Normalized positive solutions for Schrödinger equations with potentials in unbounded domains

Optimizing quality inspection and control in Powder Bed Metal Additive Manufacturing: challenges and research directions

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***Abstract*—One of the key targets of Industry 4.0 and of digital production in general is the support of faster, cleaner and increasingly customizable manufacturing processes. Additive Manufacturing (AM) is a natural fit in this context, as it offers the possibility to produce complex parts without the design constraints of traditional manufacturing routes, typically reducing both material waste and time to market. Nonetheless, the lack of repeatability of the manufacturing process, which typically translates into a lack of reproducibility and reliability of the quality of the final products compared to traditional subtractive technologies, is currently one of the major barriers to a widespread adoption of AM in mass production. To overcome this limitation, there are growing efforts in recent years towards a better integration of advanced information technologies into AM, exploiting the layer-by-layer nature of the build. The consequence of these efforts is two-fold: i) the integration of advanced sensing technologies into the AM systems, making possible the in-situ monitoring of huge amounts of data at multiple time-scales and resolutions; ii) the ever-increasing role of data-driven approaches (especially machine learning) in the analysis of such data, to provide real-time quality monitoring and process optimization. This paper introduces and reviews the key technological developments of this phenomenon, with special focus on metal Powder Bed Fusion (PBF) technologies that are attracting the highest attention by the industrial AM community. After introducing the main manufacturing quality issues and needs that have to be developed and optimized, we provide a wide overview of the latest progress of in-situ monitoring and control in metal PBF, with special regards to sensing technologies and machine learning approaches. Finally, we identify the open challenges and future research directions in this field.**

***Index Terms*—Additive Manufacturing, Metal 3D Printing, Process Optimization, Powder Bed Fusion, In-situ monitoring, Industry 4.0, Smart Manufacturing.**

I. INTRODUCTION

Additive Manufacturing (AM), also known as 3D printing, is defined as *a process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies* [1].

The de-facto standard digital flow of Additive Manufacturing, from designed to finished part, is schematically reported in Fig. 1. The geometry and characteristics of the object, fully defined by a Computer Aided Design (CAD) software, are transformed into StereoLithography Interface or Standard Triangulation Language (STL) files, which translate the CAD geometry into a triangular mesh representation. The STL is then processed by a slicer, another piece of software that converts the model into a series of ultra-thin layers, and produces instructions tailored to the specific AM system. These instructions may either direct a laser/electron beam to selectively melt specific areas in a bed of powdered material, which is a process that goes by the name of Powder Bed Fusion (PBF), or guide the path of a nozzle/print head to precisely deposit new material upon the preceding layer, which is called material extrusion. After cooling, materials fuse together and form the desired three-dimensional object.

Differently from traditional machining techniques (either formative or subtractive), in AM the CAD-to-finished-part flow is a unique process without intermediate steps, like the creation of molds or dies, and it is completely tool-free. Hence, it is virtually free from any geometric limitations. This makes Additive Manufacturing a key technology to achieve the mass customization and mass personalization production foreseen by the Industry 4.0 concept [3].

While most of the attention in the early days of 3D printing

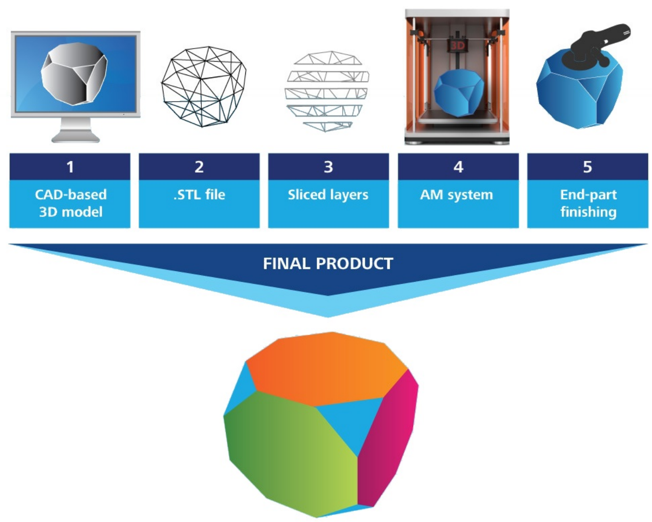

Fig. 1. Additive Manufacturing digital flow: from CAD model to finished product. Modified from [2].

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was devoted to thermoplastics as layering materials, especially for rapid prototyping applications, the material options have now grown to many different substances: ceramics, composites, glass, bio-inks to create artificial organs and soft tissues or even edibles, like chocolate. Nonetheless, due to their favorable mechanical characteristics, metals are the most commonly used materials in industrial applications after polymers. Among the most employed: titanium, steel, stainless steel, aluminium, and copper, cobalt chrome, titanium and nickel-based alloys as well as precious metals like gold, platinum, palladium and silver [4].

Early adopters of metal additive manufacturing were mainly high-end technology industries like aerospace and motorsport, where easy customization of metal parts is a key target [5]. Nonetheless, there is ever-increasing potential for this technology to become mainstream in many other different areas. Among the others:

- Automotive industry adopts metal additive manufacturing for the production of customized motor parts (e.g. cooling ducts). Thanks to AM, functional metal parts can be rapidly produced and performance tested [6], [7].
- Healthcare industry benefits from manufacturing complex and personalized geometries in high grade materials such as titanium for dental or orthopedic applications, using pre-surgery models from CT scans [8]–[10].
- Creative industries, including architecture, jewelry and entertainment, can apply AM to precious metals to obtain highly complex and customized pieces with maximum visual effect [11], [12].

The sensible advantages in terms of development time, production steps, costs and use of material are making metal additive manufacturing more and more attractive over traditional technologies. However, the lack of reliability of the process and of the qualification of the finished products is still a major barrier to its adoption to mass production.

As defined by ASTM E117, the reliability of a process (i.e., the degree to which it can be trusted as accurate) can be defined in terms of how stable its results are when the process is carried out multiple times under the same conditions and with same equipment and operator (repeatability), as well as with different equipment and operators (reproducibility). A significant body of evidence shows how the large number, level of complexity and uncontrolled interconnections between process parameters in AM translate to many repeatability/reproducibility issues compared to are traditional manufacturing methods [13].

Due to the complex interaction of many process parameters at different scales, a variety of defects may occur during the production of additive components, thus compromising the geometrical and mechanical properties of the final part. Current machines typically offer very basic monitoring functionalities of the process parameters as well as of the arising defects. To this date, the data collected during the layering is mostly used only for post-process qualification of the piece, which can be many hours after the defect has actually been generated and typically implies expensive and/or difficult inspections methodologies. This negatively impacts the production time, as well as the overall cost-effectiveness of the process.

To overcome this limitation, ever-increasing efforts are being made to optimize metal AM with online monitoring and control systems, possibly taking advantage of the inherent discretization introduced by the layering process. The process and machine data can be continuously monitored by a multiplicity of heterogeneous sensors embedded into the AM machine, and eventually integrated with images and videos of the part acquired on a layer-by-layer basis. The integration and interpretation of these data opens the way to the early detection of part defects, and possibly to a fine control of the process which may avoid the generation of defects altogether. In this regard, data-driven approaches, and especially machine learning, are playing an ever-increasingly important role.

After providing a brief overview of the metal additive manufacturing technologies (Section II), this paper introduces the main categories of part defects, with special regards to the Powder Bed Fusion process, together with their corresponding causes (Section III). Then, it provides a conceptual flow for quality assurance, which defines the key-concepts of in-situ monitoring and control into a harmonized framework. (Section IV). Using this framework as a backbone, it reviews the various sensors and techniques for in-situ process monitoring and control, identifying the open challenges and future directions of research in this field, with special regards with the use of data-driven techniques and machine learning approaches (Sections V-VIII).

A number of recent surveys already provide interesting insights on either the sensing [14]–[16] or analytics [17]–[19] aspects of in-situ AM monitoring, addressing the research interests of specific domains (mechanical, materials, process engineering, etc.). While building on top of the past works on this field, the aim of our paper is to provide a harmonized collection of concepts, tools, and methodologies into a self-contained manuscript, targeting the miscellaneous community of the *Proceedings of the IEEE*. Hence, we won't deepen too much into the topics of the individual sections, for which we refer the interested readers to the corresponding literature. On the other hand, we aim to provide a comprehensive viewpoint of the problem and of the current solutions, as well as of the open challenges that can be addressed by the ICT community.

II. Metal Additive Manufacturing technologies

Additive Manufacturing processes can be distinguished into different categories based on the materials and on the way these materials are layered to obtain a finished component. In 2010, the American Society for Testing and Materials (ASTM) group *ASTM F42 – Additive Manufacturing*, identified seven categories:

(i) Vat Photopolymerization
(ii) Material Jetting
(iii) Binder Jetting
(iv) Powder Bed Fusion
(v) Material Extrusion
(vi) Directed Energy Deposition
(vii) Sheet Lamination

The most popular processes for metal components use either Powder Bed Fusion (PBF) or Directed Energy Deposition

(DED) technologies. Again, both these categories can be categorized into different groups based on the specific layering process and on the type of metals that can be employed (see a diagram in Fig. 2).

