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In-situ monitoring in L-PBF: opportunities and challenges

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- Invited Paper -

Abstract

In the recent years, several studies and industrial developments have been devoted to the improvement of process repeatability, stability and robustness to enhance the industrial breakthrough of Additive Manufacturing (AM) technologies. Indeed, highly regulated sectors like aerospace and healthcare have been pulling the industrial innovation in metal AM, and this makes defect avoidance and qualification issues of fundamental importance. This imposes an urgent need for novel in-line and in-situ qualification and control tools able to guarantee a stable process and defect-free products. On the one hand, the layerwise paradigm of AM processes enables the capability of acquiring a large amount of data during the process to measure quality characteristics of the part and measure process signatures that are proxies of the process stability over time. On the other hand, data mining and statistical methods are needed to make sense of big data streams gathered in-line and in-situ, to design automated and robust defect detection tools. This paper reviews the opportunities and challenges related to in-situ sensing and monitoring solutions for zero-defect and first-time-right AM processes, with a special focus on metal Powder Bed Fusion (PBF) processes.

Keywords: Additive Manufacturing; in-situ monitoring; in-situ sensing; defects; quality control.

1. Introduction

Considerable effort has been devoted so far in the scientific and industrial communities to understand the nature and the source of defects in additive manufacturing (AM) processes, their effects on product quality, and how they can be mitigated or avoided by acting on controllable parameters. In the framework of metal Powder bed Fusion (PBF) processes, their lack of repeatability and stability, together with several possible sources of defects, have been widely pointed out as major issues that deserve further technological advances to meet challenging industrial requirements [1-4]. The development and implementation of in-situ sensing and monitoring solutions represents a priority to push forward the industrial breakthrough of metal AM systems.

The research in this field is growing and evolving very fast. First seminal studies were mainly aimed at demonstrating the feasibility of in-situ sensing methods and characterizing specific process phenomena with the support of in-situ gathered data. More recent studies have been proposing, testing and demonstrating in-situ measurement and monitoring methodologies. An increasing interest has also been devoted to the use of machine learning and artificial neural network techniques to make sense of large in-situ data streams for robust and reliable identification of defects and process errors [5-9]. Recent studies also proposed novel in-situ sensing solutions or the combination of multiple sensors to achieve better in-situ measurement and monitoring performance [10-11].

As far as the industrial implementation of these methods is concerned, it is worth noting that most PBF system developers

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have equipped their systems with in-situ sensing and monitoring modules and toolkits. Most of these tools are mainly used to collect data during the process and provide the user with some post-process data reporting and/or datasets to support the investigation of specific problems and defects. Further development efforts are still needed to implement analytical tools that are able to quickly make sense of gathered data during the process and automatically signal the onset of defects and process instabilities.

An exhaustive review of the rapidly evolving literature devoted to in-situ sensing, metrology and monitoring would require a much more extended paper. Nevertheless, this study aims to contribute to the AM community in two ways. On the one hand, it presents a framework to classify different methods and solutions presented in the literature into distinct categories in terms of monitoring levels and process signatures of interest. The increasing number of studies also caused an increasing variety of terminology and an increasing fragmentation of application fields. The proposed framework aims to simplify the mapping of the wide literature, aiding the identification of competitor methods belonging to the same family. On the other hand, it presents a summary of issues and challenges that still need to be tackled which may drive future research developments.

Starting from the classification of in-situ sensing and monitoring methods into different levels (Section 2), Section 3 includes a brief review of the mapping between measurable signatures of the process, categories of defects and sensing solutions. Section 4 finally reviews the major challenges and open issues in this field.

2. Classification of in-situ sensing and monitoring methods

Fig. 1 shows a classification of in-situ sensing and monitoring methods into four different categories of measurable process signatures.

