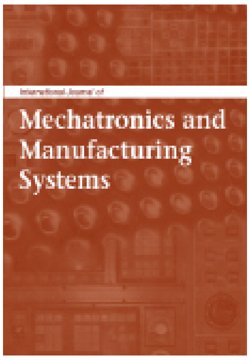

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A review on in-situ process sensing and monitoring systems for fusion-based additive manufacturing

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A review on in-situ process sensing and monitoring systems for fusion-based additive manufacturing

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Abstract: In additive manufacturing (AM), parts suffer from quality variations, defects, intricate surface topography, and anisotropy in properties that are known to be influenced by factors including process parameters, layerwise processing, and powder melting and fusion. Their influence on process signatures also makes AM processes not fully manageable creating unacceptable levels of inconsistency. To detect the fusion quality with a purpose of quality predictions, in-situ process sensing and monitoring with sensors is often utilised with the goal that AM process can be controlled for consistency in quality. This paper provides a review of the literature on in-situ process sensing and monitoring methods and discusses research challenges and future directions for further efforts. Currently, sensory data is used for data analysis and making mostly off-line quality quantifications and predictions. The future goal is to develop intelligent AM systems that use in-situ process data for making automated intervention and quality control decisions.

Keywords: additive manufacturing; smart manufacturing; PBF; powder bed fusion; metals; sensing; monitoring; fusion; sensors; measurement; quality; defects; machine learning; deep neural network.

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1 Introduction

Metal additive manufacturing (AM) is rapidly spreading and finding applications in various industries including medical implants, automotive, and aerospace parts with complex geometries and structures. In the last decade, numerous investigations have been conducted for making continuous improvements on the process consistency, system robustness, and repeatability for further applications of metal AM technologies in industry.

Most metal AM systems employ powder bed fusion (PBF) processes where PBF processes own half of the total metal AM market share (Vafadar et al., 2021). PBF processes use high laser or electron-energy beams to scan selective areas of a powder bed to generate 3D parts. Advances in powder-bed fusion techniques such as laser powder bed fusion (L-PBF) and electron beam powder bed fusion (EB-PBF) empower limitless design and hence entail far more engineering decisions to be made on the selection of predefined operational process parameters. Furthermore, the geometrical complexity and desired flexibility of an additively built structure bring substantial uncertainty about the mechanical properties as a consequence of the large number of process-design decision variables (Yadroitsev et al., 2021).

In fact, industrial sectors such as aerospace and medical that are tightly controlled and regulated have been driving the innovation in metal AM technologies. As a result, issues such as defect detection and prevention as well as rapid qualification gained more importance. This necessitated an imperative demand for discovering innovative tools and methods for process qualification and control that should achieve a robust printing process and defect-free production as pointed out by Colosimo et al. (2018). Online quality prediction and control can be achieved using physics-based models or data-driven models mapping the relationships between the process features and final quality indicators (Vastola et al., 2018; Zhu et al., 2022).

On one side, the layerwise nature of metal AM allows the ability of acquiring a large amount of process data to monitor characteristics related to part quality as well as understanding relevant process signatures that are representations of the stability and robustness of the AM system. On the other side, data analytics, statistical methods and deep learning techniques are needed to analyse the large streams of data (sometimes as large as terabytes) collected during the process, to construct effective tools for robust and automated defect detection as suggested by Kwon et al. (2020).

This review paper provides an overview of the challenges, limitations and opportunities related to in-situ process sensing and monitoring solutions for first time-right and zero-defect production in metal AM, in particular PBF, processes. This review paper also gives an overview of current monitoring systems and examples of how they are used in the fusion-based AM processes. The importance of monitoring systems can be seen in the most recent systems placed on the market over the past several years – nearly every machine manufacturer in the field of additive manufacturing provides a monitoring solution for their machines. In Section 2, a brief review of anomalies and defects in PBF processes is given. In Section 3, a review of in-situ process sensing and monitoring methods is summarised. In Section 4, research studies toward in-situ process monitoring are reviewed. In Section 5, stages of in-situ process sensing and monitoring techniques are categorised for their effectiveness in providing solutions to monitor layer, fusion, or part quality during L-PBF processes. In Section 6, some research directions toward in-situ process monitoring, and process control are reviewed and summarised. In Section 7, some remaining challenges and future research directions are portrayed. In Sections 8 and 9, some discussion and final conclusions are provided.

2 Anomalies and defects in PBF processes

PBF is an AM process where thermal energy is supplied to a powder bed for heating, melting and fusing the powder material. The laser (or e-beam) scans the 2D layers of the 3D CAD model on the powder bed, subsequently the powder bed is lowered, and another layer of the powder material is spread on the bed and the laser scans a new 2D layer. The process is repeated until all the layers of the 3D model are completed. The process can use a wide range of materials; some of them are polymers (elastomers, nylon), metals (titanium, steel), ceramics (alumina), and composites as well. Due to the wide variability in materials its applications are vast in following areas such as electronics, rapid tooling, injection mould inserts, military, casting, healthcare, and engineering design verification. Conversely, the surfaces generated by the PBF processes are also expected to satisfy the design requirements. To that end, the requirements for new and effective measurement techniques are outlined (Mani et al., 2017) and the generation AM'ed surfaces and their relations to the overall quality of the fabricated parts are studied by several research groups. Thompson et al. (2016) examined the surfaces of the printed (as-built) parts using confocal laser scanning microscopy (CLSM) and interferometry metrology. Other researchers used fringe projection methods to distinguish surface topography during L-PBF processes, e.g., Land et al. (2015) and Zhang et al. (2016). Later, Townsend et al. (2018) utilised X-ray computed tomography (XCT) to obtain surface texture data and discover internal defects underneath the as-built surfaces. Post-process investigations conducted by Özel et al. (2018, 2020) focused on analysing areal surface topography and the relations between surface texture parameters and the L-PBF process parameters by using focused variation microscopy, image processing and machine learning methodologies.

The surface topography of the PBF fabricated structures depicts various process defects and anomalies (Leach et al., 2019). As a main texture, fusion lines along tracks appear as ridge-like formations indicating the scanning path followed by the laser beam while traversing on the powder bed surface as illustrated in Figure 1.

There could be defects coming from smaller-scale ripples on the fusion lines that are formed because of meltpool thermal cycles during melting and solidification as the laser beam moves across the powder bed surface (Townsend et al., 2018). Lack of fusion defects also form on the surface during PBF such as under-melted powder particles or powder spatter fell back on the surface typically appear as small, randomly distributed sphere-like protrusions on the as fabricated part's surface (Cunningham et al., 2017; Promoppatum and Yao, 2019). Surface recesses are indicative of multiple phenomena: localised discontinuities of the fused tracks due to balling effects, incomplete powder fusion between adjacent fusion lines and porosity defects due to gas entrapment (Tammas-Williams et al., 2015). In PBF metal AM, powder spattering is a major cause of defect formation thereby affecting the quality of the component being produced (Criales et al., 2017; Ly et al., 2017; Wang et al., 2020; Yakout et al., 2021). These detrimental effects may result in part failure and that is why the study of the spatter and its effect on the part is a crucial aspect of PBF. The detailed classification of these defects and anomalies and their effects on quality is given in Table 1.

Table 1 Manufacturability issues, causes, and effects on quality in PBF

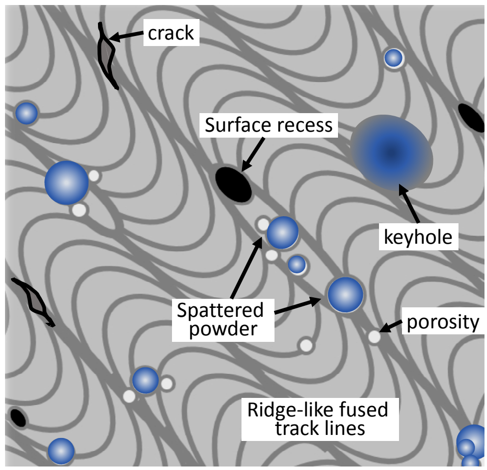
	Causes	*Effects on quality*	*References*
Porosity	Mainly due to incomplete fusion and spattered material related roughness on the surface as well as bubble entrapment during turbulent flow and gasification within the meltpool	Random occurrence of porosity creates undesirable quality issues on mechanical properties as well as deducing from full density of the fabricated parts	King et al. (2014), Ly et al. (2017), Cunningham et al. (2017), Criales et al. (2017), Wang et al. (2020) and Yakout et al. (2021)
Lack of fusion	Insufficient energy density creates a meltpool that does not sufficiently encapsulate the current powder layer thickness, track width (or hatch spacing), resulting in incomplete powder volume melting hence lack of fusion	Section of the powder bed processed with lack of fusion creates accumulation of unmolten powder particles eventually lead to large voids and porosity and locally weak mechanical properties	Cunningham et al. (2017), Promoppatum and Yao (2019) and Coeck et al. (2019)
Cracks	Thermal gradients during laser scanning on heating and cooling creates a mismatch of material thermal expansion and shrinkage behaviour causing thermal cracks to form on or below the surface of the powder bed. Solidification cracking occurs during last stages due to a combination of solute-rich liquid entrapment between solid interfaces and tensile residual stresses that pull the interfaces apart	Surface cracks can be remedied to a certain extend with polishing and post processing, but internal cracks are highly undesirable and hard to detect causing significant sacrifice in structural and surface integrity of the builds	Carter et al. (2012), Carter et al. (2014), Yadroitsev and Yadroitsava (2015) and Ghasemi-Tabasi et al. (2022)
Residual stress	Steep spatial and thermal gradients can leave some thermal stress build-up during laser scanning leading to formation of residual stresses in the parts fabricated	Residual stresses cause significant issues to the geometrical quality of the parts as well as the life cycle quality and reliability. Post-processing using heat treatment and machining can provide stress relief but cannot reverse stress-induced distortions or cracking	Mercelis and Kruth (2006), Zaeh and Branner (2010), Van Belle et al. (2013), Krauss et al. (2014), Mukherjee et al. (2017) and Serrano-Munoz et al. (2021)