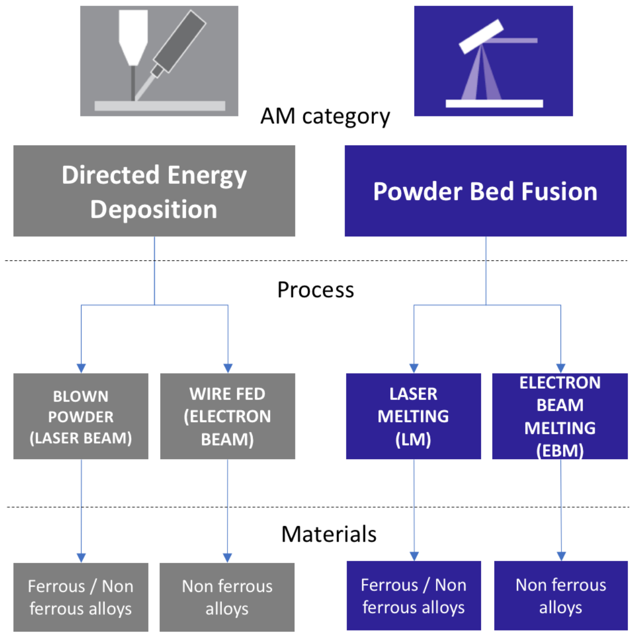

Fig. 2. Metal Additive Manufacturing: main categories, processes and materials.

DED methods deposit a melted material feedstock (either a powder, a wire, or a combination of both) through a nozzle which can move in multiple directions, using a laser or electron beam to melt the material upon deposition [20]. They are typically preferred for the manufacturing of very large components, where deposition rate is a key factor, or to repair existing components (e.g. damaged turbine blades or propellers). On the other hand, thanks to their advantages in terms of resolution and surface finish, PBF is the method of choice for building new metallic components from scratch [21].

While most of the general considerations and discussion apply to any AM method, the rest of this paper will specifically review and analyse PBF methods for metallic applications.

A. Powder Bed Fusion

PBF methods use either a laser or an electron beam power source to fuse particles of metal together, after they have been spread on top of the previous layer [22]. As shown in Fig. 3, PBF machines typically have two main chambers, one for the powder and one for the build, along with a recoater blade or roller that moves and spreads the powder across the build chamber. In some cases, there might even be an additional powder chamber to collect the excess overflow. Both the powder and the build chamber can move along a linear z-axis perpendicular to the build platform.

Main categories of PBF methods include: Selective Laser Sintering (SLS) (mostly referred to polymers instead of metals), where a laser is used to sinter the material powder layer-by-layer into a solid structure; Laser Powder Bed Fusion (LBPF), also known as Selective Laser Melting (SLM) or Direct Metal Laser Sintering (DMLS), where differently from SLS the metal powder is fully melted by a laser into a more homogeneous and stronger component; Electron Beam Melting (EBM), which uses electron beam as the power source. In this case, 3D printing setup is built inside a high vacuum chamber and filled with inert gas, to protect the molten material from corroding.

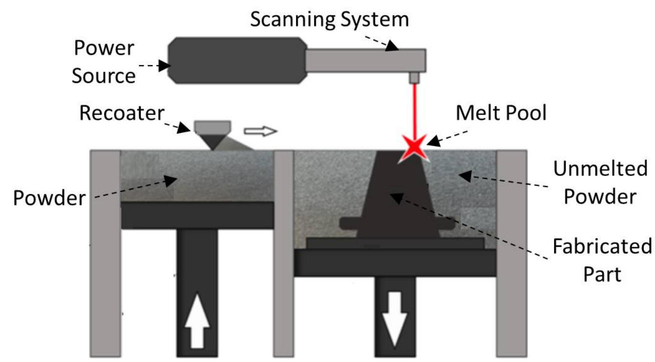

Fig. 3. Schematic representation of Powder Bed Fusion (PBF) process. Modified from [23].

Fig. 4 zooms in the different parts of a typical PBF process, by focusing on the SLM technique. Once the power source (for SLM, a laser beam) illuminates the metal powders, a portion of laser energy converts to thermal energy, causing the temperature of the metal powders to increase rapidly. As the temperature is increasing, the powders begin to melt and form a small pool of metal liquid with high temperature, called *melt pool*. As most of laser source follows a Gaussian distribution pattern, the energy absorption on the melt pool surface is thus not uniform. In case that the temperature reaches to the metal vaporization point in certain high energy absorption melt pool regions, the generated vapor will be ejected away from the melt pool surface, which goes by the name of *vapour plume*. *Spatters* are another byproduct of the PBF process: they are either powder particles blown away during the laser scan of the part, or liquid material ejected from the melt pool as a result of unstable solid-liquid transitions. As a result of unstable melting or uncontrolled interactions between the power source and the metal powder, PBF process is subject to many defects, such as the presence of *porosities*. These defects will be detailed in the next section.

The PBF process (and hence, the quality of the final part) is influenced by numerous parameters (more than 200), that determine how much energy is applied and how fast [24], [25]. Among them:

- applied power (e.g., laser power), in terms of total energy emitted per unit time;
- spot size, as the diameter of area focused by the power source;
- scanning velocity, that is the speed at which the spot is moved across the powder bed along a scan vector;

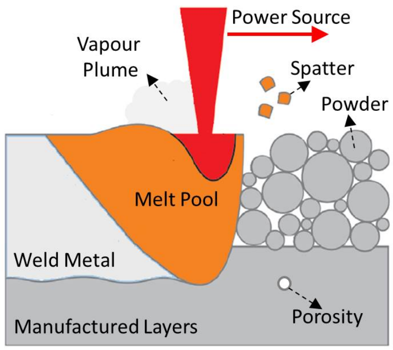

Fig. 4. Zoom-in of a typical PBF process with its main constituting parts.

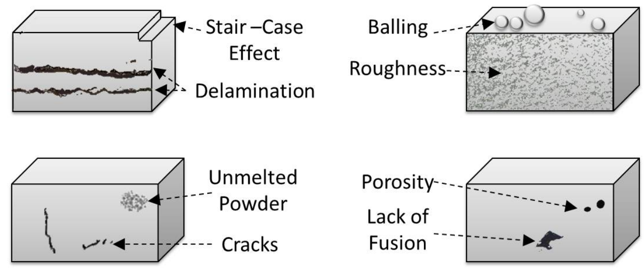

Fig. 5. Pictorial representation of the main defects affecting PBF.

- scanning strategy, including the pattern followed by the scan track;
- hatching distance (or line offset for EBM), i.e., the length between the centers of sequential tracks;
- powder material properties (e.g., shape, size, and distribution);
- layer thickness, i.e., the depth of each new powder layer to be melted.

Each of these parameters can be adjusted independently, making parameter selection a very complex multi-variable problem. Finding the correct setup is crucial so to reduce the chance for defects. E.g., if the laser scans too fast with too little power, then we will see regions of the part that do not fully melt, leading to lack of fusion and to the creation of porosity. By contrast, if the laser power is too high for the chosen speed, the melt pool may overheat causing deeper energy penetration and the generation of spatters.

III. Defects in Powder Bed Fusion processes

The quality of the manufactured parts and the designed functions can be easily compromised, due to the variety of parameters that influence the PBF process. Defects can be grouped into four general categories, based on the way they affect the printed part:

A. *geometry and dimension* (stair-case effect, shrinkage, displacement);
B. *surface quality* (roughness, balling);
C. *microstructure* (porosity, lack of fusion, cracks);
D. *mechanical properties* (cracks and holes, inadequate bonding between layers, porosity, low strength).

To enhance readability, Figure 5 shows a pictorial representation of the main defects treated in the following of this section.

A. Geometric and dimensional inaccuracy

Two defects that lead to geometric inaccuracy in terms of dimensional deviations are the stair-case effect and machine error parameters.

The so-called *stair-case effect* is manly caused by the geometric approximation of a curved surface, and thus directly stems from the layer-wise production process [26]. In case of overhang surfaces, it makes edges of individual layers observable. The thicker the layer, the larger the stair-case effect. However, a lower thickness leads to an increase in production times by increasing the overall layers to be built [27], [28]. Hence, typical layer thicknesses vary between 20 μm and 60 μm for the metal (SLM and EBM) and 100 μm for the polymer (SLS). In general, the layer thickness depends on the distribution of the material-specific powder grain size.

Machine error parameters that lead to geometric inaccuracy are due to laser positioning errors (i.e. defective laser focus) and platform-movement errors, such as defective motion of manufacturing platform in the build or vertical direction [29]. Build orientation, tap density, powder bed density, shrinkage and spot diameter are some of the most important parameters leading to dimensional inaccuracy.

Using a vertical vibration in a rotating roller for better density (*tap density*) to compress a new layer powder can lead to vertical displacement [30].

Shrinkage can be caused both by densification (sintering shrinkage) or by cyclic heating (thermal shrinkage). Shrinkage contributes to the geometrical error during melting-solidification process, which is in turn largely determined by the powder bed density. Non homogeneous temperature distributions in the surface of the powder bed are the main reason of inaccuracy, as they may lead to warping and shrinking of the part. Thermal shrinkage can be decreased by controlling process parameters [22]:

- the higher the laser power, the larger the thermal shrinkage;
- the higher the scan speed and the hatching distance, the lower the thermal shrinkage;
- temperature variation leads to non-uniform shrinkage in the layer [31];
- shrinkage decreases with increasing layer thickness, part bed temperature, and time-interval between building of two subsequent layers [32]–[34].