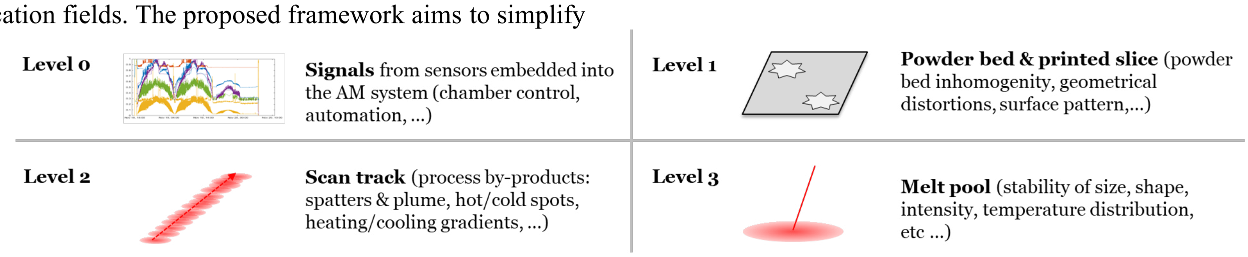

Fig. 1 – Classification of in-situ sensing and monitoring methods in PBF processes

Table 1 – Mapping between in-situ measurable signatures, sensing methods and process defects in PBF. An "X" is shown in correspondence of known relationship demonstrated in the literature, while (X) is used to represent links still not deepened in the literature or other indirect links of potential interest

Level	Process signature	In-situ sensing method	Defects					
			Porosity	Residual stresses, cracks, delaminations	Microstructural inhomogeneity	Balling	Geometrical distortions	Surface defects
1 (powder bed)	Powder bed homogeneity	Off-axis imaging, visible range	(X)	X			X	
	Slice geometry	Off-axis imaging, visible range					X	
	Slice surface pattern	Off-axis imaging, visible range, fringe projection	(X)	X		X	(X)	X
2 (track)	Hot and cold spots	Off-axis video imaging, visible or infrared range	X	X		X	X	
	Temperature profile / cooling history	Off-axis thermal imaging		X	X			
	Process by-products	Off-axis video imaging, visible or infrared range	X		(X)			
3 (melt pool)	Size	Co-axial video imaging, visible or infrared range	X	X		X		X
	Shape	Co-axial video imaging, visible or infrared range	X	X		X		X
	Average intensity	Co-axial pyrometry	X	X	(X)	X		X
	Intensity profile	Co-axial video imaging, visible or infrared range	X	X	(X)	X		X

Level 0 involves the use of signals from sensors that are already embedded into the AM system. This includes chamber pressure, temperature and oxygen content, current and torque signals from linear axis motors, etc. This type of signals potentially enables a process monitoring architecture that avoids the need for external or additional sensors. This is particularly attractive in electron beam PBF (EB-PBF), where hundreds of so-called "log signals" are freely available from embedded sensors and potentially usable in-process [12].

Level 1 consists of measurements gathered once (or more than once) per layer, with a field-of-view that covers the entire build area. This level includes quantities that are representative of the homogeneity of the powder bed, together with geometrical and dimensional features of the printed slice or its surface pattern and topography. Level 2 involves process signatures that can be measured while the laser or the electron beam is displaced within the build area to produce the current layer. This entails the capability to observe the interaction between the beam and the material, the very fast cooling history of the solidified area after the beam has moved to another location and, in the laser PBF (L-PBF) process, the by-products of the process, i.e., spatters and plume emissions. Level 3 finally consists of process signatures that are representative of the highest level of detail at which the PBF process can be observed, i.e., the melt pool. Further classifications of in-situ sensing and monitoring methods can be considered, in terms of sensing architectures (e.g., co-axial vs off-axis monitoring), sensing technologies (spatially integrated vs spatially resolved sensors), wavelength of the measured quantities (visible range, near infrared, middle and long infrared), etc. The reader is referred to [1-4] for an exhaustive classification of in-situ sensing and monitoring approaches.

3. Mapping between in-situ sensing, process signatures and process defects

Table 1 presents a mapping between the process signatures that can be measured in-situ, the corresponding defects that can be detected and the most suitable sensing methods. The relationships indicated with "X" have been already discussed and demonstrated in the literature through experimental studies. Some relationships, indicated with "(X)", represent links between defects and process signatures that have not been yet demonstrated in the literature. Despite being of potential interest, they still need to be confirmed through further research.

Embedded sensor signals (level 0) have been pointed out as possible sources of information in EB-PBF to gather information about the powder spreadability [13] and the occurrence of geometrical distortions caused by powder recoating errors [14], but various other potential uses have been pointed out in the literature and they can be explored in future studies [12]. Analogous solutions in L-PBF have been not explored so far.