Table 1 Manufacturability issues, causes, and effects on quality in PBF (continued)

	Causes	*Effects on quality*	*References*
Balling	Balling is attributed to formation of large spheroidal beads around the laser beam due to poor wetting between liquid meltpool and powder bed surface and causing not being able to form a consistent fused track during laser scanning	Creates voids, discontinuities, and high roughness on the powder bed surface and leaving a further quality issue to the newly spread powder layer and distorting fusion quality in laser scanning of next layers	Li et al. (2012), Zhou et al. (2015), Promoppatum and Yao (2019), Wang et al. (2021) and Li et al. (2021)
Keyholing	Excessive energy density applied on powder layer surface evaporates metal particles causing a cavity voided by metal vapour. In return, due to the reaction force from the liquid metal evaporation in melted region drives down liquid metal towards subsequent layers resulting in a narrow, deeper, and elongated meltpool dimension	Keyholing effects create porosities in a spheroidal shape in contrast to those from the lack of fusion the ones create greater void shape irregularity. Internal porosity causes quality issues related to lack of full density, inconsistent mechanical properties and shorter life cycle of the parts	King et al. (2014), Cunningham et al. (2017), Promoppatum and Yao (2019) and Wang et al. (2021)
Geometric distortions	The cyclic thermal expansions and contractions from laser scanning result in residual stresses that produce geometric distortion in the component	Geometric distortions negatively impact part dimensional and shape quality	Mukherjee et al. (2017), Yang et al. (2018) and Serrano-Munoz et al. (2021)
Layer delamination	Large and sudden changes in the laser energy density and slow densification can lead to layer delamination. Excessive thermal stresses cause part delamination	Layer or part delamination results in unsuccessful and non-repairable build geometries and creates scrap parts	Alimardani et al. (2009), Griffiths et al. (2020) and Yakout et al. (2021)
Surface defects	Surface roughness is predominantly caused by partially melted particles, and surface defects are mainly due to collision of recoater blade with these curled and rough areas on powder bed surface	Surface defects, irregulars on surface finish or geometrical deviation can significantly reduce the performance of the part	Leach et al. (2019), Wang et al. (2020), Jones et al. (2021) and Yakout et al. (2021)

There has been significant research effort dedicated for determining underlying causes for defect occurrences in PBF processes, correlations between these defects and the overall print quality, and how these defects can be eliminated by controlling PBF process parameters. For metal AM processes, issues associated with process stability, repeatability of print quality, and dealing with underlying causes of defects are identified as major hurdles limiting applications of these processes in industry and requiring further advances in technology for streamlined production. In that aspect, further advances in automated process sensing, monitoring, and control of metal AM systems should be a precedence for achieving a breakthrough towards effective means of production.

Figure 1 Possible defects on the as-fabricated surfaces topography in L-PBF (see online version for colours)



3 In-situ process sensing and monitoring methods

A review for in-situ sensing, process monitoring, and machine control in L-PBF is given by McCann et al. (2021). This review identified that thermographic sensors and high-resolution imaging sensors are mainly used for conducting research on in-situ, *in-process* measurements during AM processes. Also, there are a group of *post-process* measurements for the dimensional accuracy, surface roughness, porosity, mechanical strength, and residual stress that is generally focused on assessing print quality and mechanical properties. Among those, imaging-based measurements can include 3D optical scanning profilometers, white light interferometers, and confocal microscopes, which are capable of producing high-resolution 2D surface or 3D areal measurements, as well multi-scale micrographic analysis focused on microstructure characterisation.

The definition of a process signature can be made as an observable or measurable feature obtained from sensory data collected from the L-PBF process. Depending on the nature of the process interest there could be various signals to be extracted from the process using means of thermal, optical, acoustic, vibratory, electrical or magnetic field sensing at the powder bed, on the molten pool, or among the layers. The leading sensory signal has been the optical or thermal images where imaging-based in-situ process monitoring was performed using charge-coupled device (CCD) or complimentary metaloxide semiconductor (CMOS) cameras or photodiode probes either infrared (IR) or near infrared (NIR). The acoustic signal has been well studied and found useful to make characterisation about the L-PBF process when acoustic transducers or microphones are employed in the L-PBF machine (Pandiyan et al., 2020, Gutknecht et al., 2021; Kouprianoff et al., 2021; Drissi-Daoudi et al., 2022).

The monitoring of PBF processes related research efforts can be classified most generally into three major categories:

i meltpool monitoring

ii powder deposition monitoring

iii monitoring of defects on layers or parts.

The monitoring stage can be grouped into three major categories:

i in-situ process

ii ex-situ process

iii post-process stages as outlined in Table 2.

Table 2 Monitoring methods and stages for L-PBF

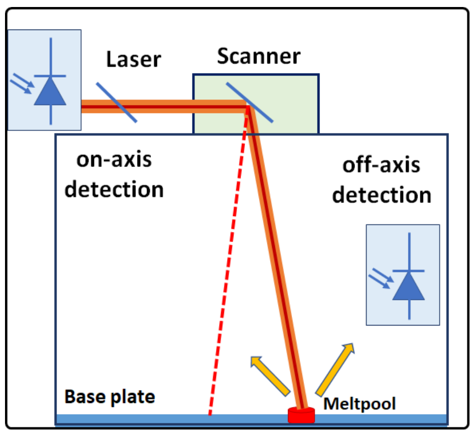
Parameter	*Monitoring method*	*Monitoring Stage*	*References*
Meltpool	Camera (CCD/CMOS)	In-situ process	Yadroitsev et al. (2014), Mazzoleni et al. (2020), Repossini et al. (2018) and Fischer et al. (2021, 2022)
	Camera (IR/NIR)		Criales et al. (2017), Yang et al. (2020) and Mohr et al. (2020)
	Pyrometry		Montazeri et al. (2020), Mitchell et al. (2020) and Dunbar and Nassar (2018)
Powder spreading and deposition	Camera (CCD/CMOS)	Ex-situ process	Craeghs et al. (2011)
	Camera (IR/NIR)		Liu et al. (2022)
	Fringe projection		Zhang et al. (2016) and Kalms et al. (2019)
Defects on layers	Camera (CCD/CMOS)	Post process	Mohr et al. (2020) and Imani et al. (2018)
	Fringe projection		Zhang et al. (2016)
	Line scanner		Fischer et al. (2021)
	Optical tomography		DePond et al. (2018)

To date, much of the early work involving *in-situ* monitoring of fusion-based AM has involved collecting *in-process measurements* (Heigel and Lane, 2015; Grasso et al., 2016; Criales et al., 2017; Yang et al., 2020) but the data is analysed after the build is complete (Townsend et al., 2018; Thompson et al., 2017; Colosimo, 2017; Grasso et al., 2017; Özel et al., 2017).

The most important constraint in in-situ process sensing and monitoring is the difficulty to observe and detect the shape and size of dynamically changing meltpool on the powder surface in the powder bed during L-PBF process. The interaction between powder material and laser beam that is moving at a high velocity generates a tumultuous phenomenon consisting of liquid bubbles, molten particles, and a plume mixture of metal vapour and gases. Those molten and flying plumes often fall back on the powder bed surfaces and weld themselves to the solidified sections producing a variety of irregularities. As a result, various sizes of gas pores, re-welded powder particles, and micro-voids form on the solidified tracks. Even though, it is highly challenging for optical and thermographic cameras to monitor and capture such anomaly occurrences and process a large volume of video and streaming image frames online and real-time by filtering and feature extraction as of yet, this technique is still a viable solution for automated defect detection and avoidance in L-PBF metal AM.

In-situ process sensing and monitoring of meltpool in L-PBF can be performed by using on-axis detection or off-axis detection techniques (see Figure 2).