Thermal gradients play an important role in the generation of *dimensional deviations*. The SLM process requires the use of support structures during the construction of a part in order to fix the part to the building platform, to prevent the warping and collapse of the part, and to conduct excess heat away [35], [36]. The optimization of the support structures in terms of geometrical design and process parameter is hence necessary to improve accuracy, sustainability and efficiency of metallic parts. In the EBM process, due to the vacuum environment and the heating steps, the total temperature gradients are much lower than in the laser process, and the built components therefore also exhibit substantially lower residual stresses and relative deformations. Thanks to this preheating, there is no need to support the structure against subsidence in EBM, but there is still the need to improve heat dissipation in order to avoid overheating effects.

Spot size is the diameter of the melted zone and it is usually larger than the laser diameter: for correction of the dimensional deviations due to this error, the laser beam should be shifted from the boundaries of the cross section of the object, which is referred to as *beam offset*.

B. Surface quality

The main sources of surface defects are surface roughness, balling, and surface deformation.

Regarding the *surface roughness* and morphology of manufactured part, there are numerous contributing process parameters such as laser power, scan speed, hatching distance, spot size, layer thickness, powder deposition, surface orientation and scan strategy for SLM process. As an example, different scan patterns (e.g., raster, spiral or zigzag) may lead to different surface roughness [37]. Re-melting and decreasing hatching distance may on the other hand reduce roughness, as an effect or improving inter-track bounding [22].

Powder deposition is crucial for surface quality, as it may lead to the presence of pits, cracks and holes in the surface. Such problems may be also a source of defect for the subsequent layers [38].

The *balling effect* is caused by an instability of the melt pool, that breaks apart into separate islands that solidify as spheres, thus causing the formation of discontinuous tracks and limiting the formation of very sharp geometries. Furthermore, the balling effect can induce a possible porosity and delamination between the layers due to a non-uniform deposition of powder on the previous layers, proving harmful for the functional performance of parts [39], [40]. The balling effect is caused by low energy density, changes in the chamber contained gas, or by quicker cooling due to the contact with a cooler substrate. Mumtaz and Hopkinson found that high laser power in SLM processes tends to reduce the surface roughness in top and side surface, while the pressures of the blade during the coating of the layer flatten out the melt pool and reduce balling formation [41].

Many other parameters impact on surface quality. It has been observed that surface roughness of EBM-manufactured parts is quite poor in comparison with the surface finish attainable by the laser beam melting technology [42]. Klingvall et al. found that the surface quality is significantly affected by the contour offset and the spacing between offsets [43]. Safdar et al. determined that an increase in the scan speed and offset focus causes a reduction of the surface roughness, which on the other side increases with the increase of the beam current and thickness of the building layers [44]. Bacchewar et al. has investigated the contribution of build orientation, laser power, layer thickness, beam speed and hatching distance on surface roughness of SLS parts [45]. In the case of upward oriented surfaces, build orientation and layer thickness were confirmed to be significant parameters, while downward oriented surfaces were also influenced by laser power.

C. Microstructure

For parts produced by PBF processes, the micro-structure is affected by processing parameters and by location and size of the parts: the heating, melting and cooling mechanisms then determine the quality of the produced parts, and the location and size dependent microstructure will influence the mechanical properties and the performance of the parts [46]. In this scenario, a big role is played by the thermal environment and the thermal history imposed on the parts during fabrication.

Residual stress is due to thermal gradients and cooling rates, that cause rapid expansion and contraction. Residual stress can cause *cracks* and *delamination* between the layers (i.e., a lack of layer adherence due to incomplete melting).

Porosity consists of gaps in the powder bed caused by gases formed within the melt pool, that are trapped due to high cooling rates, or to ridges formed in previous layers, that impede the flow of the melt pool. Porosity is one of the most frequent defects, especially for the SLS process. Numerous parameters may impact on porosity, including laser settings (i.e. power, speed and spot size), scan strategy, melt pool size, powder characteristics and presence of entrapped gas between powders [47].

Lack of fusion defects finally occur when the power source can not penetrate deeply enough to fully melt the powder layer and the top surface of the solid metal below, thus leaving unmelted powder underneath. Such defects typically occur due to insufficient input energy, and they can form through consecutive layers [48].

D. Mechanical properties

Fractures, cracks and holes, inadequate bonding between layers (inadequate fusion bond), porosity, and low strength are the defects resulting in weak mechanical properties [22].

Numerous studies have been conducted to determine the effects of various settings of the PBF process on the mechanical and material properties of the resulting part, sometimes even giving conflicting results. For example, Delgado et al. assessed the impact of changing the layer thickness on two different SLM systems with corresponding stainless-steel powders [49]. One system produced parts with lower hardness with increasing layer thickness, while the other system did not result in a significant change in hardness with increasing layer thickness. Scan speed is important for decreasing the overall build time to manufacture a PBF part. However, if the scan speed is too high, the laser may not have sufficient time to melt the powder.

Sintered and un-melted powders could also be responsible for crack initiation [50]–[52]. Decreasing the hatching distance or increasing the laser power may improve the melting process and achieve the same energy density while allowing a faster scan speed. Decreasing the hatching distance will increase the overlap of each beam pass causing excessive fusion. Increasing the hatching distance may not allow the beam to overlap enough and result in insufficient powder melting.

Vandenbroucke and Kruth optimized the hatching distance to minimize porosity, and to meet mechanical property requirements for hardness, strength, stiffness, and ductility of titanium alloy parts made on a SLM system [53]. The laser power affects the amount of energy applied to melt the powder layer and to create the melt pool. Reducing the laser power may result in insufficient melting of the powder. However, too much laser power can cause vaporization, which traps gas bubbles and creates porosity in the newly melted powder layers.

In SLM, the process parameters, such as laser power, scan speed, hatching distance, scanning strategy, layer thickness and powder material properties (shape, size and distribution) have an effect on the transient thermal behavior of the melt pool and result in defects such as pores [54], thermal cracking [55], unintended anisotropic mechanical and physical properties [56]. The way in which the laser beam, in the SLM process, interacts with the powder material during the process and the dynamics of the melt pool are largely a function of the powder material and the thermodynamic properties [57]. The powder particle shape and size distributions can also affect the absorption of light [58], [59], the packing of the powder bed, the flowability of the powder during the recoating process, and the uniformity of layers deposited in the recoating process.

IV. Quality assurance: a conceptual framework

PBF is a very complex process that is influenced by a multiplicity of parameters and factors at different scales. As a consequence, PBF quality assurance embraces variables at multiple scales and dimensions, across both time and spatial domains. Fig. 6 reports a schematic representation of this concept. The backbone of quality assurance is the identification of the inherent relations between all the controllable parameters of the process and the resulting quality of the finished product. This implies identifying correlations between three different time-domains, respectively before, during or after the layering process [16] (see time-scale in Fig. 6):

- The *Parameters* are the inputs to the AM system, which include the whole set of material properties and pre-process machine configurations that determine i) the amount of energy that will be delivered to the powder, and ii) the way this energy will interact with the layering material to build the part. While the parameters defining the material properties (for example, type, size and distribution of the powder) and chamber conditions (temperature, gas flow rate, etc.) are *pre-defined*, as they cannot (or should not) be modified during the build, some machine configurations such as laser power, scan speed, etc. are *controllable*, in that it is virtually possible to change them during the process to improve or correct the final quality of the build [22]. In this regard, TABLE I shows a list of controllable parameters, as defined and categorized by [22], mapped to the main categories of the defects that were presented in Section III.
- The *Signatures* are the characteristics of the process, that can be either directly measured during the build (by the name of *Observable signatures*, such as the shape and temperature of the melt pool), or derived by exploiting analytical models or simulations of the AM process (by the name of *Derived signatures*, such as the depth of the melt pool, or the residual stress). Both the categories of process signatures directly influence the success of the layering process, and hence the resulting quality of the build. To obtain valuable observed signatures, the process can be monitored by exploiting sensors at multiple levels of detail, respectively from melt pool to whole build (see resolution-scale in Fig. 6).
- *Performance* refer to the whole set of quality indexes that may define or characterise the success of the build. In this category, we can include post-process measurements of part quality such as dimensional and geometrical accuracy, surface roughness, porosity, mechanical properties, chemical properties, etc.

From a computational viewpoint, the sensed data can undergo processing at different levels. The first and simplest level, referred to as *In-situ Monitoring*, includes all the processing that is applied to the raw sensors data acquired during the layering process (plus, eventually, the pre-process parameters and the post-process data) in order to extract a compact set of meaningful and descriptive signatures. Hence, this category mainly refers to either i) data pre-processing and feature extraction methods, or to ii) fault detection methods, that are able to capture parts defects or machine state anomalies during the layering process. At this level, the analysis does not imply a continuous feedback to the machine, if not in the forms of alerts triggering pre-determined corrections strategies, such as powder re-depositions or re-melting, or eventually of a stop signal, in case the fault is considered critical for the continuation of the process (see *alert, stop* dashed arrow in Fig. 6. As the data may have different formats depending on the sensing technology (e.g. time-sequences, images, videos, etc.), in-situ monitoring may include approaches from different domains, from signal/image processing to spectral analysis.

The highest level of processing, namely *Process Control*, involves all the computational approaches that are able to infer a model of the inherent relation between the parameters, the signatures and the performance, and use this model to continuously improve the process, and hence ensure a better quality of the products. This may be either a separate computational step downstream of in-situ monitoring, or an end-to-end Artificial Intelligence approach with the feature extraction embedded into it, taking the raw sensors data directly as input.

The inferred model can be exploited for closed-loop process control at two possible levels (see *Improve, control* dashed arrows in Fig. 6):

(i) *offline*, to improve the parameters configurations for the next builds;
(ii) *real-time*, to adjust the controllable parameters in order to correct possible arising defects during the layering process.

