technology for improving the performance in manufacturing systems is Artificial Intelligence (AI). As AI technology becomes more mature and affordable, new applications can be introduced in production systems to support manufacturers on complex decision-making and in their business processes. **Fig. 1** shows the process of AI adoption in Additive Manufacturing. AM has been used in industry, academic and consumer alike. Creating components using AM techniques is going beyond prototyping— in many industries it has already begun to be a reasonable part of manufacturing capacity. Its application is visible in medical, defense, and aerospace industries. On the consumer level also, the technology is getting good traction.

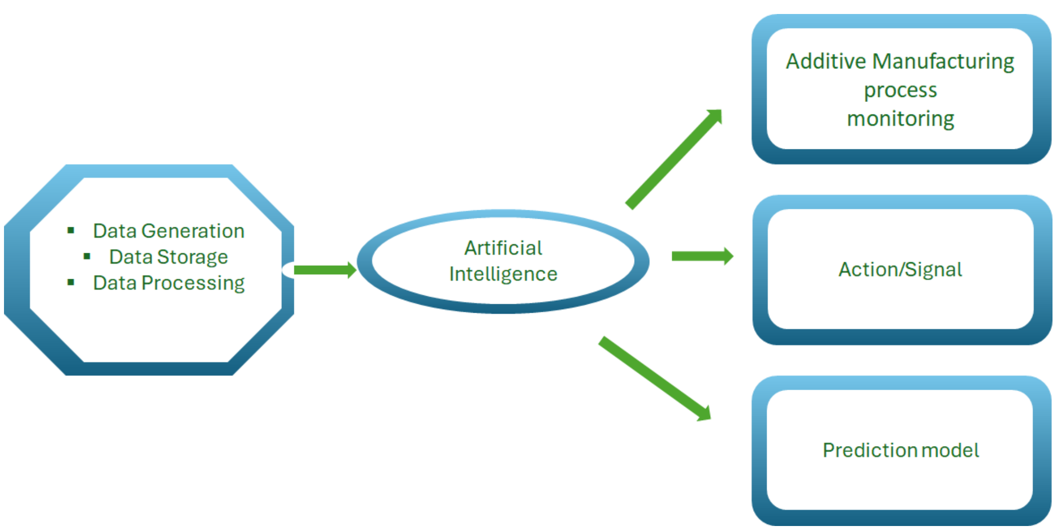

Fig. 1. Process of Artificial Intelligence adoption in Additive Manufacturing.

This paper presents a review of AI and DT enabled models in Metal Additive Manufacturing. This paper also identifies challenges and opportunities to not only further leverage emerging technologies, artificial intelligence (AI) and digital twin (DT) for metal additive manufacturing, but also influence of future development of DT and AI to better meet the needs of additive manufacturing. The analysis of the state of the art indicates that using digital simulation models for facilitating the need for training ML models for AI applications in manufacturing has been explored in a limited manner by researchers. One contribution of this work is to explore the opportunity for DT-driven AI workflows by highlighting the benefits and the challenges faced in metal additive manufacturing. Since the combination of AM, which is considered a direct digital manufacturing technology, and the DT and AI are highly promising in regard of the digital transformation of the manufacturing industry, it is of high importance to understand the current state of the application as well as future research needs to achieve the goal of a DT and AI in AM. This study aims to give an overview of the state of the art and identify the topics research needs to investigate by applying the method of a systematic review.