Figure 2 In-situ process sensing and monitoring during L-PBF (dotted line indicates the origin of the laser beam and back arrows indicate spattered particles) (see online version for colours)

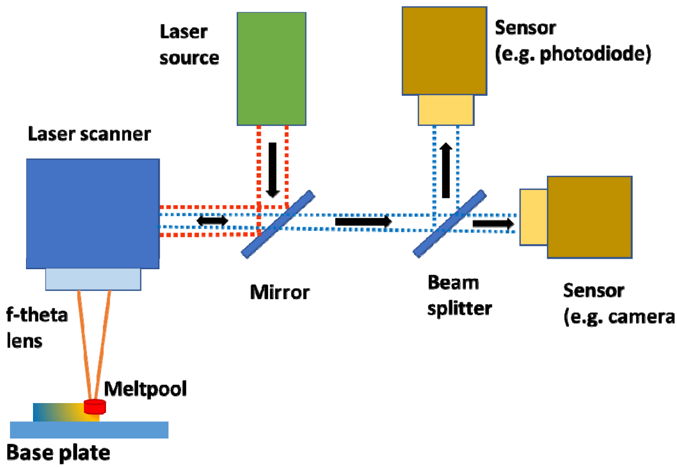


3.1 In-line and on-axis cameras

The cameras (non-visible wavelengths) deployed in-line with the laser beam (in other words on-axis) are utilised to measure directly the meltpool size and monitor its movement as well as mean radiation emitted in its vicinity so that the occurrence of high-density concentration or overmelting can be avoided together with the byproduct of forming spherical pores.

Yeung et al. (2022) utilised a co-axial meltpool monitoring camera operating at 10 kHz frame rate which was equivalent to an inter-frame interval of 80 μm at 800 mm/s laser scan speed, comparable to the 85 μm laser spot size in a custom build L-PBF testbed for processing Inconel625 alloy. According to these researchers, the emitted light from the meltpool, which is filtered at 850 nm (±20 nm bandwidth), was directed by a dichroic mirror to the camera sensor with nominal 1:1 magnification and 8 μm pixel size similar to the on-axis monitoring system depicted in Figure 3.

Figure 3 On-axis monitoring of meltpool and optical tomography during L-PBF (see online version for colours)



Other layerwise monitoring techniques include the use of high-resolution cameras (visible wavelengths) for image acquisition and a Bayesian classifier to identify layer quality and detect surface porosity from the layer cross-sections a part (Aminzadeh and Kurfess, 2019). Continuous monitoring technologies include using less expensive but high-speed optical cameras with stereo vision to observe formation of spatter and velocities of spatter particles during L-PBF process, and then to correlate with under or over melting conditions (Barrett et al., 2018). The high-speed camera technique has also been used for observation of crack formation to identify L-PBF parameters being less prone to hot cracking (Vrancken et al., 2018).

3.2 Pyrometry

Pyrometry which is known as the measurement of surface temperature by the characteristics of the radiation that is emitted, is often employed for measurement of the temperature and meltpool characteristics in-situ with an objective to observe and possibly controlling meltpool dimensions by establishing a correlation between layer thickness and meltpool size. The one-colour pyrometry can only provide single-point light emission signal or spectral irradiance at one specific wavelength which cannot be used to infer real temperature value or profile. However, a temperature known as brightness temperature can be computed from measured spectral irradiance as calibrated by using a black body source and a target spectral emissivity. The challenge in this method to be employed for meltpool temperature monitoring is that the emissivity of the meltpool region can only be guessed. The use of two different wavelength pyrometry provides a possibility to measure spectral irradiance at two wavelengths as ratio (known as two colour pyrometry ratio temperature) by calibrating the pyrometer on a black body and assuming that the target would behave as a grey body between these two wavelengths the pyrometer is calibrated for Müller and Renz (2001). The two-colour pyrometer technique is used successfully for process monitoring and measurement of meltpool temperature (Furumoto et al., 2013; Gutknecht et al., 2020; Gutknecht et al., 2021; Artzt et al., 2020; Vallabh and Zhao, 2022).

Typically, the field of camera view in CCD-cameras is restricted, while laser back-radiation distorts images and sluggish data acquisition rates cause skipping frames. Moreover, powder metal vapourisation and material spatter generate high levels of glare and noise in the imaging zone. On the other hand, both off-axis CCD-cameras and pyrometers are employed for meltpool observation to make a correlation between the data from CCD-cameras and pyrometers and the shape of the meltpool (Chivel and Smurov, 2010; Yadroitsev et al., 2013).

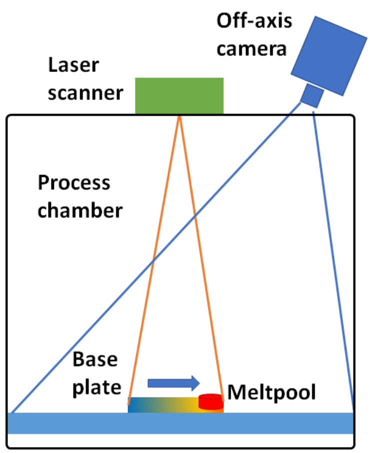
In a semantic study, Lane et al. (2020) described the use of a reflectometer-based instrument to measure the dynamic laser energy absorption during scanning of single tracks. They offered an explanation for the relationships between dynamic laser absorption, co-axial meltpool monitoring (MPM,) and surface features on these tracks. The dynamic absorption and MPM measurements showed that specific instances of meltpool instability may be observed on a bare plate, but not on powder surfaces, thereby not yielding realistic localised or point-defect monitoring. They reported that the depth of the meltpool depth is a strong indicator of keyhole mode transition. Their study included that the features they observed where dynamic laser absorption appeared highly coupled to the MPM photodetector signal when scanning on bare metal surface. They observed that the MPM photodetector signal is more related to surface morphology or keyhole depression formation than meltpool temperature or size (see Figure 3). It was also observed that MPM photodetector signal was highly correlated to the average coupling efficiency, which in turn, was observed to be correlated to the meltpool morphology. They concluded that the pyrometer signals depend on the L-PBF process parameters (power, layer thickness, hatch distance, and scanning velocity) and correlations between photodiode signals and overall porosity ought to be pursued. In addition, in their semantic study (Demir et al., 2018) used thermal emission signals in the visible range and demonstrated that it is possible to link the thermal data obtained from thermal emission tracking-based temperature monitoring to the porosity formation in L-PBF metal AM.

3.3 Thermographic imaging

The use of thermographic imaging using infrared or near infrared wavelength cameras is one more in-situ process measurement method that offers moderate fidelity with higher (>100 frames per second) frame rates (which means faster image updating or more still images are packed into each second of video). High speed IR imaging also requires fast integration times typically down to microseconds for a capability of capturing data at greater than 1000 Hz. The thermographic imaging measures heating and cooling rates as thermal gradients on the powder bed surface during L-PBF processing. In-situ process monitoring research efforts counted on thermographic IR imaging as a non-contact off-axis monitoring method. In one of the earlier studies, Krauss et al. (2014) utilised this method and attempted to evaluate residual stress initiation and heating related anomalies such as pores or surface irregularities using measured thermal gradients obtained from thermographic imaging. The limitation is mostly on the location of the camera for a better field of view and resolution with a trade-off between optical cleanliness due to intense plume accumulation and being able to obtain a high-fidelity thermal image.

The off-axis NIR camera technique is often used for monitoring the plume and spatter for obtaining a correlation between L-PBF parameters and meltpool conditions (see Figure 4). Studies are conducted (Dinwiddie et al., 2013; Grasso et al., 2018) using this technique for sensing meltpool plume during L-PBF process and correlating thermal images to identify stable or unstable processing conditions. Other studies on correlation analysis are reported for using deep neural network (DNN) methods such as deep belief networks (Ye et al., 2018). Several other studies used on-axis NIR camera that is combined with photodiode (Berumen et al., 2010) for detecting meltpool conditions (i.e., meltpool intensity, area, length and width) (Clijsters et al., 2014), identifying defects, and controlling of process parameters for meltpool control, and managing dimensional quality in overhanging section of the 3D build (Craeghs et al., 2011). It is reported that the major problem with thermographic camera imaging is the plume accumulation on camera's lens surface inside the L-PBF machine's build chamber. When the IR camera is mounted on the outside of the build chamber (typically far away from the laser scan on the powder bed surface) then there is the issue of field of view being not sufficiently close to the target, installing long range optics and possibility of obtaining poor resolution as a result.

Figure 4 Off-axis monitoring of meltpool and optical tomography during L-PBF (see online version for colours)



3.4 Off-axis cameras

Mounting the either optical (visible wavelength) or thermographic (IR ot NIR) camera off-axis to laser beam axis results in a monitoring approach that is considered an angled view to the laser beam spot and meltpool (see Figure 4). Typically, off-axis cameras offer a very limited field of view on the build plate. However, this arrangement can also be employed to monitor the powder bed surface from the top view. As an example, to the use of off-axis camera monitoring, Heigel and Lane (2018) performed high speed thermographic measurements of the meltpool length during single track laser scans on nickel alloy 625 substrates using an IR camera as off-axis for the measurements of the radiation from the powder surface at a frame rate of 1800 frames/sec. In a breaktrough study, Criales et al. (2017) analysed the powder material spattering behaviour of high velocity laser scanning from the thermal images obtained during in-situ thermal monitoring using an off-axis thermographic camera (1800 frames/sec at a resolution of 360×128 pixels) and a relevant thermography (filter with wavelength of 1350 nm to 1600 nm). They performed a quantitative analysis for the meltpool size and amount of spattering behaviour using digital image processing and machine learning methods. Furumoto et al. (2013, 2018) used high-speed cameras deployed off-axis to monitor the melting process. Yang et al. (2020) utilised a high frame rate off-axis optical camera setup mounted at the door of the L-PBF machine for monitoring and characterisation of meltpool and overall observing abnormalities in the powder bed. The meltpool shape and the surrounding region were detected in grey scale via in-situ observation to signify the causes for detecting defects and irregularities. The videos acquired were analysed by using digital image correlation techniques and statistical process control (SPC) approaches. They were able to automatically detect from the analysed video images occurrences of undermelting, overmelting, and material spatter and concluded that this technique can be used for correlating the streaming images to localised defects, layerwise anomalies and layer delamination.