In the next sections, we review the available systems for quality assurance in metal PBF, with special regards with in-situ monitoring and process control. We discuss the most recent systems first from a technological viewpoint, focusing on the sensing approaches (Section V), and then from a com-

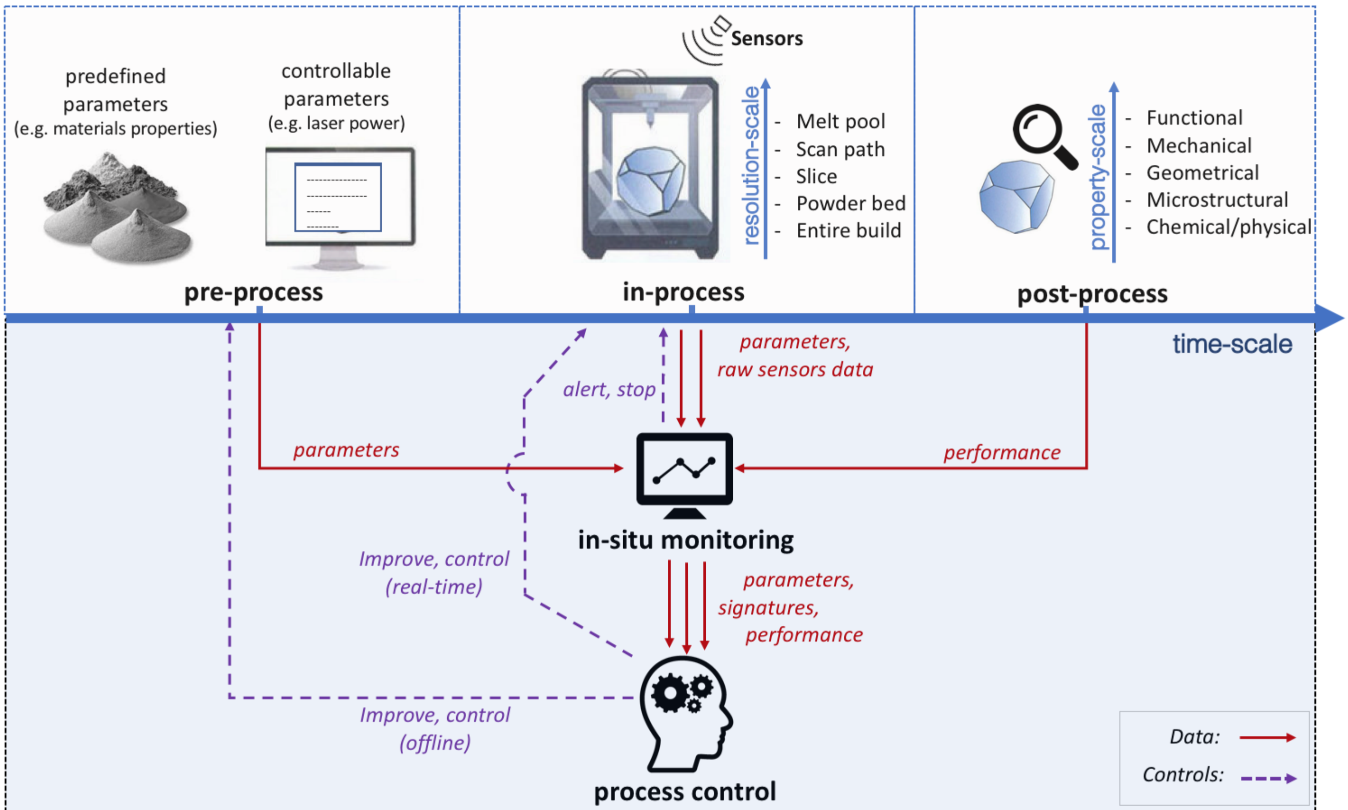

Fig. 6. Conceptual flow of quality assurance in PBF Additive Manufacturing.

TABLE I
CONTROLLABLE PARAMETERS FOR MAIN CATEGORIES OF PBF DEFECTS

Defect group	Defect name	Controllable Parameters								
		Laser Power	Scan			Laser Positioning	Platform movement	Hatching distance	Layer thickness	Substrate temp.
			Speed	Length	Pattern					
Geometry & Dimension	Stair-case effect								x	
	Shrinkage	x	x	x				x	x	x
	Displacement					x	x			
Surface quality	Roughness	x	x		x			x	x	
	Balling	x	x						x	x
Microstructure	Porosity	x	x	x	x			x		
	Lack of fusion	x	x					x		x
	Cracks							x	x	
Mechanical properties	Cracks & Holes	x	x	x	x			x	x	
	Inadeq. layer bonding								x	
	Porosity	x	x		x			x	x	
	Low strength				x			x		

putational viewpoint, focusing on the Artificial Intelligence approaches (Section VI). Then, in Section VII we discuss the main characteristics and/or limitations of the commercial solutions.

V. SENSORS AND MONITORING TECHNOLOGIES

In-situ sensing is necessary to determine the quality and the stability of the process during production, to give meaningful inputs to process monitoring and optimization. Detecting and avoiding defects is indeed crucial to adapt process parameters (like scan speed, scan power, scan pattern, and layer thickness) and to implement closed-loop repairing and adjustment actions, based on the measured quantities [60], [61].

As anticipated in Section IV, the characteristics of interest of the process are called *signatures*, i.e., dynamic characteristics of the powder heating, melting, and solidification processes that are either observed or derived during the build. According to the categorization introduced by [15] based on the required level of detail of observation, signatures can be grouped into five major categories:

(i) at the level of the *melt pool*, i.e. a zone at the micrometer spatial scale, formed by harsh solidification conditions of the metal powder on a millisecond temporal scale;
(ii) at the level of the *scan path*, i.e. the track followed by the power source;
(iii) at the *slice* level, i.e. at the level of a single layer obtained after the solidification of the melted powder in the entire processed area;
(iv) at the *powder bed* level, i.e. the thin layer of unmelted powder before the action of the power source;
(v) at the *entire build* level, i.e. the final result of the layering process.

Each category is characterized by different signatures of interest, that reflect the different impact of process parameters and configuration, and the phenomena that are visible at each scale. This may require the adoption of different sensors and/or of different sensing structures, by identifying which of the many process signatures may provide the most valuable information while being at the same time accessible to measurement and analysis.

It is important to note that different technologies imply different sensing solutions. In particular, SLM systems allow a wider range of sensing techniques, as it allows to exploit the laser optical path to monitor the melt pool. Vice versa, in EBM the electron magnetic coil deflects the electron beam, and thus does not allow to exploit the optical path. In addition, EBM has a higher scanning speed, thus making continuous monitoring of the melt pool and heat more challenging [15].

Sensors and data collection devices are of four main types:

- non-contact temperature measurements based on emitted thermal radiation, like pyrometers and InfraRed (IR) imaging;
- contact measurement of temperature, like thermocouples;
- imaging in the visible range;
- low-coherence interferometric imaging.

These sensors are used across all levels of detail; other sensors may be used at each level, to address specific requirements, like thermo-couples, x-ray detectors, ultrasonic devices, tomography devices, and displacement sensors.

Independently from sensor type, sensors can be categorized according to three orthogonal dimensions [62]:

- *spatial resolution:*
  - *single-channel detectors*, such as photodiodes and pyrometers, reduce the signal from the field-of-view to a single number, e.g., a voltage corresponding to the amount of light that strikes the detector. This ensures low costs, high sensitivity and fast data collection rates;
  - *spatially resolved sensors*, like cameras, enable spatial resolution of the signal, and thus allow analysis like detecting the melt pool size by counting the number of "hot" pixels that detect a light intensity above a given threshold. As a drawback, data management becomes challenging as large amounts of data are collected;
- *sensor mounting:*
  - in *co-axial* configurations, the sensor exploits the optical path of the power source (left of Fig. 7). This technique can be exploited only in case of the SLM technique, and usually refers to melt pool monitoring;
  - in *off-axial* configurations, the sensors are placed outside of the optical path of the power source, and thus have a certain angle-of-view w.r.t. the region of interest (right of Fig. 7). Off-axial configurations are used to gather information usually from the scan path level up.
- *field-of-view:*
  - a *moving* field-of-view implies that sensors may move to follow the build process and the melt pool, e.g., with a Lagrangian reference frame, by integrating the sensor in the scanning equipment (eased in case of co-axial mounting). This configuration has shown significant promise, as it allows to monitor in real time melt pool instabilities and variations [62];
  - *fixed* field-of-view sensors do not move to follow the build process, as they rather monitor the whole area on the build surface. This allows to keep a thermal history of the material, that can be used in correlation with the signatures to derive information about the build status. However, this configuration is less frequent.

The following subsections will analyse the main sensing techniques adopted at each level of detail, with a review of the main solutions proposed in the literature.

A. Melt pool sensing

The majority of the latest monitoring approaches focus on the melt pool and on the surrounding heat affected zone. Monitoring the melt pool is indeed relevant to estimate the power source-material interaction, as the stability, dimensions and behavior of the melt pool determine quality and stability of the build process. The melt pool properties indeed heavily impact on final product qualities and performance: as anticipated in Section III, they determine geometrical accuracy of the track and surface, they influence the porosity and the presence of partially melted (or unmelted) particles, together with the development of residual stress, cracking and delaminations.

