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Melt Pool Monitoring as a Defect Detection Method for Quality Control of AlSi10Mg Parts Produced by PBF-LB/M

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Abstract

Additive Manufacturing (AM), particularly Laser Powder Bed Fusion of Metals (PBF-LB/M), has become a key technology in the aeronautical industry to produce lightweight, high-performance components with complex geometries. However, the quality and reliability of AM parts remain critical concerns due to the potential formation of process-induced defects such as lack of fusion, keyhole, and gas porosity. Ensuring structural integrity requires robust, efficient, and non-destructive quality control methods. This study investigates the use of a Melt Pool Monitoring (MPM) software as a non-destructive defect detection method for AlSi10Mg components manufactured via PBF-LB/M. By analysing thermal emission data captured during the build process, histogram-based profiles were generated and correlated with defects identified through high-resolution X-Ray computed microtomography (μ CT). The correlation between both methods validates the MPM capability to detect and identify different forms of defects. Samples were manufactured under both optimal and intentionally varied process parameters to induce different types of defects. The resulting MPM histograms revealed distinct patterns associated with specific morphologies of defects, enabling rapid classification of part quality. This approach demonstrates the potential of MPM as a pragmatic and versatile solution for in situ quality assurance in AM, reducing time-consuming post-production inspections. The findings support the integration of MPM into quality control workflows for aeronautical AlSi10Mg components, contributing to improved process monitoring, defect mitigation, and certification readiness. Furthermore, this methodology lays the groundwork for future implementation of artificial intelligence (AI) models trained on MPM data. By training machine learning (ML) models on MPM derived histogram data and corresponding μ CT

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validation, it is possible to automate the classification of parts as acceptable or defective in real time, streamlining quality control in production.

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1. Introduction

Laser Beam Powder Bed Fusion of metals (PBF-LB/M) is an advanced additive manufacturing (AM) technique that has seen widespread adoption across diverse industries, including biomedical, automotive, aerospace, and transportation sectors. In this process, a laser beam selectively melts and fuses metallic powders layer by layer within an inert atmosphere (typically argon) until the complete part is produced. Aluminium, nickel, titanium, cobalt, copper, magnesium, steel alloys, and other pure metals are examples of common feedstock materials. The exceptional strength-to-weight ratio, performance potential, and affordability of aluminium alloys, especially cast grades, make them ideal for PBF-LB/M. Using PBF-LB/M to process aluminium cast alloys has several advantages, one of which is the improvement of microstructure, which results in better static mechanical properties. AlSi10Mg has gained notable interest in additive manufacturing (AM) due to its ability to produce complex, lightweight, and high-density components when optimal process parameters are applied (Ferreira et al. 2024; Luo et al. 2022). Despite its reliability, deviations in these parameters can lead to both process-related and material-related defects, particularly pores. Since pore formation is highly sensitive to printing conditions, understanding their formation mechanisms, classifications, and morphologies is critical for improving AM outcomes. X-ray tomography has proven to be an effective non-destructive technique (NDT) for identifying and characterizing defects in AM parts across various materials. It enables classification based on features like diameter, volume, sphericity, compactness, and aspect ratio (Livings et al. 2020), (Nudelis and Mayr 2021). While many pore types are well understood, current diagnostic methods can be time-consuming and costly. Therefore, advancing faster and more reliable defect assessment tools is essential, especially in industries like aerospace and transportation, where component certification is vital. Melt pool monitoring (MPM) systems arise as an in-situ NDT solution that can bypass the complexity, costs, preparation and time-consuming nature of other methods. In this way, in-situ process monitoring approaches may play an important role in detection and identification of defects while having a positive impact in economic and environmental terms regarding time and usage of resources (Alberts, Schwarze, and Witt 2017; Uhlmann et al. 2025). This work aims to correlate the information obtained from a MPM system in PBF-LB/M technology with the porosity detected through μ CT. To this end, a methodology based on MPM emission data is proposed to detect and identify defects originating from manufacturing and printing parameters. μ CT analyses were conducted to locate and characterize defects within the specimens. Once the defect locations were identified, the corresponding MPM data were analysed to determine whether specific emission profiles were associated with the presence of these defects. This approach enables the evaluation of MPM data as a potential pass/fail criterion for assessing component quality, thereby simplifying the complex certification and qualification process of additively manufactured components in industry.