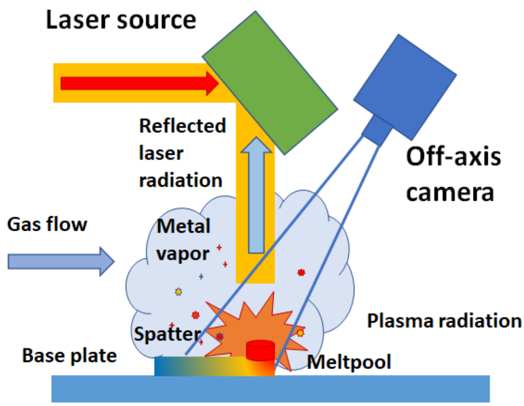
3.5 Thermoelectric magnetic field

The thermoelectric magnetohydrodynamic method used by Kao et al. (2020) investigated the hydrodynamic mechanisms introduced by magnetic field and then they used the result of steady state solutions to predict microstructure evolution using cellular automaton-based grain growth. The research results clearly state that microstructure characteristics are strongly dependent on magnetic field orientation. A large thermal gradient is produced by rapid heating and rapid cooling in metal AM process resulting in large thermoelectric currents and when a magnetic field is applied to process it creates thermoelectric magnetohydrodynamic effect that causes forces that alter the meltpool flow. In their earlier experiments Kao et al. (2018) used a pyrometer to measure the surface temperature of the sample during each cycle of melting and subsequent solidification and a high-speed camera to monitor and record the thermal front progression in nickel dendrites in a vacuum chamber with heating coils. Later studies by Fan et al. (2023) demonstrated some advanced uses of the thermoelectric magnetohydrodynamic effect in characterising meltpool flow during directed energy deposition (DED) based metal AM. They revealed that when no magnetic field is used, Maragoni convection in meltpool is in effect during meltpool flow, but when a magnetic field is imposed it can disrupt meltpool flow and be utilised as a characterisation tool by tracking the flow of certain particles in combination with in-situ high-speed synchrotron X-ray radiography-based process monitoring.

A laser source typically generates reflected radiation, plasma radiation, airborne sound, and acoustic waves on the surface of the powder bed (see Figure 5). The infrared from the radiation can be used to detect the meltpool, metal vapour, material spatter by using measurement methods such as Eddy current, X-ray backscattering, radio frequency emission, and optical coherence tomography.

All of these monitoring techniques have demonstrated effectiveness in meltpool control (shape, size and consistency in response to change in L-PBF process parameters), detecting anomalies and irregularities in build quality by acquiring in-process data but oftentimes analysing the data off-line. However, they are based for monitoring only the surface of the powder bed and are not utilised within a quality control framework to obtain process signatures that can be used to rapidly qualify and certify the build layer quality or for controlling the part defects.

Figure 5 Laser source, reflected radiation, plasma radiation, metal vapour, and spatter during L-PBF (see online version for colours)



4 Research using in-situ process sensing and monitoring

There have been reviews conducted that summarise the research studies toward process monitoring specifically statistical methods in AM processes (Tapia and Elwany, 2014). Various in-process monitoring capabilities for laser-based AM processes, and mostly for L-PBF systems) have been developed and employed to measure meltpool conditions. In separate works, both Everton et al. (2016) and Grasso and Colosimo (2017) provided extensive reviews on in-situ process monitoring for laser-based AM techniques. Grasso et al. (2016) utilised an off-axial imaging system and obtained a principal component analysis (PCA)-based statistical descriptor that is employed to the acquired images and revealed that their technique was appropriate for the detection of faulty spots. Soon after, Repossini et al. (2018) separated both spatter- and plume-related elements using a thermal imaging method and explained their potential for identifying in-situ process situations. Around the same time, Grasso and Colosimo (2017) suggested a real-time process monitoring system with spatter evaluation to accomplish the desired characteristics by using feedback control in metal L-PBF technique.

Previous research studies on L-PBF process monitoring have concerned with gathering digitised data from the process and analysing the process data after the part build is done as a post-processing scheme. Berumen et al. (2010) offered a co-axial monitoring system using a photodiode for measurement of the optical intensity. Later on, Craeghs et al. (2011) and Clijsters et al. (2014) measured meltpool conditions such as meltpool area, length, and width, as obtained from imaging measurements by using this co-axial monitoring system and determined that these were successful for detecting localised voids and pores.

Other research studies utilised in-line cameras for monitoring and measuring the meltpool dimensions using the radiation back-emitted with an aim to reduce the occurrence of over-melting and the likelihood of forming pores. Kanko et al. (2016) relied on an in-line coherent imaging for in-situ detection of defects in L-PBF. Spears and

Gold (2016) utilised another imaging technique for similar reasons. Some other research efforts by Doubenskaia et al. (2010, 2012) counted on the pyrometry technique for in-situ monitoring meltpool size and measurements of temperature and with an objective of regulating meltpool and correlating its size with the layer thickness. However, this procedure was found to have several shortcomings such as the problem of the field of view, the challenge in obtaining good data capture rates, imaging distorted by radiation, required handling of filters in order to deal with laser back-emittance and radiation.

Other research studies utilised high-speed cameras mounted on the L-PBF machine for the purpose of monitoring the meltpool and examining anomalies on the powder surface. Lott et al. (2011) devised a system by using three optics principles (i.e., a relay, a telephoto, and a single objective lenses) with a goal of high quality and obtaining high meltpool magnification during in-situ monitoring of L-PBF process. This technique was noticed to be very helpful where the accumulated data volumes are often evaluated after the build is finished. The spattering and the haze caused by powder particles splattering (scattering large particles of molten particles) are detected through high-frame rate imaging. To spatter means to scatter small particles of the powder material in L-PBF. A spatter is the pattern of molten drops that result from spattering. A splatter is the pattern of drops that result from splattering. Due to splattering particles developing during L-PBF activity, powder haze may harshly impact the quality of the manufactured parts and produce defects within the microstructure to reduce the mechanical properties. It was noted that significant powder spatter discharged from the meltpool as the laser light irradiated and illuminated on the surfaces of the powder layer (Ly et al., 2017).

Arnold et al. (2018) used a backscatter electron detector in the interior of the build chamber of the EB-PBF machine that is utilised for image collection through commercial Arcam LayerQam process monitoring system that functioned in the range of visible light with some extension into the IR region. They provided in-situ images obtained by in-process layerwise electron optics image acquisition and compared images obtained with the ones from optical microscopy and XCT. They concluded that spatial resolution was found sufficient for detecting major flaws like surface defects while disadvantages restricting other monitoring techniques and pointed out that presenting extra off-axial detectors to collect more data about surface topography would advance monitoring competences.

Egan and Dowling (2019) investigated L-PBF of lattice structures in Ti-6Al-4V alloy with intended porosity (major pore diameter ranging from 1106 μm to 932 μm) using a co-axial in-situ monitoring system. Their monitoring system provided feedback on the laser energy input and the level of intensity of emissions from the meltpool during processing where collected data was used in reconstructing 2D/3D in-situ views in near real time. Specifically, they altered the laser beam spot size to observe its effects on the cellular structures fabricated with L-PBF and noted that a broadly linear correlation was obtained between the laser input energy, the associated process monitoring data generated and the mechanical strength of the lattice structures. Egan et al. (2021) investigated the defective layers in lattice structures fabricated in Ti-6Al-4V alloy via L-PBF using in-situ process data obtained with a co-axial photodiode-based monitoring system and statistical anomaly detection techniques. They used the generalised extreme studentised deviate (GESD) test technique to detect one or more anomalies in a univariate dataset and then to classify each layer as ‘defective’ or ‘no defective’ that occurred during the L-PBF build process.

Yang et al. (2020) used a high frame rate camera-based imaging system for in-process monitoring of L-PBF process and determined that the spattering is separated from the meltpool and its surrounding area and indicates remarkable variations in size and spluttering direction. They stated that the spatter due to high laser density produces different irregularities and decreases the quality of the build. High laser energy densities can produce overmelting and also initiates wide heat affected regions consequently resulting in substantial spattered particles causing internal voids, pores, hot cracking, and layer separation. These irregularities triggered by overmelting and undermelting can be alleviated by employing an adaptive control scheme that can selectively modify localised laser energy density by sensing the spatter intensity at a certain spatial and temporal occurrence.