At this level, typical signatures are the (i) size, (ii) geometry and (iii) temperature distribution of the melt pool. All such signatures are strongly affected by process parameters (e.g., powder characteristics, layer thickness) and by the scanning strategy (e.g., power, scan speed, spot size). In situ sensing at the melt pool level requires to measure the characteristics of a very small region (a few hundreds of microns of diameter) with a sufficient spatial resolution and a very high sample rate. This poses major challenges to the sensing infrastructure. To have a better perspective on the build process, melt pool monitoring systems are co-axial.

Both visible and IR cameras have been employed for melt pool monitoring to estimate geometry-related properties or temperature distribution. IR images allow to measure temperature variations within a part [63]–[65]. Visual camera images

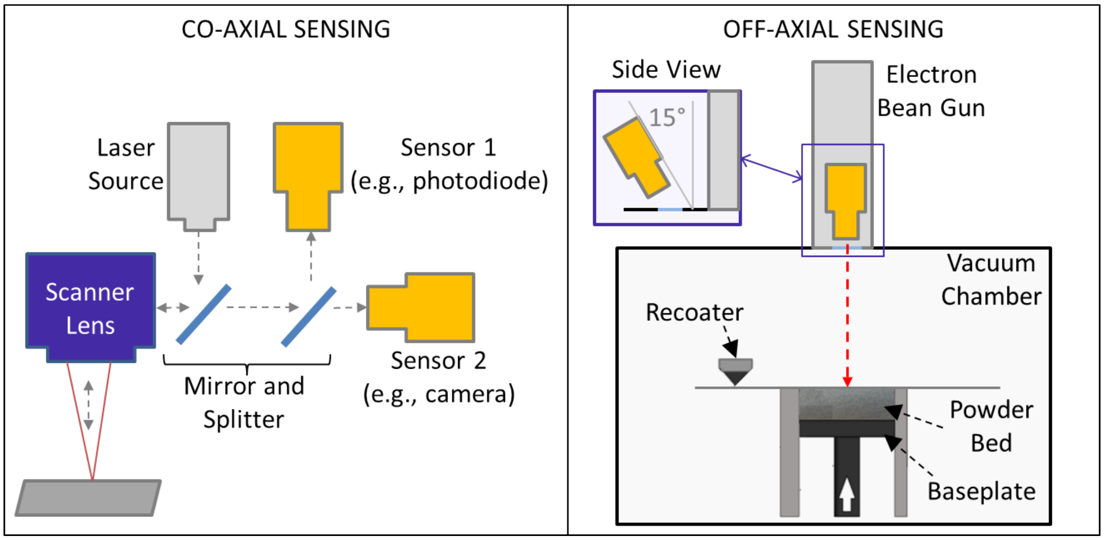

Fig. 7. Sensor mounting strategies: co-axial (i.e., the sensor exploits the path of the power source, left) and off-axial (i.e., the sensor has a given angle-of-view w.r.t. the area of interest).

can be taken both before or after the completion of laser scanning. If images are taken right after laser scanning, they allow to evaluate errors related to the geometry, the superelevation of parts, and connection errors [66], [67]. If images are taken after powder recoating, but before laser scanning, they allow to detect also irregularities in the recoating process, and to identify damages to the recoating mechanisms or parts protruding through the powder bed due to thermal stress [68].

Cameras can be used jointly with CMOS sensors, photodiodes or pyrometers to capture temperature distribution, melt pool size and intensity [15]. Photodiodes are especially useful to test quality in special geometry (e.g., overhang and down-facing structures or acute corners) and to implement simple feedback control for improving geometrical accuracy of overhang regions [69]–[73]. Pyrometers are instead adopted to enhance temperature distribution measurement and to estimate more accurately the size of the melt pool [74]–[77].

Visual imaging equipment is relatively unexpensive and easy to install. However, image analysis is complicated by uneven exposure and by the moving field-of-view. Additionally, the choice of an on-axial or off-axial configuration heavily impacts on the resulting image perspective. Illumination systems and pre-focusing units can be included in the monitoring system, to enhance the visualization of melt pool dynamics [78]. Nonetheless, significant image post-processing is thus necessary to correct image perspective and contrast between the parts and the powder [67], [79].

Another issue of melt pool monitoring is the size of sensed data. At a typical laser scan speed, a melt pool will persist only for about 0.001s, with heating and cooling rates in the order of 10^6K/s [62]. Capturing melt pool dynamics requires thus data collection rates on the order of at least 10kHz, with typical system configuration of 50kHz [62], [72]. This high data rate, considered together with the memory necessary to save the sensed information (e.g., the images), sums up to a significant amount of memory, above all when considering hours- or day-long builds. These considerations clearly lead to the conclusion that data management strategies are necessary to allow effective process monitoring.

B. Scan path sensing

The second level of detail is the scan path level, i.e. the track followed by the power source. Important signatures are (i) the geometry of the track, (ii) its temperature profile, and (iii) the presence of material ejected from the melt pool or the surrounding area during the process (i.e., spatters). These phenomena indeed determine the presence of balling phenomena, lack of fusion, local overheating, creation of porosity, and surface or geometric errors. Similarly to the melt pool level, monitoring the scan path poses challenges in terms of required spatial and temporal resolution, and requires high-speed vision systems, like thermal and IR cameras.

A *thermal camera* can be used to monitor spatter ejection and temperature profile produced during the beam-material interaction. In [80]–[82], the IR cameras (with sensitivity from short lo long-wavelength IR) have been used in off-axial configuration and are mounted outside the building chamber, to acquire the thermogram of the heat affected zone and the surrounding areas along the scan path. Other works couple the off-axial IR camera with a pyrometer to monitor temperature evolution of each slice and observe ejected spatters [83].

Coarse sensed data can be elaborated to extract more refined information and implement monitoring strategies. A typical approach is to use information collected by thermal cameras and pyrometers to detect local overheating phenomena along the scan path [84], or to detect regions of the scan path where deviations from the normal melting state occurred [85], [86].

C. Slice level sensing

The slice level implies a monitoring of a single layer obtained after the solidification of the melted powder in the entire processed area. The characteristics of each slice are influenced by the stability of the melting process, and hence represent a fundamental source of information to determine process quality on a layer-per-layer basis.

The main signatures of interest are:

(i) the surface pattern, that may reveal balling and porosity;
(ii) the geometry of the slice, to reconstruct the shape of the slice and to estimate the deviation from nominal dimensions;
(iii) the local thickness profile, allowing detection of super-elevated edges and surface irregularities that impact on the wear of the recoating system and determine defect propagation;
(iv) the temperature profile, to determine irregularities caused by unmelted material or by overheating.

Solutions for slice level sensing typically rely on image acquisition through camera mounted either inside of outside of the build chamber. Approaches in the visible range exploit illumination systems or fringe projectors to highlight surface patterns, to detect defects related to elevated edges and surface irregularities, but also to reconstruct geometric properties of the slice [87]–[90]. The field of view is enlarged to up to 100×100mm, with a resolution of up to tens of μm/pixel. Given that the interest is on static properties of the slice, rather than on dynamic properties of a process, frame rate is not an issue at this level (even if high-speed camera approaches have been proposed, too [84]).

Additional approaches use IR cameras to characterize the surface, to detect flaws and surface defect and to determine temperature distribution [91]–[94]. Thermal detectors can finally be used to evaluate local maximum temperature and the cool-down behavior [95]. Finally, ultrasound and interferometer sensors can be used to detect surface defect through the analysis of the reflected and diffracted wave signals [96]–[98].

Critical regions, e.g., with super-elevated edges, can trigger alerts to allow the application of correction strategies like Selective Laser Erosion, SLE or to stop the build process (e.g., to re-scan the affected region) [87], [92].

D. Powder bed sensing

Monitoring the powder bed implies observing the thin layer of unmelted powder before the action of the power source. Signal acquisition can thus be performed after or during the deposition of the powder bed itself, before the next layer is started. In-process detection of powder bed defects can be used to activate simple corrective actions, e.g. a re-deposition of the powder bed and/or the substitution of a worn recoating system.

At this level, the signatures of interest are (i) bed uniformity, crucial to determine rippling and rectilinear grooves, (ii) temperature and (iii) temperature profile, useful to characterize the temporal and spatial evolution of the process.

It is important to note that approaches used at the slice level, like [68], [87]–[89], can be used to monitor also powder bed homogeneity if the images are taken after powder deposition. Specific to powder bed sensing, IR images have been proposed to monitor temperature variations, to estimate thermal distribution and stress [63]. Other sensors can be used to monitor different aspects of the powder, ranging from displacement and vibration sensors (used to reconstruct the 3D powder bed topography, to detect inhomogeneities and surface irregularities [87], [99], [100]) to thermocouples (useful to measure the temperature on the powder bed [101]).

E. Entire build sensing

It is possible to monitor the PBF process at the entire build level, i.e. the end result of the layering process. As discussed earlier in this section, the most widespread sensing solutions limit inspection on the surface of the process, and mostly rely on cameras or thermal sensors. However, other methods investigated how to gain greater inspection penetration into the material, at the price of a more complex integration in the processing environment. Such approaches, based on ultrasonic and X-ray technologies, have the potential to identify material discontinuities and asses material characteristics such as the microstructure [14].

Laser ultrasonic techniques generate and detect ultrasonic waves, that can be used to detect defects (such as pores, voids, bondlines and cracks) and to achieve material characterization. A pulsed laser is used to generate an ultrasonic wave, and any distortions are detected by a detector sensor in terms of displacement, reflection and discontinuity [96], [102]–[105]. X-ray technology is suited for inspecting AM parts as it is not susceptible to surface roughness and it allows easy detection of corrosion, cracks and voids [106], [107]. However, the large equipment required for scanning, the limited availability of tailored X-ray sources and the relatively long inspection time limit the effectiveness of this kind of sensing equipment [14].