Overview of Federal Grant

This work refers to a federal grant awarded to the University. This project was proposed to develop campus wide advanced manufacturing center of excellence. The key objectives of the project were: 1) to study the process of AI and DT adoption in metal additive manufacturing domain and learn some manufacturing parameters as being monitored by AI/DT; 2) increase the number of technicians with the skills necessary for an immediate contribution to the additive manufacturing industry; 3) provide students with a more personalized and adaptive educational experience with Digital Twin and other technologies; 4) enhance practicing professionals' knowledge of advanced manufacturing and direct digital manufacturing; 5) New AI models with intrinsic interpretability and increased adaptability to support Additive Manufacturing. University thus far has already completed developing the certificate program and its courses related to Additive Manufacturing Engineering Certificate. Currently, the certificate program is being offered at the university for undergraduate students and Industry partners. However, this paper specifically addresses objective number 4 and 5 which are focused on developing short courses on high value manufacturing topics for returning industry professionals. As a part of short courses and research, the university will do a review of AI and DT enabled models in Metal Additive Manufacturing. The university are partnered with local companies, community colleges and other higher education to collaborate on state-of-the-art demonstration facilities that will allow the University Campus partnership to showcase, train, and consult in these Industry 4.0 technologies. The project goal strives to create a pipeline of the next generation workforce that is empowered with the skills to merge additive manufacturing with DT & AI. The first step for achieving this is to conduct industry-needs analyses in metal additive manufacturing via organization of annual curriculum road mapping workshops where all relevant stakeholders can together explore and chart us how to respond to the changing industrial landscape. Drawing from theses workshop outcomes, curricula will be developed in collaboration with all stakeholders to create a course material and hands-on labs that allow for manufacturing technology students to gain an appropriate level of understanding of the essentials of each other's programs. The influence that industry 4.0 has on the industrial sector has been projected to the topic of engineering education. Sakhapov et al, state that industry 4.0 has already started due to industrial changes in IoT, integration of cyber physical systems (CPS) in manufacturing processes and application of neural networks. For education, and especially for engineering education, this brings important implications such as individualization and digitization of education, empowerment of projects and multi disciplinarity of engineering education, as well as interaction of education resources [6]. This educational research study aims to establish a knowledge base for end-users of metal additive manufacturing.

Powder Bed Fusion (PBF) Metal Additive Manufacturing (MAM)

Powder bed fusion (PBF) is a 3D printing method that joins powdered material point by point using an energy source, typically a laser beam or an electron beam. PBF is the AM process most applied to metals. If a laser source is adopted, the deposition process is carried out in an inert atmosphere such as argon or helium chamber to prevent material from oxidation at elevated temperature. Electron beam melting (EBM), methods require a vacuum but can be used with metals and alloys in the creation of functional parts. In this technique illustrated in **Fig. 2**, the powder is spread on a flat metal plate called the “build platform” to create a powder layer called the “powder bed”. The powder bed is then irradiated with a laser beam or electron beam to scan and melt a layer of fine metal powder to build up a component in a layer-by-layer manned. PBF provides the ability to produce in-process support structures for overhangs and undercuts. Thus, highly complex shapes with high geometric accuracy can be manufactured. Ideally, AM generates a part that requires a minimum amount of post processing. However, often several post process steps are necessary to prepare the part for the final application. There is a large range of postprocessing methods available, meaning that PBF parts can achieve a very smooth finish, and for this reason, they are often used to manufacture end products. The limitations of PBF often center around surface roughness and internal porosity of the as-printed parts, shrinkage or distortion during processing, and the challenges associated with powder handling and disposal. For MAM to reach its full potential, a realistic virtual representation of the complete process is required. Insufficient melting or unstable flow can leave voids after solidification, which can cause defects. Additive manufacturing plays an important role in the industry 4.0 revolution and the implementation of DT using AI must be explored further. The adaptation of DT and AI for MAM is relatively new, and studies were demonstrated in process parameter optimization for defects, geometric deviation, and in-situ imaging for real-time defect detection. The powder bed can also reduce thermal gradients, cooling rates, and residual stress by insulating the build and removing convective heat transfer. With DT in PBF, it is usually necessary to obtain large amount of data to achieve manufacturing control, through this data to optimize the whole process during the PBF deposition. Digital twin can provide great digital assistance facilitation in the process pre-design phase and fabrication control phase. Artificial intelligence through machine learning and deep learning is one of the best methods to optimize input parameters for every layer fabricated to obtain a repeatable-quality MAM part. By predicting manufacturing process and outcome, defects reappeared in the follow-up process to a certain extent. For defect detection in PBF builds, various sensor technologies were used in conjunction with ML techniques. These technologies included visible light cameras, infrared cameras, high speed cameras and acoustic sensors. There were also efforts that combined multiple sensor technologies for ML training. It indicates that using digital twin and artificial intelligence are necessary in PBF based additive manufacturing.

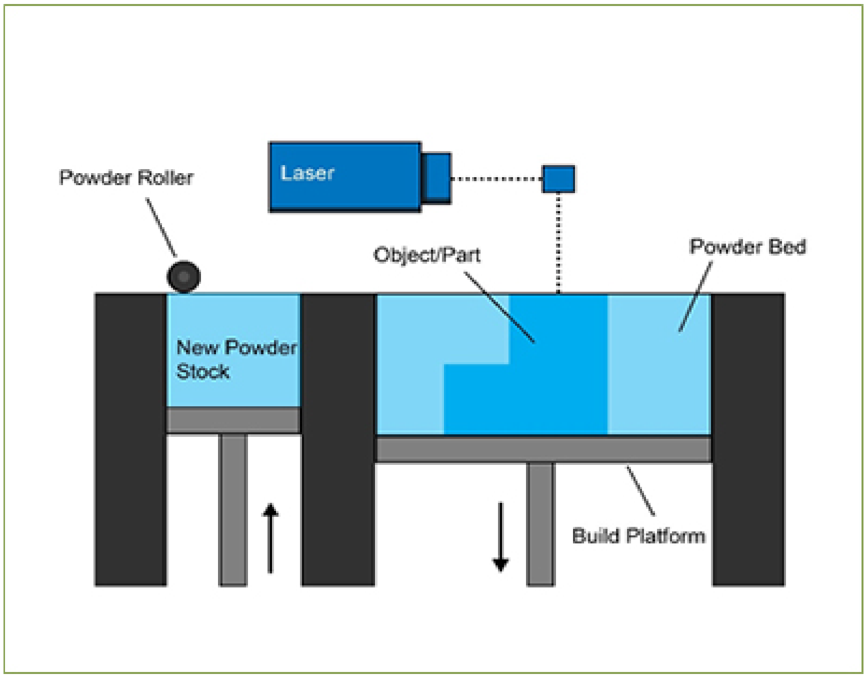

Fig. 2. Schematic of PBF AM process.

Artificial Intelligence Adoption in Metal Additive Manufacturing

In general, the applications of AI in MAM can be breakdown into pre-process, process and post process as shown in **Fig. 3**. In the pre-process, ML can be used in design space (CAD design, topology optimization, powder materials and its properties). In the area of raw materials design, recent advancement of ML allows for prediction of materials properties [7-8]. Wang et al. [9] highlighted the state-of the-art ML applications in AM design, processing, and production. In the design for additive manufacturing (DfAM), AI can be leveraged to output new high-performance metamaterials and optimized topological designs. In AM processing, contemporary ML algorithms can help optimize process parameters, examine powder spreading, and conduct in-process defect monitoring. In process, AI can assist manufacturers in premanufacturing planning, and product quality assessment and control. AI algorithms are being employed to optimize various aspects of metal AM processes, such as parameter optimization, defect detection, and material characterization. Lui et al [10] presented a collaborative data management framework for metal AM, where a cloud application as the core of the framework communicates with distributed sub-frameworks of the different product lifecycle stages. They suggested a unique collaborative data management architecture based on DT support for metal additive systems. This architecture involves a cloud DT that connects with dispersed edge DTs at different stages of the product lifecycle.

A metal AM product data model is proposed, containing a list of specific product lifecycle data that influences the product quality. This group also developed an application scenario of machine learning-based layer defect analysis, aiming to enable both off-line product design and process optimization and on-line layer defect detection. They proposed a conceptual MAM integrated data model where the AM data are modelled as entities under three categories, i.e., product, process and resource, and the fundamental relationships among the entities are defined. The post processing steps of AM has benefitted from ML and AI in a very limited manner. Given the importance of surface roughness and microstructural variations in long term behavior of the AM parts, there are opportunities to apply ML in evaluation of these types of process outcomes.

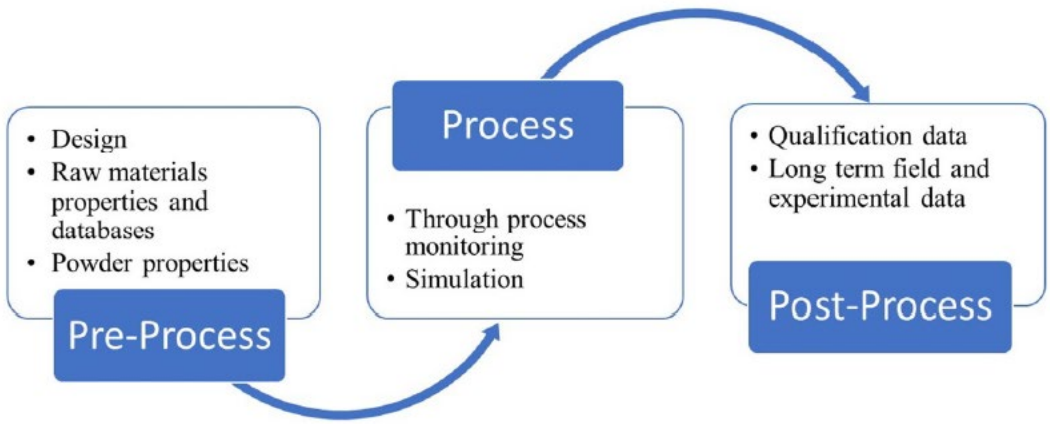

Fig. 3. AM powder bed fusion manufacturing process [7].

The main field of application of AI in MAM has been identified as the quality assurance during or after the manufacturing. Khorasani et al applied an artificial neural network (ANN) to model the influence of post-processing techniques such as heat treatment and machining on the final surface roughness of parts manufactured by PBF [11]. Focusing on AI model, Wu et al tested various AI generated models to compare the performance in surface roughness prediction. No significant difference in the accuracy of the models was found, highlighting the importance of training data for reasonable results. Given the importance of surface roughness and microstructural variations in long term behavior of the AM parts, there are opportunities to apply ML in evaluation of these types of process outcomes.

Digital twin technologies in Metal Additive Manufacturing

A digital twin is a digital model of a real-life object, process, or system. For Metal Additive Manufacturing (MAM), digital twin is an effective solution to predict component geometrical accuracy and quality performance. The fabrication data can be obtained from experiments, physical entities, and statistical models, and trained through machine learning (ML) to achieve an intelligent management during additive manufacturing process. The three main aspects of Digital Twins are data acquisition, data modeling, and data application [12]. Digital Twins use IoT as its primary technology in every application. IoT uses sensors to collect data from real-world objects. The data transmitted by IoT is used to create a digital duplication of a physical object. The digital version then can then be analyzed, manipulated, and optimized. IoT constantly updates data and helps Digital Twin applications create a real-time virtual representation of a physical object. AI can assist DT by providing an advanced analytical tool capable of automatically analyzing obtained data and providing valuable insights, making predictions about outcomes, and giving suggestions as to how to avoid potential problems [13]. The key concept of DT is to interconnect the experimental data with real-time monitoring (IoT's/sensors) or with simulation by adopting AI, to identify the inconsistencies in MAM. Knapp et al. [14] presented a novel framework of a mechanistic model to predict the melt-pool level phenomena. The 3D curved surface deposit geometry for single-pass deposits, transient temperature, and velocity distributions, cooling rates, solidification parameters, and secondary arm spacing, and micro-hardness were accurately estimated by the proposed building blocks in a computationally efficient manner. A hierarchical structure for the DT of metal AM has been proposed by Phua et al., comprising four levels: the implicit DT, the instantiated DT, the interfaced DT, and the intelligent DT [15]. These levels correspond to modeling, sensing, control, and customization, respectively, and illustrate the ongoing and complex development of the DT as well as its constituent structures. The largest body of research on metal AM digital twins has been focused on the case of the Instantiated digital twin and in particular AM specific sensor development. **Fig. 4**, presents a general process diagram for an Instantiated Digital Twin, showing how key components fit together. DT first helps determine the optimum processing window for a part, and then ensures that the manufacturing process stays within boundaries established using that processing window, the quality of the process will be assured. Metal AM sensors for monitoring the powder, melt-pool and geometry are progressing through lab validation, with future work toward printer integration. Furthermore, maintaining the Digital Twin infrastructure can be costly, requiring significant investment in operations. The high fixed cost and the complex infrastructure of Digital Twins are expected to slow down the deployment of Digital Twin technologies.

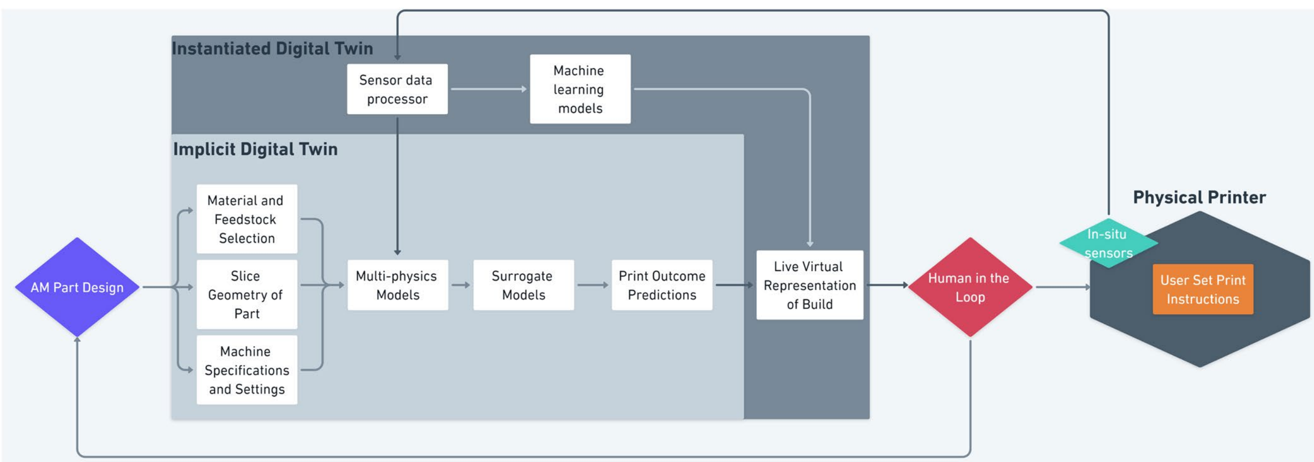

Fig. 4. Process Diagram for the Instantiated Digital Twin [15].

Digital Twin driven Artificial Intelligence for Metal Additive Manufacturing

The analysis of the state of the art indicates that using digital twin models for facilitating the need for training ML models for AI application in MAM has been explored in a limited manner by researchers. This section discusses on a framework that combines the DT technology together with AI and ML for introducing AI applications in metal additive manufacturing. When integrated with sensing systems and control equipment, the MAM with DT has the potential to regulate the physical object by providing real-time closed-loop feedback based on sensor-monitored data. This capability can effectively minimize or eliminate defects, leading to improved part performance and quality [16, 17]. By leveraging ML algorithms, advanced data management techniques, and simulations, the DT can significantly reduce manufacturing time and costs while enhancing productivity and quality. Currently, most ML techniques employed in MAM processes rely on data sets obtained from numerical simulations, experimental observations, or combinations of both. Nikolakis et al presented a digital twin driven framework to enable the optimization of the planning and commissioning of human-based manufacturing processes using simulation [18]. The adaptation of ML for MAM is relatively new, and studies were demonstrated in process parameter optimization for defects, geometric deviation, and in-situ imaging for real-time defect detection [19]. A detailed view of applications using ML and AI in MAM for different areas such as defect detection and correction, reducing residual stresses and failure during and after build, in situ metrology and design accuracy, microstructural design, alloy design and optimization are described by Jannesari et al [20]. Yang et al developed a physics-based simulation model and conceptual framework comparing DTs with physical simulations [21, 22]. They provided gray-box modeling for a PBF AM process and demonstrated that it can lower predictive errors, the basic idea of Yang's team is to make predictions through calculation based on the data obtained, and gray-box modeling is the term used by them, not digital twin. Gaikwad et al. [23] demonstrated an early foray of the digital twin paradigm for real-time process monitoring and defect prediction. In this research, the combination of physics-driven predictions with in-situ sensor data and machine learning led to higher statistical fidelity in detecting process flaws. In PBF, the main objective of DT is to simulate, monitor and control manufacturing parameters and objects.

Artificial Intelligence and Digital Twins drivers and challenges

As discussed in this paper, Digital Twins technology has many advantages; however, the technology currently faces shared challenges in parallel with AI and IoT technologies. Those include data standardization, data management, and data security, as well as barriers to its implementation and legacy system transformation [9]. DT combined with AI algorithms will enable closed-loop manufacturing systems where real-time data from in-process monitoring is used to dynamically adjust input parameters and optimize the metal additive manufacturing process. By extending ML with DT adoption in MAM, it is possible to reduce the consumption of materials, reduce the trial and error of experiments, predict potential problems that may arise in the future, and reduce manufactured part defects. The development of machine learning has shown to be a precursor for the implementation of AI in metal additive manufacturing and hence achieving closed-loop AM systems or for the development of digital twins. There is an urgent need to develop a metal additive manufacturing standard and an online database covering different materials needs to be developed [24]. At the same time, this driving method with a large amount of detection data as the core combined with basic physics knowledge can make key quality control for monitoring MAM.

Artificial Intelligence will play an important role in accelerating materials innovation of metal additive manufacturing by predicting material properties, optimizing material compositions, and facilitating the development of new alloys tailored for metal additive manufactured products. DT combined with ai will enable the rapid customization and personalization of metal AM products, catering to individual customer requirements with minimal lead time and cost. However, the main hurdle at the current time is availability and reliability of the data that are needed for training the AI model algorithms. Additionally, the challenges involved with the process itself such as high temperatures or high speeds pose difficulty on monitoring and measurements of the process. The post processing steps of AM has benefitted from DT and AI in a very limited manner. This is due to the fact that at the post process stage, the parts have already been built and in situ control and improvement opportunity has passed. The challenge in process control of MAM is the number of parameters – controlled and uncontrolled, affect the part quality. There is a compelling case for the development of DTs of MAM processes. However, this remains a challenging task that will require the skills and collaboration of scientists and engineers from many disciplines.

Conclusion

In recent years, Digital Twin and Artificial Intelligence technologies has garnered significant attention from both industry and academia. The concept of a Digital Twin can be described as the seamless data integration between a physical and virtual machine in both directions. Building a bridge between the physical and virtual object of metal additive manufacturing by creating a digital twin and AI adoption will reduce the number of trial-and-error tests, minimize defects, reduce the time between the design and production and make manufacturing of more metallic products cost effective. As presented in this paper, most of the manuscripts published in academic journals discuss the application of Digital Twin solutions in additive manufacturing, particularly within the context of Industry 4.0. Although some progress has been made, applications of DT and AI in streamlining MAM to be integrated into other manufacturing techniques or becoming a commodity for users is still far in the future. Future advancements should focus on integrating new optimization technologies, such as IoT, to enhance real-time data-driven processes that inform the system of its objectives. Future advancements should focus on integrating new optimization technologies, such as internet of things, to enhane real-time data-driven aditive processes that inform the sustem of its objectives. The DT and AI adoption is still under development, and this technology possesses immense potential to advance metal additive manufacturing. It demands significant efforts in development, data analysis, DT and AI integration, and the incorporation of various devices into the framework. The growing demand for automation in various industries are the anticipated factors to trigger the high demand for the Digital Twin platform over the forecast period.

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