Becker et al. (2022) discusses about an optical tomography technique using a bi-chromatic optical tomography to simultaneously monitor the emitted process radiation of two separate wavelengths using two temperature calibrated cameras for in-situ quality control. This approach helps in estimating the local maximum temperatures which in turn increases the comparability of monitoring data. An NIR spectrum operated off-axis positioned camera is used to capture spatially determined extended-time exposure images of the L-PBF process. It is observed that interpreting temperature association of process data that is filmed using a camera that works on a particular wavelength is difficult due to the process intrinsic factors such as vapour plume on the meltpool, spattering, emissivity values. Their bandpass filter range was close to each other between 500 nm and 550 nm and the range for monitored temperature differences of signal intensity ratio measured was very little and within the range of signal noise. They concluded that to get better resolution, fine tuning of individual cameras needs to be optimised to avoid additional median blurring of one image. Furthermore, to reduce the quantifying uncertainty due to intrinsic precise image fitting, industrial dual-wavelength cameras can be used. Finally, they proposed that bi-chromatic tomography can be used to measure the temperature on the surface using a low-cost apparatus in the visible range.

Chicote et al. (2022) studied different defect identification techniques related to L-PBF of Inconel 718 alloy using an integrated co-axial in-situ process monitoring technique. The commercial LaserVIEW and MeltVIEW systems in Renishaw RenAM500Q L-PBF machine were operated. They reported that the LaserVIEW system is an IR photodiode integrated on the optical component to measure lasers emissions, operating at 1070 nm wavelength while MeltVIEW system is an optomechanical set that obtains the L-PBF process emissions with two photodiodes to detect plasma emissions (700–1050 nm) and thermal radiation (1080–1700 nm). Both monitoring systems are able to measure emission levels at 100 kHz sampling rate without interfering laser system's function. The layerwise data from laser position coordinates is constructed as acquired from the position data in galvanometer. After the build process, this data is analysed using the InfiniAM Spectral software that provides a virtual environment to monitor the emission levels by constructing layerwise or 3D views from the fabricated build geometry. This system was used in their research to evaluate the various build samples according to emission levels to identify the produced defects and quantify their geometry. Chicote et al. (2022) concluded that the resolution of this commercial on-axis monitoring system is not enough to determine the gap related dark zone even though the system is useful for visual inspection of build samples for defects detection.

Pandiyan et al. (2022) utilised a monitoring strategy that measure different aspects of L-PBF process with sensing system that uses signals from optical coherence collimator, namely photodiode detector with back reflection capability, visible, infrared, as well as acoustic sensor that releases structure-borne acoustic emission signal coming from the base plate. The system was connected to deep learning system for training and prediction purposes. The resultant system was able to detect operation regimes including the conduction mode, keyholing, and lack of fusion during L-PBF process. The learning process for the convolutional neural networks was reported to be quite time consuming although yielded good prediction accuracy on the operation regimes that the system is trained for.

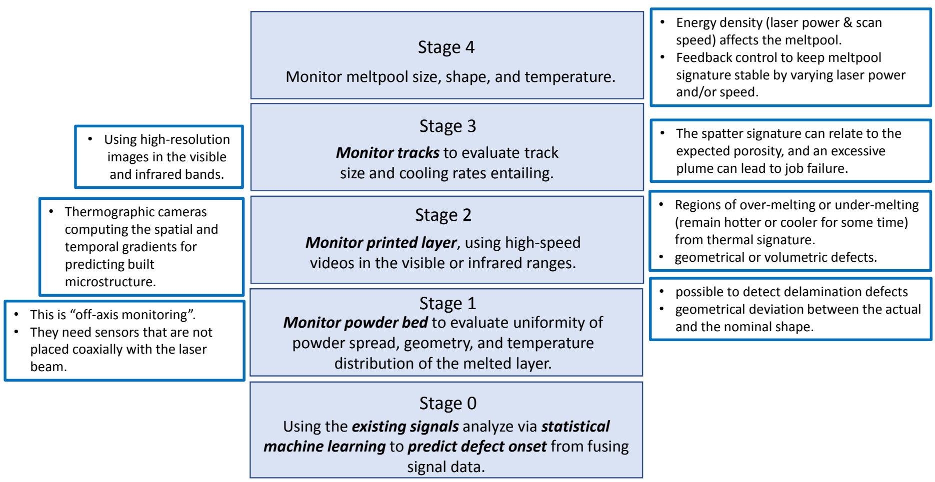
All these methods have been demonstrated useful in meltpool monitoring, spatter detection, and other material gaps and surface anomalies in L-PBF and other metal AM processes.

5 Stages of in-situ process sensing and monitoring techniques

A classification of in-situ process sensing and monitoring methods into four different groups of measurable process signatures as adopted from Grasso et al. (2021) is shown in Figure 6. This classification originally proposed by Grasso et al. (2021) involves 5 levels (Stage 0 through Stage 4). Stage 0 involves the use of signals from sensors that are already embedded into the AM system. This contains compartment pressure, base plate temperature, and oxygen ratio, as well as signals from galvanometers and axis motor drives etc. These types of signals potentially allow a framework for designing a process monitoring system that precludes the necessity for peripheral or extra sensors. This is especially appealing in electron beam PBF (EB-PBF), where easily attainable log signals from embedded sensors are available and possibly usable during the processing (Steed et al., 2017). In Figure 6, Stage 1 comprises of signals collected per layer with a level of view that encompasses the entire build surface. This stage contains characteristic measures about the homogeneity of the powder bed, geometrical and dimensional elements of the printed layer or its surface curvature and topography. Stage 2 consists of process signatures that can be determined while the laser or the electron beam is moved within the build section to generate the current layer in PBF. This implies the ability to examine the interaction between the beam and the powder (spatters and plumes in the case of L-PBF) and the cooling profile of the solidified region after the beam has shifted to another locality. Stage 3 includes monitoring of fused or weld tracks, their sizes as well as track-to-track overlaps. Stage 4 finally contains process signatures that are characteristic of the finest level of detail i.e., the meltpool and its vicinity during PBF processes. Further categories of in-situ process sensing and monitoring methods can be studied, in terms of monitoring approach (e.g., on-axis vs off-axis), sensing tools (spatially integrated vs spatially resolved sensors), wavelength of the evaluated quantities (visible range, near infrared, or infrared), etc.

The input parameters such as material properties, recoating system parameters are mostly pre-defined and the most crucial process parameters are predefined in the laser scanning and path planning software and often kept constant during processing. The mappings of the L-PBF or L-DED input (controllable or uncontrollable) process parameters into the process generated track-to-track, stripe-to-stripe, and layerwise signatures to the quality state of interest are highly essential for the m-AM process monitoring. Also, robust mapping from in-situ sensing collected signals to the process signatures and defects incurred should be performed to fully utilise the capabilities of the AM monitoring system. The relation between process sensing, process signatures and defects will be discussed next.

Figure 6 Classification of in-situ process sensing and monitoring methods in PBF processes (see online version for colours)



5.1 Relation between sensing, process signatures, and defects

The process signatures and the sensing methods discussed previously can be linked to the targeted process defects. Although some of these process signatures can be sensed in-situ using certain sensors and techniques, some process signatures cannot be measured such as residual stresses during the L-PBF processing. The ones that can be sensed or measured are listed as they relate to certain in-situ sensing techniques and are mapped into process defects.

Therefore, Table 3 presents such a relation mapping (as adopted from Colosimo and Grasso, 2020 and modified) between the process signatures that can be evaluated in-situ, the resultant defects that can be identified and the most appropriate sensing techniques. The relationships are specified with several types of symbols as the symbol "●○○" means already appeared in the literature as experimental findings. Some relationships, showed with the symbol "●○○", denote connections between defects and process signatures that have not been yet determined in the literature. In spite of having a potential these factors are yet to be checked with further research.

Table 3 Relations between in-situ measurable process signatures, sensing methods and process defects. The symbol "●○○" is indicative of the degree of known correlation exhibited in the literature, while the symbol "◉○○" is used to correspond to the degree of connections still not supported in the literature or other indirect connections of potential interest

Stage of Monitoring	*Process signature*	*In-situ sensing method*	*Qualities monitored*							
			Porosity	*Cracks*	*Residual stresses*	*Layer delamination*	*Grain anisotropy*	*Balling keyhole*	*Geometrical distortions*	*Surface defects*
Stage 1: powder bed monitoring	Powder bed homogeneity	Off-axis, visible range	◉◉○	●●○	●●○	●●○	◉○○	○○○	●●●	○○○
	Slice geometry	Off-axis, visible range	○○○	○○○	○○○	○○○	○○○	○○○	●●●	○○○
	Slice surface pattern	Off-axis, visible range, fringe projection	◉◉○	●●○	●●○	●●○	○○○	●●●	◉○○	●●●
Stage 2: tracks monitoring	High and low density spots	Off-axis, visible or infrared range	●●●	●●○	●●●	●●○	○○○	●●●	●●●	○○○
	Temperature profile / cooling history	Off-axis, thermal imaging	○○○	○○○	●●○	○○○	●●○	○○○	○○○	○○○
	Process by-products	Off-axis, visible or infrared range	●●○	○○○	○○○	○○○	◉◉○	○○○	○○○	○○○

Table 3 Relations between in-situ measurable process signatures, sensing methods and process defects. The symbol "●○○" is indicative of the degree of known correlation exhibited in the literature, while the symbol "◐○○" is used to correspond to the degree of connections still not supported in the literature or other indirect connections of potential interest (continued)

Stage of Monitoring	*Process signature*	*In-situ sensing method*	*Qualities monitored*							
			Porosity	*Cracks*	*Residual stresses*	*Layer delamination*	*Grain anisotropy*	*Balling keyhole*	*Geometrical distortions*	*Surface defects*
Stage 3: meltpool and spatter monitoring	Size	On-axis, visible or infrared range	●●○	●●○	●●○	●●○	○○○	●●○	○○○	●●○
	Shape	On-axis, visible or infrared range	●●○	○○○	●●○	○○○	○○○	●●○	○○○	●●○
	Average intensity	On-axis, pyrometry	●●○	○○○	●●○	○○○	◐◐○	●●○	○○○	●●○
	Intensity profile	On-axis, visible or infrared range	●●○	○○○	●●○	○○○	◐◐○	●●○	○○○	●●○

The signals of embedded sensors (Stage 0) have been indicated as possible sources of information in EB-PBF to collect information about the powder spreadability (Chandrasekar et al., 2020) and the existence of geometrical distortions triggered by powder recoating errors (Grasso et al., 2018), but various other potential applications have been noted in the literature and they can be studied in future investigations (Steed et al., 2017). Similar results in L-PBF have not been discovered so far. The absence of powder bed homogeneity (Stage 1) may alter the local layer thickness leading to potential volumetric and geometrical defects because of inadequate energy density differences. Inaccuracies in the powder recoating of the layer can also initiate incomplete fusion between current layer with the previous layer, with resultant possibility of delamination, together with potential geometrical deformation in the existence of serious recoating inaccuracies and impurity. Diverse authors have explored in-situ process sensing and monitoring methods fit to differentiate the surface shape and surface topography of the fabricated layer and the complete powder bed as a likely source of information about process stability alongside volumetric and surface defects (Foster et al., 2015; Zhang et al., 2016). The in-situ monitoring of the layerwise part has drawn an increasing interest to rapidly identify quality of fusion and defect formations in every layer (Aminzadeh and Kurfess, 2019; Caltanissetta et al., 2018). Concerning Stage 2 process signatures, the exposure of high and low energy density locations may be appropriate to detect either geometrical deformations (disproportionate heating) or lack-of-fusion situations (Grasso et al., 2016; Colosimo and Grasso, 2018). Static and dynamic thermal fields, thermal gradients and relations obtained though in-situ thermography can offer knowledge about geometrical distortions, changes in the part microstructure and thermal stress generation due to disproportionate heating (Raplee et al., 2017).

A growing interest in the literature has been dedicated to focus on spattering and plume formations in L-PBF, as prospective representations of volumetric defects (Respossini et al., 2018; Grasso, Demir et al., 2018; Grasso and Colosimo, 2019; Eschner et al., 2019; Nassar et al., 2019; Zhang et al., 2019; Wang et al., 2020). Spatters are triggered by departing particles from the meltpool surface and the adjacent region on the powder bed, resulting in creation of denudation areas around the meltpool and a likely deficiency of material in the solidified path, which may affect the development of voids and pores (Yakout et al., 2021). In the case of excessive plume generation, the debris rising from this region may be absorbed by the laser beam and can compromise beam quality decreasing the energy concentration on the power surface or layer leading to lack-of-fusion porosity formation.

5.2 Relation of research studies on defect sources and categories of defects

Table 4 shows the relations between equipment related defect sources and types of defects as adopted from Grasso and Colosimo (2017). The information has been extended by including more recent studies in this paper. Several pieces of information about the process stability and the build quality can be collected by monitoring the meltpool signatures (Stage 3) and their evolution over time. Undeniably, the meltpool conditions are relevant to identify the likely development of volumetric defects (both keyhole and lack-of-fusion porosity), thermal stress generation due to deficient heat dissipation and surface defects connected to the solidification characteristics of fused tracks (Kwon et al., 2020; Kolb et al., 2019). Additionally, Table 5 provides a relationship overview between process associated defect sources and types of defects and Table 6 offers another relationship overview for design options and feedstock related defect sources and types of defects. The mapping information is adopted from Grasso and Colosimo (2017) and has been extended by including more recent studies in this paper.

5.3 Industrial implementation of in-situ process monitoring

According to Colosimo and Grasso (2020), the industrial implementation of these methods has been performed by PBF system developers and their systems are now equipped with in-situ process sensing and monitoring modules and toolkits. These implemented in-situ L-PBF process monitoring technologies include both on-axis and off-axis sensors to monitor the build process, optical tomography, and thermal emission systems to view meltpool and spatter. 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. Data analytics and machine learning related development efforts in the form of intelligent software tool are being developed for implementation of analytical quality monitoring tools that are able to quickly analyse the sensed data during the process and automatically signal the onset of defects and process instabilities. Real-time laser power control tools are also found available in some commercially available L-PBF systems (Table 7) where a summary of in-situ process monitoring systems is also given for each L-PBF technology. Manufacturers of PBF systems continuously deploy on-axis optical (spectral) emission using pyrometers or photodiodes for monitoring of both the laser output and thermal emissions with high bandwidth and integrate the data with intelligent software solutions for in-situ monitoring of layer, build, and part quality. As a common thread to all monitoring systems emissivity issues (e.g., the emissivity of the meltpool region) with the accurate measurement of temperature still remain as a challenge. A more exhaustive review of the rapidly evolving literature devoted to in-situ sensing, metrology, and monitoring systems in commercially available L-BPF systems would require a much more extended review paper. Nonetheless, this review study aims to contribute to the AM community in several ways. First, it presents a framework to classify different methods and solutions presented in the literature into distinct categories in terms of monitoring stages and process signatures of interest. Secondly, it aims to provide a more consolidated terminology since increasing number of studies on in-situ monitoring of PBF processes also caused an increasing variety of terminology and an increasing fragmentation of application fields.

Table 4 Relations between equipment related defect sources and defect types

	Defect sources	Defect types					
		Porosity	*Balling*	*Geometric defects*	*Surface defects*	*Cracks and delamination*	*Microstructural inhomogeneity and impurity*
Equipment	Beam scanning/deflection	Foster et al. (2015), Criales et al. (2017) and Coeck et al. (2019)		Moylan et al. (2014) and Foster et al. (2015)	Arisoy et al. (2017)		Arisoy et al. (2017)
	Build chamber environment	Ferrar et al. (2012), Spears and Gold (2016)	Li et al. (2012), Zhou et al. (2015) and Fischer et al. (2021)			Edwards et al. (2013), Chlebus et al. (2011), Buchbinder et al. (2014) and Kempen et al. (2013)	Spears and Gold (2016)
	Powder handling and deposition	Foster et al. (2015		Foster et al. (2015) and Kleszczynski et al. (2012)	Foster et al. (2015), Kleszczynski et al. (2012)		Foster et al. (2015
	Baseplate			Prabhakar et al. (2015)		Prabhakar et al. (2015)	

Table 5 Relations between process related defect sources and defect types

Defect sources		*Defect types*					
		Porosity	*Balling*	*Geometric defects*	*Surface defects*	*Cracks and delamination*	*Microstructural inhomogeneity and impurity*
Process	Parameters and scan strategy	Matthews et al. (2016), Yasa et al. (2009), Attar (2011)), Gong et al. (2013), Read et al. (2015), Kruth et al. (2004), Weingarten et al. (2015), Thijs et al. (2010), Scharowsky et al. (2015), Puebla et al. (2012), Biamino et al. (2011), Zeng (2015), Criales et al. (2017), Coeck et al. (2019) and Fischer et al. (2021)	Li et al. (2012), Kruth et al. (2004), Tolochko et al. (2004), Zhou et al. (2015), Attar 2011), Gong et al. (2013), Li et al. (2021), Wang et al. (2021), Fischer et al. (2021)	Yasa et al. (2009), Mousa (2016), Kleszczynski et al. (2012), Thomas (2009) and Zaeh and Kanhert (2009)	Li et al. (2012), Kruth et al. (2004), Matthews et al. (2016), Attar (2011), Gong et al. (2013), Zaeh and Kanhert (2009), Delgado et al. (2012)	Mercelis and Kruth (2006), Parry et al. (2016), Cheng et al. (2016), Van Belle et al. (2013), Casavola et al. (2008), Zäh and Lutzmann (2010), Zaeh and Branner (2010), Kempen et al. (2013), Kruth et al. (2004), Carter et al. (2014), Arisoy et al. (2017), Niu and Chang 1999), Huang et al. (2016), Thijs et al. (2010), Scharowsky et al. (2015), Puebla et al. (2012), Biamino et al. (2011) and Arisoy et al. (2016)	
	By-products and material ejections	Liu et al. (2015) and Khairallah et al. (2016)					Liu et al. (2015) and Khairallah et al. (2016)

Table 6 Relations between design choices and feedstock related defect sources and defect types

Defect sources		*Defect types*					
		Porosity	*Balling*	*Geometric defects*	*Surface defects*	*Cracks and delamination*	*Microstructural inhomogeneity and impurity*
Design choices	Supports			Foster et al. (2015), Kleszczynski et al. (2012) and Zeng (2015)	Foster et al. (2015), Kleszczynski et al. (2012) and Zeng (2015)	Foster et al. (2015), Kleszczynski et al. (2012) and Zeng (2015)	
	Orientation		Li et al. (2012), Strano et al. (2013), Li et al. (2012) and Tolochko et al. (2004)	Delgado et al. (2012)	Delgado et al. (2012), Fox et al. (2016) and Strano et al. (2013)		Meier and Haberland (2008)
Feedstock material (powder)		Liu et al. (2015), Van Elsen (2007), Das (2003) and Coeck et al. (2019)		Das (2003)	Seyda et al. (2012)		Das (2003), Niu and Chang (1999) and Huang et al. (2016)

Table 7 Commercially available major powder bed fusion systems and in-situ process monitoring capabilities

PBF system	*Manufacturer*	*Powder bed*	*Laser powder*	*Meltpool*	*Spatter*	*Defects*
Direct metal printing	3D Systems (Factory 500) (500×500×500 mm)	Optical	–	Optical	Optical	Lump formation
Metal powder bed fusion	Renishaw (RenAM 500)	Optical (CameraView)	On-axis (LaserView)	Thermal emission (MeltView)	NIR Optical emission (MeltView)	–
Selective laser melting	SLM Solutions (SLM 500)	Optical (Layer control system)	On-axis emitted laser output	Thermal emission (Meltpool monitoring)	Optical emission (Meltpool monitoring)	–
Direct metal laser melting	GE Concept Laser (M2 Series 5)) (245×245×350 mm)	Optical and sensors (Build explorer)	–	Optical emission (QM Meltpool 3D)	Optical emission (QM Meltpool 3D)	–
Direct metal laser Sintering	EOS Electro Optical Systems (M 300) (300×300×300 mm)	Optical tomography (Exposure OT)	Online laser power control (System)	Optical camera (MeltPool)		Optical (PowderBed)
Selective laser melting	DMG Mori Lasertec 12 (125×125×200 mm)	–	–	On-axis photodiode (PrintRite3D)	–	–

6 Research directions toward in-situ process monitoring and process control

A recent survey presented in this paper indicates that the research is still on-going and new studies are proposing, testing, and demonstrating in-situ measurement and monitoring methodologies for PBF systems. In fact, since the last report on the advances in this field there has been significant increases in publications on in-situ monitoring and process control in metal AM. When it was reported by Colosimo and Grasso (2020), most of these studies were mainly directed to showing the viability of in-situ sensing techniques and differentiating specific process signatures most popularly about meltpool conditions by utilising the collected data from the in-situ sensing and observations. Since then, better process monitoring tools have been developed and employed in PBF systems with many commercially available options offered to the users. Recent findings also recommended new in-situ sensing solutions or the combination of multiple sensors to accomplish better in-situ measurement and monitoring implementation (Tan Phuc and Seita, 2019; Barrett et al., 2018).

In parallel, fast-growing interests has been dedicated to the deployment of machine learning, deep learning and surrogate modelling techniques to make use of the in-situ data fusion for more reliable, robust and rapid identification of process anomalies, faults, and defects (Colosimo and Grasso, 2020; Kwon et al., 2020; Gobert et al., 2018; Okaro et al., 2019; Scime and Beuth, 2018; Shevchik et al., 2018). Thermal images are connected to high/ low density meltpool classification using deep learning (Guo et al., 2022). Some researchers connected in-situ sensing using airborne acoustic signals to identify different L-PBF operational regimes using machine learning and deep learning approaches for quick response in process behaviour (Jayashinge et al., 2021; Drissi-Daoudi et al., 2022).

A review of the research work in applications of machine learning in process monitoring and control and perspectives of using machine learning in L-PBF metal AM has been provided (Mahmoud et al., 2021; Sing et al., 2021). Machine learning has been identified as a potential tool by utilising process insight and in-situ data obtained at various stages of the process chain to overcome obstacles in part inconsistency obtained from L-PBF. Machine learning algorithms are found to be applicable for process parameter optimisation, processing data fusion coming from in-situ sensing, and to be integrated into the post-processing. However, it is also recognised that such techniques require time consuming data analysis, feature extraction, image augmentation, image segmentation, training, and validation efforts in deep learning architectures before even put to use in L-PBF monitoring and control systems. At this moment, these techniques are promising but far from practical implementation.

Investigatory studies are performed for L-PBF process control by employing in-situ sensory data streams for feedback process control where sensors are utilised to generate an error signal from the process deviations and adjustments are made to the controllable process variables (Clijsters et al., 2014; Craeghs et al., 2010). On the other hand, model-based feed forward process control studies are conducted to utilise process information to construct process models either by mathematical modelling (Matthews et al., 2016; Wang et al., 2020; Ren and Wang, 2022) or simulation modelling (Lee and Prabhu, 2016; Irwin et al., 2021) and to make proper adjustments to the controllable process variables (Yeung et al., 2019). In addition, process optimisation studies are performed by utilising the process knowledge to make adjustments to controllable L-PBF variables such as laser power, layer thickness, scan velocity, and hatch distance (Lapointe et al., 2022; Druzgalski et al., 2020; Criales et al., 2017).

There are numerous parameters that affect the quality and properties of the final part. Most of these parameters are predefined, that is, their values must be adjusted before processing and some are controllable, that is, they can be modified during processing. Lastly, some criteria are classified as undefined, that is, they depend on other parameter adjustments. The quality of the process and/or products involves criteria that are related to reliability, durability, serviceability, aesthetics, and compliance to certain standards. Qualification processes generally involve the repeatability of production processes and consistency in the quality of manufactured components which are currently considerable challenges, especially when producing components in larger quantities. Compared to alloys manufactured by traditional processes, AM alloys lack a large database and agreed upon properties. Therefore, a fuller understanding of the L-PBF process is crucial to develop process control for rapidly qualifying and certifying the quality of the AM parts. Hence measurements at pre-process, in-process, and post-process stages are required. Basically, pre-process measurements are vital in establishing relationships between input process parameters and part characteristics. These measurements often relate to powder properties (particle size distribution, density, thermal conductivity, spreadability etc.) and intrinsic characteristics of the L-PBF system (laser power, powder absorptivity, etc.). In-situ measurements are typically in-process monitoring tools such as measuring surface temperature, monitoring meltpool shape and size, and spatter of the molten powder material.

In this paper, a review for in-situ sensing, process monitoring and control in L-PBF is given, and it is stated that being able to characterise the process signatures is key to improving AM part quality.

Most of the research on in-situ AM metrology focuses on two types of sensors, namely thermographic sensors and high-resolution imaging sensors. However, they only monitor the surface of the powder bed and are not utilised within a quality control framework that can be used to rapidly qualify and certify the build layer quality (Jayasinghe et al., 2022). The post-process measurements focus on the quality of interest (QoI) such as material/part quality: dimensional accuracy, surface roughness, porosity, mechanical performance, residual stress, etc. Image-based measurements can include optical profilers, such as white light interferometers and confocal microscopes, as well as multi-scale XCT.

To establish foundations for L-PBF process control, process parameters are sub-categorised as process signatures and product build quality according to the abilities to be measured and/or controlled. Process parameters are input to the process, and they are either potentially controllable or predefined. In this control scheme, predefined input parameters are given as set parameters and they will include factory specified powder feedstock related parameters such as powder material particle size, and L-PBF equipment specific parameters such as layer thickness, build plate temperature, etc.

Furthermore, the future research should consider the predefined input parameters as uncontrollable inputs, $\underline{\boldsymbol{r}} = [\boldsymbol{r}_1, \boldsymbol{r}_2, \ldots, \boldsymbol{r}_n]^T$ together with parameters of uncertainty, controllable variables $\underline{\boldsymbol{u}} = [\boldsymbol{u}_1, \boldsymbol{u}_2, \ldots, \boldsymbol{u}_m]^T$ e.g., laser power and scan velocity that are effective on controlling the melting of powder material and solidifying fused tracks through cooling rates and hence finalising the build quality. These parameters and variables usually relate to the observable and resulting process signatures such as meltpool volume, temperature, porosity, deformation, or residual stress. Derivable parameters cannot be directly determined but can be estimated using numerical models. The uncontrollable process signatures, $\underline{\boldsymbol{v}} = [\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_p]^T$, and the build quality measures, $\underline{\boldsymbol{y}} = [\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_m]^T$, are to be quantified to complete the framework necessary to understand not only the L-PBF process taking place on the powder bed surface but also subsequent intrinsic heat treatment effects below the powder bed. For correlation purposes, the study should further split process signatures into three groups namely: meltpool related, solidified track related, and fused layer related. Process signatures define the final product characteristics (geometric, mechanistic, and physical). Expanding relationships between the controllable PBF parameters and process signatures should help process control with the objective of setting in process knowledge into future control policies.

Furthermore, there should be designs offered for surrogate models to utilise the in-situ monitoring data and analyse their effects on the quality of interest (QoI) such as fused tracks and layers.

For instance, a simple modelling could offer $\boldsymbol{y}_s(\mathbf{x}, \boldsymbol{\theta})$ and $\boldsymbol{y}_e(\mathbf{x})$ to characterise L-PBF data-driven surrogate model projection and the subsequent experimental observation for the quality of interest of $\boldsymbol{y}$. They are merely connected by the following expression $\boldsymbol{y}_e(\mathbf{x}) = \boldsymbol{y}_s(\mathbf{x}, \boldsymbol{\theta}) + \boldsymbol{\delta}(\mathbf{x})$ where $\boldsymbol{\delta}(\mathbf{x})$ is the model bias between the data-driven or surrogate model estimate and the experimental measurement, $\mathbf{x}$ signifies controllable variables that can be correctly controlled during tests (e.g., laser power and scan velocity), and $\boldsymbol{\theta}$ is the uncertainty source term to be adjusted or minimised.

7 Remaining challenges and future research directions

This review paper builds upon previous work presented on the topic of in-situ process sensing and monitoring methods for AM systems, in particular, PBF technology by Colosimo and Grasso, 2020; Colosimo et al., 2018; Colosimo, 2018. Later, Colosimo and Grasso (2020) reviewed several seminal studies (Renken et al., 2019) conducted on closed-loop control in L-PBF and concluded that there is still progress needed to transfer the technology from highly sensorised machines to intelligent machines in metal AM. They observed that several in-situ defect mitigation or defect correction solutions are presented in literature (Colosimo et al., 2019; Grasso et al., 2019; Heeling and Wegener, 2018; Mireles et al., 2015) and pointed out that further studies are needed adapting process parameters based on model outputs or real- time sensor signals.

As of today, there are a number of challenges and technological barriers still remain in establishing robust and smart AM machines for fabrication of zero-defect parts at first-time in PBF machines. Even though new technological advances in new sensors, faster sensing methods, data fusion and processing developments and improvements are made to the existing in-situ process monitoring techniques, systems integration related limitations and challenges are yet to be resolved.

The major limitation in PBF processes using current in-situ process sensing and monitoring methods is their inability to sense and gather necessary insights about the physical phenomenon taking place among the layers below the powder surface. The sensing information collected from the powder bed's surface is not sufficient to understand effects of re-melting, keyholing, intrinsic heat treatment or conduction vs convection shifts that are repeatedly occurring below the top layer during processing.

A second limitation is that there is not a robust and cost-effective in-situ technique to sense, monitor and detect porosity in solidified sections of the 3D build. The quantification of such volumetric defects using optical tomography or X-ray tomography are considered critical in several applications in industry, but sensor technology is not matured to be deployed in PBF systems.

Dealing with large data streams collected through in-situ process sensing and monitoring is another challenge that is still open. Besides computational tools for real-time management of such data streams are also not well developed yet. The systems can gather terabytes of in-situ data during the fabrication of a 3D build but the lack of computationally efficient methodologies for data processing hinders the potential of utilising such process insight effectively.

Another issue is the interoperability related and lack of transferring solutions learned because there is no viable platform to transfer knowledge quicky and share process models generated about a 3D build obtained in one PBF-AM system to be utilised for parts produced even with the same machine but by other users at other locations. Only a few studies are available about the application of transfer learning methods to AM (Sabbaghi and Huang, 2018; Fischer et al., 2022).

There is a need to establish transferring knowledge more effectively. Ideally, it would be fairly expedient to conduct selected experiments in a controlled setting of process conditions, and then transfer this base knowledge to other process conditions. This would reduce the cost of experimentation and lead time for new parts. The major challenge in achieving this is the large variability among the PBF systems and laboratories.

There is a pressing need to develop digital twin frameworks and cyber-physical systems that can integrate theories, experiments, and process simulations of L-PBF and other metal AM processes. Validated models and simulations have potential to enhance AM process performance and act as a technological enabler to achieve AM capabilities in zero-defect production (Arisoy et al., 2019; Yang and Özel, 2021; Jarosz and Özel, 2022). The vision for a digital twin framework that combines in-situ sensing data with process simulation is a field that deserves further attention albeit with more intense research efforts.

There is further research opportunity to extend in-situ process sensing and monitoring data to adaptively control the L-PBF AM processes. Even though some control strategies are developed to enable a feedforward approach for adjusting process parameters on the fly, the process insight gathered through in-situ sensing is not effectively used for achieving a fuller control that predicts and compensates occurrence of defects and porosity.

Achieving capabilities for defect-free and first time-correct part production will not only depend upon in-situ process sensing and monitoring technologies, but also developing robust and optimal control strategies. A knowledge gap still exists to be able to develop intelligent process control tools and deliver solutions to the AM industry.

Nevertheless, further research is deemed critical for real-time control of PBF processes to deal with automatic defect identification and subsequent correction of defects in futuristic smart AM systems.

8 Discussion

The process signatures obtained through data collected from machine's control systems and sensors via in-situ process sensing and monitoring, which in return represents the health of the L-PBF AM process, can provide insights into techniques to control the structural integrity, surface roughness, and overall quality of the 3D build. In an ideal world, a real time enabled in-situ monitoring system should quickly identify process anomalies and product defects and generate a corrective action to the L-PBF process parameters or the machine appropriately.

In-situ process sensing, and in-situ monitoring can increase understanding of the L-PBF metal AM process, permitting further adjustment and calibration of the AM process digital models and process simulations, enhance layerwise build quality by perceiving, averting, or even balancing the process parameters for defect-avoidance, and backing quick process qualification.

There is a lot to be done to address the issue of obtaining correlations between aforementioned process signature and quality attributes as defined by the user, and hence characterising anomalies and defects correctly.

The proper selection of appropriate sensors along with monitoring techniques (more specifically choosing their spatial and temporal resolutions) is still an ongoing discussion among the researchers.

Another issue is to certify the accuracy required for in-situ process sensing in L-PBF processes and machines. There might be further needs in using additional tools and methods for achieving data fusion with high dimensional sensory data not just meltpool related monitoring and sensing.

It is often times overlooked how much measurement error is involved in such sensing and monitoring systems that requires a closer look at uncertainty quantification. Further challenges exist about the certifying measurements for precision, how to interpret the measurement data to assess overall health state of a L-PBF system. There is further research required to get a grip about the challenges involved for adopting an on-axis or off-axis process sensing and monitoring as functions of accuracy, frequency, and spatial and temporal resolution.

Further understanding about the correlation between process signatures and related anomalies and defects occurring during the L-PBF process as well as the resultant part quality is needed. On that note, there should be deeper investigations conducted on the relation between the frequency of defect occurrences and the qualification of the as-built part or component using the probability of the successfully detected anomalies, flaws, defects and connecting them with the part qualification metrics. One other problem is the challenges associated with the transfer of knowledge and expertise from one L-PBF machine to another one since mostly each machine would have unique characteristics and path planning or process parameters. Ultimately, the key challenge is to move the process sensing and monitoring technology from just observing the process to the adaptive control, feed forward or feedback control strategies to build control system architectures that already exist in other manufacturing processes and equipment.

9 Conclusions

This paper reviewed the literature on in-situ process sensing and monitoring methods and discussed research challenges and future directions for further efforts. As additively fabricated metal products mostly suffer from large variations in quality attributes that are known to be influenced by a large number of factors and these outside factors and their influence on various process signatures also make metal AM processes not fully manageable creating unacceptable levels of part-to-part inconsistency in quality. The process monitoring techniques should be integrated into robust quality control methodologies for a wider adoption of metal AM processes. The current challenge is to fully understand which monitoring techniques offer the best performance in terms of quality measurement and smooth integration into the manufacturing operation. The near-term targets can be identified as improving imaging capabilities, clarifying what to monitor and when, setting expectations for assessing what can and cannot be done, and establishing better calibration procedures. The mid-term targets can be listed as establishing real-time control strategies, refining the use of statistical analyses to regulate the optimal signal flow into the control system, improving physically informed modelling abilities and enabling algorithms for speedier computations. The long-term aims can include utilising machine learning and artificial intelligence to develop processes that are self-learning and intelligent, and also transferable from machine-to-machine.

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Abbreviations

AM	*Additive manufacturing*
CCD	Charge-coupled device
CMOS	Complementary metal oxide semiconductor
CLSM	Confocal laser scanning microscopy
DNN	Deep neural network
EB-PBF	Electron beam powder bed fusion
IR	Infrared
L-PBF	Laser powder bed fusion
MPM	Meltpool monitoring
NIR	Near infrared
PBF	Powder bed fusion
PCA	Principal component analysis
QoI	Quality of interest
SPC	Statistical process control
XCT	X-ray computed tomography