VI. The role of Artificial Intelligence

As it stems from Section V, in-situ sensing and monitoring technologies for metal PBF processes are facing continuous developments, which make possible the monitoring of a large number of heterogeneous parameters at multiple time-scales and resolutions. The main consequence of such developments is the explosion of data that needs to be stored and analyzed, encompassing the characteristics of so-called *big data* [18], [108], [109]. In this regard, we can re-consider the four *big V's* that traditionally define big data (i.e. Volume, Variety, Velocity, Veracity) for this specific scenario:

- *Volume* of AM data refers to the size of the data sets that need to be analyzed and processed, which for a typical PBF process with current solutions can be roughly quantified in the range of TBs per build [110].
- *Variety* refers to the necessity of analysing multi-modal sensing data, with very different formats and resolutions. Depending on the sensing technology and applications: numerical data from machine logs, 2D images from high speed cameras and thermal cameras, 3D models from CAD, acoustic signals, videos, etc [15], [16].
- *Velocity* can be roughly quantified by the rate at which new process variables are generated and logged during a build (up to 600 per second), or by the rate at which experimental data are captured by the sensors (for example, around 75 GB/s of image data, in recent in-situ monitoring systems [111]).

- *Veracity* refers to the quality and meaningfulness of the data that are being analyzed. Given the complexity and number of influencing parameters, the control strategies for metal Additive Manufacturing, with special regards with PBF technology, are still at a low maturity stage, with very limited a priori knowledge about which sensor data is most meaningful for controlling specific characteristics of the build. Hence, in spite of the high dimensionality, the reported veracity for AM sensing data is low. Indeed, metal PBF at the moment is a domain that is data-rich but knowledge-sparse [18].

As a matter of fact, the necessity of dealing with large numbers of high-complexity and high-dimensionality data is fostering the use of advanced analytical approaches to solve the problem of PBF quality assurance. In this regard, data-driven techniques, and more specifically machine learning and deep learning architectures, are having an increasingly more important role in in-situ monitoring and process control tasks.

For the reader's convenience, in the following we first provide a general overview of these data-driven techniques, where the main concepts and approaches of machine learning and deep learning are introduced. Then, we review the major applications of these approaches to the specific context of in-situ monitoring and control of metal PBF processes.

A. General overview

In Computer Science, Artificial Intelligence (AI) refers to the capability of a machine of interacting with the environment to take decisions, exploiting attitudes that are traditionally associated to humans [112]. In this regard, Machine Learning (ML) includes a large family of Artificial Intelligence algorithms that provide a computerized system the ability to learn the solution of a complex problem directly from experience (i.e. from a set of training data examples), without being specifically programmed for it [113]. ML applies exploratory data analysis, in the form of statistical techniques and algorithms, to perform predictions and forecasting. Hence, it uses information extracted from the data rather than relying on a-priori knowledge. The main advantages of this data-driven approach are:

- Identifying unknown trends and production patterns.
- Making human expert intervention less needed or unnecessary.
- Allowing continuous improvement.
- Handling multidimensional heterogeneous data.

ML algorithms can be categorized into three broad categories [114]:

- *Supervised learning*, where the training set consist in a labeled set of experimental data. The label (either a continuous or a categorical value) provides an example of the expected output for the corresponding input data. The training algorithm learns a model of the correspondence between input and label, typically working towards the minimization of the prediction error on the training set. Supervised applications can be either classification, where the label is a categorical value representing a specific class, or regression, where the label is a continuous value. For example, classification can be exploited to predict failure of a process based on a historical dataset where the success/failure of a large set of experiments was stored. Supervised techniques are generally possible only when a problem can be easily interpreted by identifying a given number of classes (for example, two classes: failure/success), for which a large set of input data-label pairs are available in advance.
- *Unsupervised learning*, where the algorithm is fed with unlabelled training examples, and the model takes into account only inherent characteristics of the experimental data. Typical applications are: i) dimensionality reduction techniques like Principal Component Analysis (PCA), where orthogonal transformations are applied to the original data to obtain a reduced set of uncorrelated variables [115], or ii) clustering methodologies, where the data are grouped into different categories based on their similarity/dissimilarity (e.g. K-means [116], hierarchical clustering [117], gaussian mixture models [118], etc.). Dimensionality reduction is often exploited as a pre-processing step prior to classification or clustering, to ease downstream algorithms. Typical applications of clustering are exploratory data analysis or generic anomaly detection tasks.
- *Reinforcement learning*, where a semi-supervised goal-oriented algorithm (the agent) takes actions within a virtual representation of the environment (the state, typically modelled in the form of a Markov Decision Process (MDP)), in order to maximize some notion of cumulative reward [118]. Unlike supervised techniques, the learning algorithm does not need to be fed with labelled training examples, and the decisions are made sequentially (i.e. the decision depends on the state of the current input, and the next input depends on the output of the previous input, etc.). Then, reinforcement learning is most useful for adaptive control applications, when there is a necessity of adapting the ML model to the environment, and dynamically change the action based on the new perceived conditions.

The most popular ML techniques depend on the specific goal. Traditionally, the preferential approaches for supervised tasks were either statistical classifiers, Support Vector Machines or Random Forests. Statistical classifiers apply statistical methods (e.g. *Bayesian inference*) to the experimental data to infer membership probabilities for each class, so that each instance can be assigned to the class with the highest probability [114], [119]. Nonetheless, they usually make strong assumptions on the distributions of the data (e.g. statistical independence of the features). Support Vector Machines (SVMs) and Random Forests, on the other hand, are completely distribution-free. SVMs build a classification model by identifying a maximum-margin hyper-plane to separate the training instances into the different classes [120]. This makes it very suitable for handling small training sets. Random Forests is a so-called *ensemble approach*, in that it operates by constructing a multitude of classification models, each implemented like a decision tree [121]. By combining the decision of different types of classifiers, Random Forests is especially good at avoiding overfitting, that is the type of error that occurs when the ML model fits too closely to a limited set of training points.

In the last few years, the most popular approaches for all types of ML tasks, from supervised to reinforcement learning applications, are based on Artificial Neural Networks (ANNs). ANNs are computational models vaguely inspired by the biological neural networks, consisting in an interconnected network of nodes (the neurons) and weighted links (the edges), where the weight is a numerical value representing the interconnection strength [122]. Each neuron is an independent computational unit with its own inputs and output. The output of a neuron is computed by some non-linear function of the weighted sum of the inputs, and the weights (i.e. the parameters of the neuron) adjust as the learning proceeds. Typically, neurons are aggregated into multiple layers, that may perform very different transformations on their inputs. Hence, ANNs are very versatile techniques that may be used for predictive modeling, classification, regression or even adaptive control tasks, with inputs that can span from one-dimensional sequences to n-dimensional images or videos.

Traditionally, ML techniques (including classic ANNs like multilayer perceptrons [123]) are not applied directly on the raw data, but downstream of a feature extraction and/or pre-processing module (e.g. dimensionality reduction, denoising, etc.), that takes care of obtaining a compact set of significant descriptors. These descriptors are then fed to the ML algorithm (see top part of Fig. 8) to obtain the final prediction output. The goodness of the feature extraction step has typically a major impact on the overall performance of the ML task. This has two major implications. First, as different tasks will unavoidably require very different feature extractions, it will limit the generalization capability of the ML technique. Second, it will make the task more challenging when there is little or no knowledge on the specific inputs that are most influential for a certain process.

As a solution to this problem, a new class of ANNs, *deep neural networks*, provide an end-to-end architecture with embedded feature extraction. They take the raw data directly as the input, and stack a large number of locally connected hidden layers of neurons that can extract features at a progressively higher level of abstraction [124], [125] (see bottom part of Fig. 8). For example, if the input is a two-dimensional image, the first layers of the network will compute simple and generalizable image descriptors, such as edges and textures. The following layers will extract more complex descriptors, such as combinations of textures and object parts. As the parameters of the layers (and hence, of the feature extraction) are learnt during the training, the deep network will be able to learn the most suitable representation of the input directly from the raw training data, without requiring any additional a-priori knowledge. This inherent capability has made deep networks the undisputed state of the art in many ML applications, including image classification, natural language processing, time sequence analysis etc.

Most popular deep architectures, especially with images as the input, are Convolutional Neural Networks (CNNs), that implement feature extraction by stacking a large number of bi-dimensional digital convolutions, followed by dimensionality reduction operators (i.e. pooling) to prevent overfitting [126]. While classic CNNs are meant for supervised image classification, recent literature provides specialized deep architectures that can be applied to a multiplicity of different tasks other than classification, including regression, clustering and adaptive control.

Major challenges of deep learning, compared to traditional ML techniques, are the computational burden and long training time, especially for high-dimensional data, and the necessity of very large training sets to avoid overfitting problems.

B. Applications to metal PBF

Early works on AM quality assurance were mainly exploratory, combining a-priori knowledge on process physics and materials with controlled experiments to achieve a deeper insight on the nature of defects in PBF process, as well as of the corresponding causes and control strategies (see Section III).

With the increased availability of big streams of multi-modal data collected from AM machines, the role of data-driven approaches, with special regards with Machine Learning, is rapidly growing. The research efforts on this matter are not completely mature yet, in that they only partially address the conceptual framework depicted in Fig. 6. Most of the works in literature apply ML to i) extract a reduced set of significant process signatures from the raw sensing data and to ii) provide more efficient real-time monitoring of the quality of the part. To do so, they either focus on the early detection of defects during the layering process, or on identifying anomalies in the machine states that can possibly lead to a failure of the process. Most of these approaches are limited in their scope, in that they focus only on a sub-set of the available process parameters or on a specific level of sensing detail, without considering the interaction of data obtained from

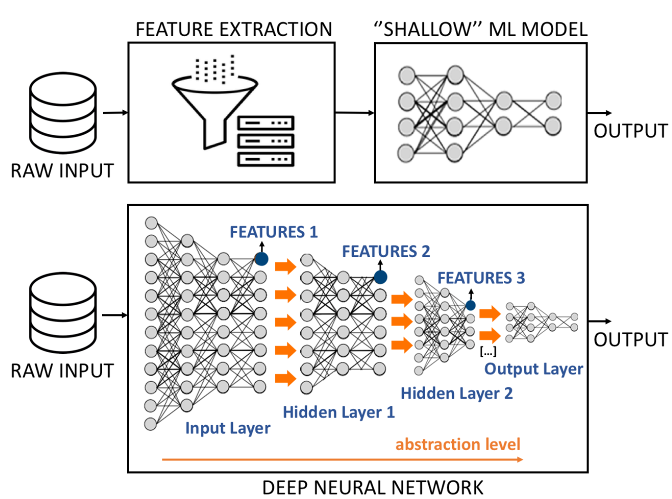

Fig. 8. Top: conceptual representation of a traditional ML model, with separate feature extraction module. Bottom: conceptual representation of an end-to-end deep learning model, with embedded feature extraction layers at increasing levels of abstraction.

different types of sensors and/or at different resolution scales. Nonetheless, they show very promising examples of how ML can strengthen and improve the study of complex parameters-signatures-performance relations in metal PBF systems. Few recent works are also providing first attempts of process optimization and automated control strategies.

In the following, some peculiar examples are provided, grouped by the specific focus of the ML approach.

- *Early detection of defective parts*
  As anticipated in Section III, parts produced with metal PBF technologies can be affected by a multiplicity of defects. Each of them is influenced by many parameters at different scales, that can be monitored by very different type of sensors. A rough categorization of the ML approaches for defects detection can be hence made based on the nature of the type of input data they exploit.
  - Defects detectors taking *in-situ images* as the input apply ML in combination with Computer Vision techniques. As anticipated in Section V, the image analysis can happen at different levels of detail, from the lowest (powder bed) to the highest (melt pool).
    Works focusing on the *powder bed* defects prior to fusion (among the others, local powder deficits) extract classic textural descriptors from visible range images, and feed them into unsupervised clustering approaches to identify discontinuities in the pixels intensity distribution [127], [128]. Given the limited complexity of this task, supervised methods, which require considerable efforts into creating labelled training sets, are much less popular, even though they show promising results [129].
    On the other hand, supervised ML are predominant when the analysis is performed at a higher level of detail. At the *slice level*, supervised techniques are used to classify post-fusion layer-wise images into defective/non-defective, either using post-build porosity measures or CT scans to label the training set [130], [131]. Again, most techniques in literature employ a separate feature extraction approach: for example, [132] fed a Bayesian classifier with frequency domain descriptors.
    Finally, at the highest level of detail of the analysis, the *melt pool*, ML methods use different types of scale-invariant textural descriptors (for example, Scale-Invariant Feature Transform (SIFT) or Histogram of Oriented Gradients (HOG) [133]) to represent melt pool morphology, as well as to characterize the appearance of the spatters and of the vapor plume around the melt pool area [134]. These descriptors are then used to train supervised techniques, such as Support Vector Machines [135]. Deep learning techniques are also becoming more popular by the day: in this regard, the inherent feature extraction capability of deep networks is exploited to identify possible hidden characteristics of the melt pool that cannot be easily captured by traditional image descriptors [136]–[138]. Nonetheless, most of the available approaches are still limited in their scope, in that they are not directly tied to post-process outcomes (e.g. part porosity or density), but only to process parameters such as the power of the laser.
  - *Spectral data* can also be used as the input for the real-time detection of defects. For this purpose, deep learning is the most popular approach, exploiting variants of the deep architectures that are traditionally applied to image classification tasks. For example, [139] and [140] respectively proposed Deep Belief Networks (DBNs), a probabilistic family of deep neural networks, and spectral CNNs, the spectral counterpart of classic CNNs, to recognize several type of part defects in a PBF process, using acoustic emission data from Ultrasound sensors as the input. Other types of spectral data, e.g. from Optical Coherence Tomography(OCT) sensors, are still under exploration.
  - Given the complexity of the phenomena that influence the PBF process, the majority of methods reviewed so far are limited in their representation capability, in that they exploit only one type of sensor. Hence, growing efforts are being devoted into ML frameworks able to combine multivariate *multi-sensors data*. For example, [141] recently investigated a data fusion methodology based on one-class-classification variant of the SVM formalism, Support Vector Data Description (SVDD) [142], to combine in-situ data from multiple sensors in EBM.
- *Early detection of build state anomalies*
  Another way of applying a ML framework to PBF quality assessment is by observing the machine instead of the manufactured part, with the aim of identifying possible anomalies that may translate into a faulty process, and hence into a defective part. To do so, the input data may be either machine logs or data from sensors that are installed directly on top of the machines. These data are fed into ML methodologies, either unsupervised or supervised. In the former, a clustering algorithm recognizes the abnormal states based on their inherent difference with baseline data. In the latter, the abnormal states are obtained by classification, exploiting a historical database of processes of a-priori known outcome (e.g. finished with success/unfinished/finished with errors). For example, in [143] both the strategies were explored, adopting k-means algorithm for clustering and a Bayes Classifier and SVM for classification. The input data were process parameters extracted from the machine logs (among the others, platform temperature, optical bank temperature, and process oxygen level).
- *Closed-loop process control*
  As anticipated at the beginning of this section, closed-loop control is still an open problem in metal PBF processes. In this regard, few early works proposed to automatically control the laser power in a SLM process, using the melt pool area as the observed process parameter [144]. Nonetheless, they did not employ ML but instead a Proportional–Integral–Derivative (PID) controller,

a classic control loop mechanism that is widely used in industrial systems [145]. More recently, a preliminary work by [146] proposed a closed-loop control system for laser PBF empowering ML with a reinforcement learning strategy. Specifically, the in-situ AM control problem was modelled as a Markov Decision Process, using the defects detected from layer-wise imaging data to predict the evolution of the next layers, and hence derive an optimal control policy.

VII. Commercial solutions for in-situ monitoring and control

In the earliest stages of AM, producers directed most of their efforts to the improvement of electro-mechanic technologies employed by their machines, with the aim of making additive systems competitive with traditional production methodologies. Less attention was originally devoted to secondary aspects of the production, such as post-process qualification of the products as well as real-time monitoring and control of the process. With the recent explosion of AM in the context of Industry 4.0 and the ever-increasing number of companies approaching AM production systems, the need to improve the repeatability of the process to meet the industrial requirements has become more and more important. Hence, several machine producers have now identified the improvement of in-situ quality monitoring and control functionalities of their machines as a key target. Following closely the research trends, they started equipping their systems with self-developed suites that can help users to monitor the process at different time and space resolutions. These suites are usually sold in the form of additional software toolkits, tailored to specific single-brand machines.

At a later stage, as the market of AM and AM-related applications is continuing to grow, even third-part solutions have now become available, which provide customizable platform-independent toolkits for multi-brand machines. The advantage of these solutions is two-fold: i) for the machine producers, that are released from the burden of having to develop their own analytics suites, which might not be their specific core-business; and ii) for the users, that are released from the one of learning a completely new framework when they change the machine. Furthermore, the possibility of integrating the same toolkits into different machines ensures a better interoperability of different systems.

TABLE II provides a list of available toolkits for PBF systems, divided into two different sections: the top one for the proprietary software toolkits of specific single-brand machines, the bottom one for the third-party solutions. Based on documentation and information made available online by the producers of the toolkits, we reported in different columns:

(i) The specific PBF process addressed by the monitoring suite. Besides already defined EBM, SLM and DMLS processes, the table reports two additional proprietary laser sintering technologies, Direct Melt Pool (DMP) and Laser Metal Fusion (LMF), patented by their respective producers (references in the table).
(ii) The name of the producer, with respective reference.
(iii) The name of the toolkit.
(iv) The object of the monitoring (e.g. powder bed, melt pool) and, where available, the monitored signatures.
(v) Where available, a description of the sensing technology exploited by the toolkit (e.g. co-axial or off-axial cameras).
(vi) Where available, the control functionalities of the toolkit, categorized into:
   a) *Alert*, when the control triggers alarms to the user without interfering with the process;
   b) *Stop*, when the system is able to early stop the process in case of specific problems or state anomaly identified by the monitoring kit;
   c) *Post-process*, when the monitored information is exploited only *after* the process is ended, to say whether the part is compliant with the minimum quality requirements;
   d) *Closed-loop*, when there is some form of real-time control of specific process parameters. Whenever reported, we also provide information on the controlled variable.

As it can be observed from the table, out of the fifteen producers gathered online, only Arcam and Sigma Labs target EBM technology. The rest of the toolkits are specifically designed for laser-based machines (either SLM or DMLS).

The majority of the producers do not offer a single monitoring solution, but a set of standalone packages, each addressing the monitoring and/or control of different sets of variables. In some cases, sensing packs and data analytics packs are also decoupled.

As far as the monitoring is concerned, most toolkits provide powder bed and/or melt pool sensing solutions, either exploiting co-axial or off-axial high-resolution cameras, as well as laser power sensing, either with optic fibers or infrared photodiodes. Several producers also provide system status monitoring, in the form of ambient condition data points measured inside the production chamber.

As far as the control is concerned, the majority of the tools offer very basic functionalities, using the collected data only for the post-process qualification of the piece or to trigger alarms during the production. In the most recent versions, some packages are able to perform early stop of the process or also to apply simple corrections (for example, re-distributing the powder on the build plate) or closed-loop control of a limited number of process parameters.

VIII. Open issues and future directions

From the review of the previous sections it is possible to derive a few final considerations.

To meet the industrial requirements in terms of part quality and process repeatability, metal PBF processes still need considerable improvements. In this regard, the latest advancements of in-situ monitoring technologies are creating new opportunities for the qualification and optimization of the process.

From the early stages of PBF technology, the highest amount of efforts have been devoted to:

TABLE II
COMMERCIAL TOOLKITS FOR IN-SITU MONITORING AND CONTROL. DASHES (–) ARE REPORTED WHENEVER INFORMATION WAS NOT PUBLICLY AVAILABLE AT THE TIME OF DATA COLLECTION.

PROPRIETARY SOFTWARE FOR SINGLE-BRAND MACHINES

PROCESS	PRODUCER	TOOLKIT NAME	MONITORED VARIABLES	SENSING TECHNOLOGY	TYPE OF CONTROL
DMLS	Concept Laser [147]	QM Meltpool 3D	Melt pool (area and intensity)	Co-axial camera and photodiode	Post-process
		QM Coating	Powder bed, metal powder (distribution)	High-resolution off-axial camera	Closed-Loop (powder distribution)
		QM Fiber Power	Laser power, melt pool (emission intensity)	Co-axial photodiode, co-axial IR camera	Alert + Post-process
		QM Powder	Metal powder (dimension, quality, and chemical composition)	Sieves	Alert
	EOS [148]	EOSTATE MeltPool	Melt pool (radiation intensity, emitted light), hatching distance	Co-axial and off-axial photodiodes with filters	Stop
		EOSTATE Exposure OT	Melt pool (emitted light), layer, entire build	Optical tomography, off-axial IR camera	Stop
		EOSTATE PowderBed	Powder bed (porosity, distribution)	Off-axial camera	Stop
		EOSTATE Base	Laser and scanner status, build platform position, build chamber conditions, recoater speed	Sensors (details not provided)	Stop
	Prima Additive [149]	Remote Care	Operation history, component usage	–	Post-process
		Human-Machine Interface	Building plate, dispenser, recoater, environment	–	Alert
DMP/DMLS	3D Systems [150]	DMP Inspection	Lack of fusion, warpage, roughness	Off-axial photodiodes	Post-process
		DMP Monitoring	Melt pool, surface (porosity), spatters	Integrated live cameras	Alert + Stop + Post-process
EBM	Arcam [151]	LayerQam	Layer (pattern, geometry, porosity), entire build	Off-axial high resolution camera	Alert
		xQuam Autocalibration	–	X-ray detection system	Closed-loop
		xQuam Future App	Material characterization	X-ray detection system	Alert
LMF	TRUMPF [152]	Process monitoring	Powder bed, melt pool, layer	Integrated cameras, sensors (details not provided)	Alert
		Condition Monitoring	Build chamber state (e.g. humidity, substrate plate temperature), ambient conditions, filter data, machine axes	Sensors (details not provided)	Alert + Stop + Post-process
		Performance Monitoring	–	–	Post-process
SLM	SLM Solutions [153]	Melt Pool Monitoring	Melt pool	Co-axial pyrometer, photodiodes	Alert + Stop
		Laser Power Monitoring	Laser output	Co-axial photodiode	Alert + Post-process
		Layer Control System	Powder bed	Off-axial camera	Closed-loop (powder bed)
		Sensors Systems	Machine environment	Machine dependent	Alert
		Live Camera	Entire process	Off-axial camera	Alert
	DMG MORI [154]	CELOS Watcher Monitor	Layer	Camera and sensors	Alert
		Optomet	Laser power, scan speed, hatching space	–	Closed-loop (inter-production)
	Matsuura [155]	LUMEX Avance-25 Run monitor screen	Laser sintering and milling	Camera, temperature sensor, auto tool measurement	Post-process
	SISMA [156]	MYSINT100 Monitoring	Operating parameters, powder bed (amount of powder)	Camera and sensors	Alert + Post-process + Closed-loop (powder amount)
	Renishaw [157]	InfiniAM Spectral	Melt pool, laser output	Co-axial camera, IR photodiode	Alert + Post-process
		InfiniAM Central	System status (e.g. running, cooling, idle)	–	Alert + Post-process
	ORLASER [158]	Creator	Laser speed, oxygen, gas flow, temperature	–	Alert + Closed-loop (input parameters)
	Xact Metal [159]	XM200C	Powder bed temperature, chamber temperature and pressure, oxygen	Two cameras, sensors (details not provided)	Post-process

THIRD-PARTY SOLUTIONS

PROCESS	PRODUCER	TOOLKIT NAME	MONITORED VARIABLES	SENSING TECHNOLOGY	TYPE OF CONTROL
DMLS	Stratonics [160]	ThermaViz Sensor suite	Melt pool, global heat flow	Two-wavelength pyrometer, IR thermal imaging sensor, both co-axial and off-axial	Alert + Closed-loop (process parameters) + Post-process
EBM/DMLS	Sigma Labs [161]	PrintRite 3D SENSORPAK	–	Co-axial and off-axial sensors	–
		PrintRite 3D INSPECT	Machine environment, melt pool (spectral data)	Co-axial sensors, thermal emission density	Alert + Stop + Post-process
		PrintRite 3D CONTOUR	Geometric information	Camera and sensors	Alert + Stop + Post-process
		PrintRite 3D ANALYTICS	–	–	Closed-loop (process parameters)

(i) characterising the process, by identifying the number and types of parameters involved, as well as the relation between specific parameters and part quality (see Section III);
(ii) designing in-situ monitoring technologies, by integrating multiple sensors able to inspect the layering process at all time and space scales (see Section V).

For the latter point, main open issues are related to the very tight requirements in terms of scale and time resolution for acquiring the signals (for example, for melt-pool monitoring), as well as in terms of data management and storage. On top of that, the harsh operating conditions of specific PBF processes (for example, the metallic vapour generated in the vacuum environment of EMB technology) set additional challenges for the hardware.

Even though a considerable gap between research and commercial products exists, the most advanced PBF systems are already offering large possibilities in terms of in-situ monitoring: as demonstrated by our review, sensors can be deployed to precisely detect and measure multiple types of signals and to deliver valuable insights for a deeper understanding of the PBF process. On top of that, the sensing capabilities of PBF machines are growing by the day (see Section VII).

Nonetheless, while the generation of huge amounts of sensing data are opening new unforeseen possibilities, especially for approaches employing data-driven models and machine learning (see Section VI), there are also major issues related to the efficient storage, retrieval, visualization and systematic analysis of such data. In our view, the research in this specific context is still at its very early stages.

The most critical obstacle to a full maturation of process control approaches is the lack of standardization. While each PBF build can potentially produce terabytes of data, there is a lack of a common reference data structure, as well as of standard practices and unified Application Programming Interfaces (API) for storing and handling information with a real *big data* approach. In absence of this standardization, the accessibility and integration of these data is considerably limited. This, added to the difficulty and costs related to data annotation, sets many challenges to the creation of suitable databases to train and validate ML algorithms. Indeed, most research groups develop their algorithms on very small data sets in terms of number of builds and experimental conditions, narrowing down their scope to a small sub-set of the process parameters or to a specific level of sensing detail. This raises the risks of overfitting and reduces the actual robustness and significance of the proposed models.

A first step towards the development of a standard and well-defined data-structure for AM processes, including PBF, is the AM Material Database (AMMD) [162]. This is an open platform developed by the National Institute of Standards and Technology (NIST) leveraging a Not Only Structured Query Language (NoSQL) engine, which provides a flexible data schema that is suitable to AM, and a Representational State Transfer (REST) API to allow the integration with other Web services, data entry, query, and retrieval. As it is conceived as a collaboration platform, the database is set to evolve through the open data access and material data sharing among the AM community. Hence, as datasets provided by different research groups will continue to accumulate, it will hopefully help establishing new correlations between processes, materials and parts, and provide a reliable benchmark for the training and validation of new ML solutions.

In conclusion, the standardization of data acquisition and management and the development of unified and large datasets for PBF process characterization will strengthen the use of data fusion and deep learning techniques, fostering a more holistic approach to the qualification and optimization of PBF processes. In the long run, the standardization of the data-formats will also enable a better interoperability of different machines and systems within the factory, finally achieving a full compliance of AM with the emergent Industry 4.0 standards and reference architectures [163], [164].

Acronyms

AM Additive Manufacturing.
DED Directed Energy Deposition.
DMLS Direct Metal Laser Sintering.
DMP Direct Melt Pool.
EBM Electron Beam Melting.
LBPF Laser Powder Bed Fusion.
LMF Laser Metal Fusion.
PBF Powder Bed Fusion.
SLE Selective Laser Erosion.
SLM Selective Laser Melting.
SLS Selective Laser Sintering.
STL Standard Triangulation Language.

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