A lack of powder bed homogeneity (level 1) may change the local layer thickness leading to possible volumetric and geometrical defects because of improper energy density variations. Errors in the powder recoating of the slice can also lead to poor welding between one layer and the following layer, with consequent risk of delamination, together with possible geometrical distortion in the presence of severe recoating errors and contamination. Different authors have investigated in-situ sensing and monitoring methods suitable to characterize the surface pattern and surface topography of the printed slice and the entire powder bed as a possible source of information about process stability and surface and volumetric defects [10, 15-16]. The in-situ reconstruction of the layerwise geometry of the part has attracted an increasing attention in the literature too, to quickly detect geometrical distortions [17-18]. Regarding level 2 process signatures, the detection of hot and cold spots may be suitable to identify either geometrical distortions (in case of excessive heat accumulations) or lack-of-fusion conditions [19-20]. Static and dynamic thermal mapping through in-situ thermography can provide information about geometrical distortions, variations in the microstructure of the part and thermal stress accumulation related to improper heat exchanges [21]. An increasing attention in the literature has been devoted to the use of process by-products, such as spatter and plume emissions in L-PBF, as potential proxies of volumetric defects [11, 22 – 27]. Spatters are caused by an ejection of material from the melt pool and the surrounding powder bed, leading to the formation of denudation zones around the melt pool and a possible lack of material in the solidified track, which may influence the formation of pores. Large and intense plume emissions may partially absorb and deflect the laser beam reducing the energy input provided to the part, with consequent lack-of-fusion porosity.

Several information about the process stability and the part quality can be gathered by monitoring the melt pool signatures (level 3) and their evolution over time. Indeed, the melt pool properties are relevant to determine the possible formation of volumetric defects (both key-hole and lack-of-fusion porosity), thermal stress accumulation because of insufficient heat dissipation and surface defects related to the solidification properties of scanned tracks [5, 28].

4. Open issues and future challenges

Despite continuous and fast technological developments related to in-situ sensing and monitoring methods, several challenges and open issues must be faced to develop new generations of smart PBF machines able to achieve first-time-right and zero-defect production capabilities [1, 29].

One challenge regards the limitation of the layerwise monitoring paradigm. Indeed, looking at the current layer prevents the gathering of information about physical phenomena that are occurring below the layer, involving partial re-melting, heat accumulation and dissipation, and consequent effects on volumetric, microstructural and thermal stress properties of the material. Another challenge regards the lack of robust in-situ porosity detection methods. Volumetric defects are particularly critical in many industrial applications, but accurate methods – so called "optical tomography" – for their robust identification by means of in-situ sensors are still missing. Several process signatures can be used as proxies of either lack-of-fusion or key-hole porosity, but further research efforts are needed to achieve robust in-situ porosity detection capabilities. One additional challenge regards the management of big data streams gathered with in-situ sensing methods. Several gigabytes of data may be generated during the production of a part, and this pushes the need for computationally efficient methodologies for in-situ and in-process data processing. There is also the need for transfer learning solutions, suitable to transfer knowledge and empirical models gathered on one part by using one AM system to other parts produced with the same machine or with different machines. As an example, it would be relatively convenient to carry out experimental conditions in a limited and controlled set of process conditions, and to transfer the acquired knowledge to other conditions, reducing experimental costs and time-to-market. However, this is still an open issue, inflated by the large system-to-system and lab-to-lab variability that characterizes metal AM applications. Only a small number of seminal studies have investigated the application of transfer learning methods to AM [30]. One interesting opportunity for future research regards the development and implementation of cyber-physical approaches. Process simulations have a great potential as technological enablers of novel enhanced AM performance and zero-defect production capabilities. As an example, simulations enable feedforward control strategies for local process parameter adjustment, but they also allow the development of in-situ monitoring methods augmented by process simulations, and vice versa. The combination of real data with process simulation is a field that deserves novel and additional research effort. Eventually, the achievement of zero-defect and first-time-right production capabilities relies not only on in-situ sensing and monitoring technologies, but also on effective and robust process control strategies. Despite seminal studies on closed-loop control in L-PBF and a few recent developments [31], a wide gap still needs to be filled in order to make intelligent control solutions industrially available. Rather than adapting the process parameters based on model outputs or real-time sensor signals, other in-situ defect mitigation or defect correction solutions have been proposed in the literature [32-35]. In-situ defect correction represents a further research field that may contribute to the development of novel generations of smart AM systems, passing from highly sensorised machines to intelligent machines that are able to autonomously identify and remove the defect.

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