2. PBF-LB/M

The quality of PBF LB/M parts depends strongly on printing parameters such as laser power, hatch spacing, layer thickness, scanning strategy, and scan speed. Laser power affects the energy delivered to the material, while scan speed influences melting and solidification rates (Aboulkhair et al. 2019). Together, they shape the porosity and overall component quality (Nudelis and Mayr 2022a). AlSi10Mg often shows internal and surface defects due to its rapid solidification behaviour. The most common pore types are hydrogen-induced porosity, lack of fusion, and keyhole pores. Hydrogen-induced pores form from moisture and hydrogen trapped during processing, typically spherical and between 1 and 10 microns (Nudelis and Mayr 2022b; Yang et al. 2018). These can appear even under optimal conditions due to volatile elements like aluminium, magnesium, and zinc (Pu et al. 2024), (Kong, Bennett, and Hyde 2020). Lack of fusion pores result from low energy input and fast scan speeds. They are irregular and range from 10 to 400 microns (Kan et al. 2020; Luo et al. 2022). These defects may also relate to unmelted powder or oxide formation (Aboulkhair et al. 2014). Keyhole pores are larger and spherical, usually between 50 and 200 microns, and

occur when the melt pool becomes deep and unstable due to high power and slow scan speeds (Xiao et al. 2022), (Hyer et al. 2020; Rios et al. 2023). Balling is another defect where the melt pool breaks into droplets, often at high scan speeds due to surface tension effects (Aboulkhair et al. 2016; Saunders 2019).

In summary, Keyhole defects tend to form under high laser power and low scanning speed conditions, as shown in Fig. 1 (a), while lack of fusion defects are more common with low power or high scanning speed, as illustrated in Fig. 1 (c). Finding a balanced combination of these parameters defines an optimal processing window. This relationship is depicted in the laser power versus scanning speed chart in Fig. 1 (b), highlighting how different settings influence defect formation and part quality (Saunders 2019).

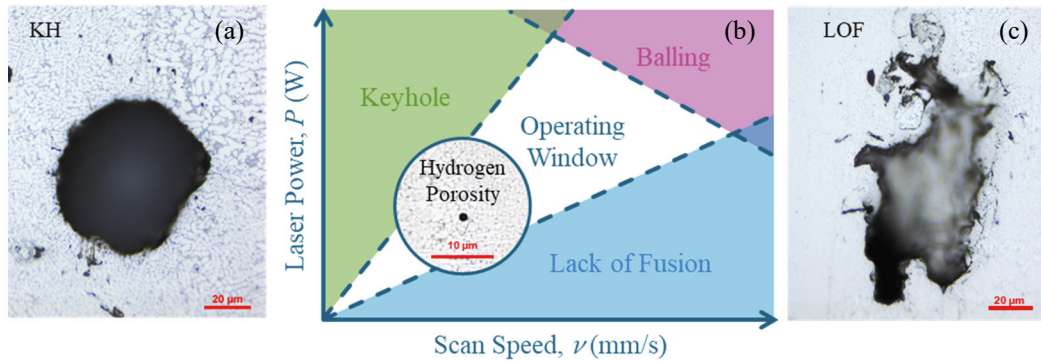


Fig. 1. Laser power vs scanning speed chart (b), adapted from (Oliveira, LaLonde, and Ma 2020; Saunders 2019), and the respective typical morphology of a keyhole pore (a), and a lack of fusion pore (c), representative of PBF-LB/M process (Kan et al. 2020).

2.1. Printing of Specimens and Experimental Setup

Dogbone uniaxial tensile test specimens were designed in SolidWorks18 following the ASTM E8/E8M standard (ASTM E8/E8M - 22 Test Methods for Tension Testing of Metallic Materials 2022). Specimens with nominal thicknesses of 1.5, 3.0 and 4 mm were fabricated using the PBF-LB/M process on a Renishaw RenAM 500S Flex machine with an AlSi10Mg powder supplied by Renishaw. The specimen geometry and dimensions (in mm) are shown in Fig. 2. Build preparation, including part arrangement and support generation, was carried out using QuantAM v. 6.0.15.1 software from Renishaw.

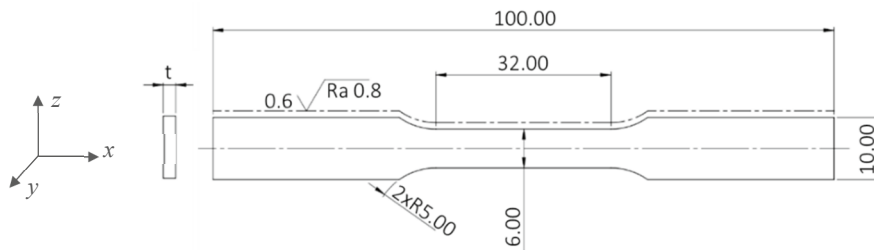


Fig. 2. Schematic of the geometry and dimensions (in mm) of dogbone specimens used for uniaxial tensile testing. Based on (ASTM E8/E8M - 22 Test Methods for Tension Testing of Metallic Materials 2022).

Three distinct printing strategies were employed to intentionally induce different pore types. To achieve this, keyhole and lack of fusion defects were generated by varying the scan speed relative to the optimized processing parameters. All printing parameters other than the scan speed were set constant. A meander scanning strategy was adopted, with each successive layer rotated 67° relative to the preceding one. Different scan speeds of 1500, 2500, and 3500 mm/s were used to produce optimal processing conditions (OP), keyhole (KH), and lack of fusion (LOF) induced conditions, respectively. In Table 1 are presented the printing parameters used in this work. Samples were removed

from the built plate and were laterally machined using CNC. To perform the tensile tests, an INSTRON 1342 servo-hydraulic testing machine equipped with a 250 kN load cell was operated at a crosshead speed of 5 mm/min.

Table 1. Printing parameters used to manufacture the three different set of conditions tested.

Printing Conditions	Printing Strategy	Number of borders	Laser Power P (W)	Exposure time (μ s)	Scan Speed v (mm/s)	Hatch Space h (μ m)	Layer Thickness t (μ m)
OP	Meander	2	500	20	2500	90	60
KH	Meander	2	500	20	1500	90	60
LOF	Meander	2	500	20	3500	90	60

3. X-Ray Computed Microtomography

Micro-computed tomography (μ CT) works by exposing a sample to X-rays and capturing absorption images, which are then reconstructed into a 3D model made of volumetric pixels called voxels. μ CT is widely used in AM as a NDT analysis to detect unexpected internal porosity and defects in printed parts. This allows for confident pass or fail decisions on components used in critical applications, helping simplify the certification and qualification process for materials, parts, and additive manufacturing technologies (Nudelis and Mayr 2022a). Internal defects act as process fingerprints, reflecting key printing conditions. X-ray analysis enables the development of classification tools based on defect size and shape, using three main indicators, namely, sphericity, compactness, and bounding box factor. Sphericity, Ψ , is the ratio between the surface area of an ideal sphere with the same volume as the pore, V_{Defect} and the actual surface area of the pore, A_{Defect} , equation 1. Compactness, Ω , defined in equation 2, compares the defect volume to that of a sphere based on its maximum diameter, ϕ_{Defect} . Additionally, the bounding box factor, or BB factor, uses three-dimensional descriptors, namely, the shortest (S), medium (M), and largest (L) dimensions, to characterize the shape of a defect, and it is calculated as the ratio of S to L, equation 3, and helps classifying pores as spherical or non-spherical (Nudelis and Mayr 2021).

$$\Psi = \frac{\pi^{\frac{1}{3}}(6 \cdot V_{Defect})^{\frac{1}{3}}}{A_{Defect}} \quad (1)$$

$$\Omega = \frac{6 \cdot V_{Defect}}{\pi \cdot \phi_{Defect}^3} \quad (2)$$

$$BB = \frac{S}{L} \quad (3)$$

A defect can be identified as spherical when the following criteria of $\Psi > 0.6$, $\Omega > 0.4$, and $BB > 0.6$ is satisfied. Subsequent classification based on defect volume and diameter allows differentiation between hydrogen porosity, keyhole, and lack-of-fusion types (Nudelis and Mayr 2021). A Werth TomoScape XS Plus computed tomography equipment with a permissible length measurement error up to 4.5 μ m was used to analyse the three specimens. Samples were analysed using a resolution of 10 μ m and a filter of 8 voxel, which allows for the detection of defects with a minimum volume of 10^{-6} mm³. