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Advancements in Process Monitoring and Control in Metal Additive Manufacturing: A Review

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Abstract

Metal Additive Manufacturing (MAM) is now a ground-breaking technology that enables the production of complex geometries at high material efficiency. The problem of process instability, formation of defects, and non-repeatability, however, restrict its scalability in industrial application. To overcome such challenges, the process monitoring and control systems have made and still making a great progress. The paper will present a review of the state-of-the-art monitoring techniques, sensor technologies, and control solutions in the metal additive manufacturing processes of the Laser Powder Bed Fusion (LPBF) and Directed Energy Deposition (DED). It discusses also the combination of artificial intelligence, machine learning, and multi-sensor data fusion. Further, problems, gaps in research and directions are also raised to help future studies with regard to intelligent and autonomous production systems.

Keywords

Metal Additive Manufacturing, Process Monitoring, Closed-loop Control, Laser Powder Bed Fusion, Machine Learning, Defect Detection, Smart Manufacturing

1. Introduction

Metal 3D printing or Metal Additive Manufacturing (MAM) is now a ground-breaking technology which is transforming the existing paradigms in manufacturing. By just building parts layer-by-layer, then out of computer-generated digital models, MAM can be employed to produce very complex geometries never before feasible as well as too expensive to produce using traditional subtractive or formative techniques. Other advantages of MAM besides geometrical flexibility are material efficiency, reduced lead times, mass customization, and lightweight structure through the optimization of topology. Such abilities have seen it gain rapid adoption in some of the most important sectors of the economy such as aerospace, automotive, biomedical and energy sectors where performance, precision, and customization are crucial factors[1].

Some of the processes that have gained great relevance to the industry are Laser Powder Bed Fusion (LPBF), Selective Laser Melding (SLM), and Directed Energy Deposition (DED) among various other MAM technologies. LPBF and SLM are high energy lasers, which melt fine powdered metals selectively in a powder bed to create high resolution and quality surfaced components. However, it is the concomitant deposition and melting of material with a directed flow of energy that specially makes it suitable in repair, remanufacturing and large-scale fabrication of parts, hence its name; DED.

These processes are complex in nature even though they are technologically mature because of the presence of rapid thermal cycles, localized melting and solidification, and other complicated material-energy interactions [2,3].

Nevertheless, the large-scale industrial implementation of MAM is still impeded by a number of key issues. Variability of the process is still one of the primary concerns because the changes in the process parameters, including laser power, scan speed, and powder properties, can result in the considerable variation of the quality of the parts. Another enduring problem which directly influences the mechanical performance and reliability of fabricated components is the formation of defects in form of porosity, cracks, absence of fusion, and residual stresses. Moreover, the anisotropy in the material properties is provided by the layer-by-layer character of MAM, and the microstructural heterogeneity is also introduced by the rapid solidification and steep thermal gradients. All these lead to poor repeatability and the inability to obtain consistent part quality, which is critical in safety-critical applications.

To address these shortcomings, the advanced process monitoring and control systems have been designed and are being incorporated more and more into the current MAM platform. Process monitoring refers to the instantaneous collection and analysis of data of a number of sensors to trace the main process variables like temperature distribution, melt pool behavior, and layer integrity. This enables the identification of the imperfection and potential anomalies in the fabrication at an early phase. To supplement this, in process control systems, monitoring data feedback is used to adjust dynamically the process parameters e.g. laser power, scan speed and deposition rate, to provide the optimum processing conditions. Integration of monitoring and control will transform MAM into a trial and error process into a manufacturing system that is more predictable, reliable and intelligent.

2. Process Monitoring in Metal AM

Process monitoring of metal additive manufacturing (MAM) is a core facilitator towards the realization of quality, reliability, and repeatability in production of components. The nature of MAM processes, Laser Powder Bed Fusion (LPBF) and Directed Energy Deposition (DED) are in fact complicated by high-speed thermal cycles, localized meltdown and solidification, and complicated interactions between process parameters and material behavior. These considerations prearrange the process to be very sensitive to variations and in most cases it leads to defects of porosity, cracks, non-fusion and residual stresses. In order to overcome these challenges the process monitoring systems are used to monitor and analyze the manufacturing process in real time.

In-situ monitoring technologies have many types of sensors such as high-speed optical cameras, infrared thermography, photodiodes, pyrometers, acoustic emission sensors, to measure process signals of interest, such as melt pool geometry, temperature distribution, energy input, and acoustic responses. The measurements are also useful in the study of stability of the melt pool, processes of heat transfer and quality of layer-wise deposition. Through the correlation of sensor data with defect formation it can be made possible to detect anomalies early and make corrective measures. Ex-situ, conversely, are used to test defects, microstructural, and internal characteristics and overall part integrity in ex-situ, such as X-ray computer tomography (CT), ultrasonic testing, and scanning electron microscopy (SEM).

The current advances in data acquisition systems and computing power have enabled it to combine process monitoring with the application of highly developed methods of data analytics and machine learning. These techniques give the possibility of on-the-fly prediction of defects, mode detection, and process optimization by means of the analysis of mass data of multi-modal sensors. Moreover, closed-

loop control systems can be developed which means that major process parameters, including laser power, scan speed, and material feed rate, can be dynamically varied on the basis of feedback provided by monitoring systems, which improves process stability and decreases variability. Digital twin technology also enables predictive modelling and virtualisation of the production process, which enables the controlling and optimization of the manufacturing process in advance, which can be enabled by the introduction of digital twin technology further [7,8].

Overall, process monitoring is one of the keys to the creation of smart metal additive manufacturing systems. It play a role in moving MAM out of the trial-and-error method of managing manufacturing procedures to a concrete and automated manufacturing solution that is industrially feasible through enabling real-time defects identification, superior insight into the process, and agile control measures.

3. Process Monitoring Techniques

The process monitoring methods in metal additive manufacturing (MAM) play a crucial role in maintaining stability in the processes, minimizing defects, and achieving uniform quality of the parts. These methods can be widely divided into in-situ and ex-situ methods of monitoring. In-situ monitoring is a type of real-time monitoring of the manufacturing process throughout the fabrication process, especially in those processes that require complex thermal cycles and rapid solidification like Laser Powder Bed Fusion (LPBF) and Directed Energy Deposition (DED), where complex thermal control and rapid solidification play a significant role in determining the quality of the part. To measure important process parameters, a number of sensors are used (high-speed optical cameras, infrared thermography systems, photodiodes, pyrometers and acoustic emission sensors) in order to measure melt pool geometry, temperature distribution, emission intensity and acoustic signals. The measurements can be of great help in understanding the stability of the melt pool, heat transfer character and layer-wise bonding and hence allow detection of defects in early stages (porosity, cracks, keyholing, and absence of fusion).

Conversely, ex-situ supervision is conducted after the building process is over and it is aimed at the detailed examination and characterization of the fabricated parts. X-ray computed tomography (CT), ultrasonic testing, optical microscopy, and scanning electron microscopy (SEM) are techniques that are used extensively to assess internal defects, surface morphology and microstructural detail. Although ex-situ procedures are very accurate and analytical, they are slow, expensive and cannot give real time feedback to correct the process. Thus, in-situ monitoring with ex-situ validation is essential in obtaining reliable and high-quality manufacturing. These methods combined with recent innovations in data analytics and intelligent control systems are leading to the creation of adaptive and resilient metal additive manufacturing processes.[12]

3.1 In-situ Monitoring

In-situ monitoring of metal additive manufacturing (MAM) is the real-time observation of the process phenomena during component fabrication, which allows constant evaluation of process stability and quality. Because of the complicated nature of the thermal cycles, high-rate melting and solidification, and layer-by-layer deposition characteristic of, e.g., Laser Powder Bed Fusion (LPBF) and Directed Energy Deposition (DED), in-situ monitoring has become necessary to understand the behavior of processes and identify defects early in their formation. The use of different sensing technologies, such as high-speed optical cameras, infrared thermography systems, photodiodes, pyrometers, and acoustic emission sensors, is used in the capture of critical process signatures of melt pool geometry, temperature

distribution, radiation intensity, and acoustic responses. These measurements give information about the stability of the melt pool, heat transfer and the quality of the interlayer bonding. Porosity, absence of fusion, keyholing, and cracking are some of the anomalies detected by real-time data during fabrication. Additionally, in-situ monitoring is a crucial facilitator to more advanced closed-loop control systems, in which the parameters of the process can be dynamically controlled based on sensor feedback and so provide better consistency, fewer defects, and more general process reliability.

3.2 Ex-situ Monitoring

Ex-situ monitoring in metal additive manufacturing is a post-process inspection and characterization method of assessing the quality and integrity of fabricated parts. Such techniques are essential in the determination of the existence of defects, study of microstructural characteristics, and evaluation of the mechanical performance following the build process. Some of the common ex-situ methods are X-ray computed tomography (CT), ultrasonic testing, optical microscopy, and scanning electron microscopy (SEM). X-ray CT can be especially useful in the non-destructive examination of the internal defects which can be seen in the three-dimensional form, like porosity, cracks, and absence of fusion. The most common applications of ultrasonic testing are to identify discontinuities in the subsurface of the large components, whereas optical and electron microscopy are the best methods to study the morphology of the surface, the grain structure, and the phase distribution at the high resolution. Though these methods are very accurate and provide in-depth information on part quality, they are usually time-consuming, expensive, and could not provide real-time feedback in the manufacturing process. As a result, ex-situ monitoring is frequently applied together with in-situ methods to guarantee the immediate detection of defects and the comprehensive validation of the post-process, thus, enhancing the quality and efficiency of metal additive manufacturing systems[14].

4. Sensor Technologies in Metal Additive Manufacturing

The use of sensor technologies is central to the process monitoring and control of metal additive manufacturing (MAM). The dynamics of processes like Laser Powder Bed Fusion (LPBF) and Directed Energy Deposition (DED) can be considered to be complex and highly dynamic, this is why advanced sensors are needed to record the real-time information about the melt pool behavior, thermal gradients, material deposition, and the formation of defects. Different sensors are used such as optical, thermal, acoustic, and advanced imaging systems, each of which gives different insights into certain issues of the manufacturing process. High-speed cameras and photodiodes are common optical sensors, which are used to measure melt-pool geometry, spatter formation, and emission intensity. Thermal sensors, such as infrared cameras and pyrometers, are used to measure temperature distribution and cooling rates which are important to analyze microstructure evolution and in the development of residual stress. The sensors of acoustic emission help to sense the presence of stress waves in the process of crack propagation and initiation, and therefore, detect subsurface defects that are not necessarily discernible using optical techniques. Also, more sophisticated methods, including x-ray imaging, can be used to view internal characteristics and defect formation in real-time, but their use is commonly restricted to research settings due to cost and complexity[3,15].

Recently, the focus on the concept of multi-sensor fusion (integrating information of one or more sensor type to obtain a more detailed and more accurate picture of the process) has increased. This technique assists in overcoming the drawbacks of single sensors, enhances the defect detection precision and minimizes uncertainty within the monitoring systems. Hybridization of sensor technologies with

superior data analytics, machine learning, and control approaches is fueling intelligent and adaptive metal additive manufacturing systems. Consequently, sensor-based monitoring is emerging as a pillar of attaining quality, repeatable and industrial level production in metal additive manufacturing.[16, 17].

5. Data-Driven Monitoring Using AI and Machine Learning

The growing complexity of metal additive manufacturing (MAM) processes and the massive amount of data produced by contemporary sensor systems have prompted the data-driven methods of process monitoring and control, which are framed in artificial intelligence (AI) and machine learning (ML). Conventional monitoring techniques are based on predetermined thresholds and empirically observed processes which, in many cases, are not enough to describe nonlinear and multi-physics processes like Laser Powder Bed Fusion (LPBF) and Directed Energy Deposition (DED). Conversely, AI and ML methods allow analysing more multi-dimensional sensor data with high dimensions to detect patterns, anomalies, and predict defects with greater accuracy and efficiency.[18,19].

Supervised, unsupervised, and reinforcement learning models are all machine learning algorithms frequently used to develop a relationship between process parameters and sensor signals and the ultimate part quality. The use of supervised learning techniques, including support vectors machines (SVM), the random forest, and the artificial neural network (ANN), is the common practice in the classification and prediction of defects based on the labelled data sets, where models are trained to capture the features which are related to porosity, cracks, or absence of fusion. Unsupervised learning methods, including dimensionality reduction and clustering, are used to detect the latent trends and abnormalities in process data without the need to be fed with labelled inputs. Moreover, deep learning methods specifically convolutional neural networks (CNNs) have shown great potential in processing high-speed imaging and thermal data to monitor melt pools in real-time and detect defects[19,20,21].

The interplay between AI and multi-sensor data fusion also adds to the monitoring capabilities since it provides the ability to combine optical, thermal, and acoustic data streams and present a single framework. This allows stronger and consistent detection of process instabilities and the possibility of false positives is minimized. Moreover, AI-based models can be integrated into closed-loop control systems, where the real-time predictions are utilized to reformulate the process parameters (i.e., laser power, scan speed, and material feed rate) dynamically. This makes adaptive manufacturing possible, enhances stability of processes and reduces the formation of defects[22].

In recent times, there have also been digital twin models and edge computing systems, where real-time simulation, prediction, and decision-making can be made directly at the machine level. With these developments, issues like the quality of data, generalization of models, computing demands, and non-standardized datasets still pose major obstacles to their large-scale industrial usage. Nonetheless, AI-based data-driven monitoring and machine learning is an important milestone towards intelligent, autonomous and self-optimizing metal additive manufacturing systems. [23,24].

6. Conclusion

Metal additive manufacturing (MAM) has become a disruptive technology that can potentially revolutionize the current manufacturing process because it allows to produce complex, lightweight, and customized parts. Nonetheless, process variability, defect formation, and low repeatability remain some of the major challenges that restrict its large-scale implementation in industries. This review recognizes

the importance of process monitoring and control in dealing with these issues and enhancing reliability and quality of MAM processes.

Extensive process monitoring methods, such as in-situ and ex-situ methods, give useful information about the behavior of melt pools, thermal distributions as well as the mechanisms of defect formation. The combination of multiple sensor technologies like optical, thermal, acoustic, and X-ray sensors has contributed greatly to the capacity to identify and analyze the process anomalies. Moreover, the appearance of data-driven methods based on artificial intelligence and machine learning has made it possible to predict defects more accurately, make decisions in real-time, and optimize the processes. The advancement of multi-sensor fusion strategies and closed-loop control systems is a significant move towards realising adaptive and intelligent manufacturing environments.

Although these improvements have been made, a number of issues have not been overcome and this includes the high costs of implementation, complexities in data management, absence of standardization, and constraints in real-time control processes. To overcome these challenges, the current research efforts should be aimed at enhancing the sensor integration, creating powerful AI engines, and creating the standardized monitoring systems. It is anticipated that in the future digital twin technologies, edge computing, and autonomous control systems would be used to further improve the efficiency and reliability of the process.

To sum up, the integration of advanced monitoring systems, sensor technologies, and smart data-driven approaches is setting the stage of the next generation of metal additive manufacturing systems. Such innovations should allow zero-defect manufacturing, increase the scalability, and speed up the process of transforming MAM into a full-fledged and commercially viable manufacturing solution.

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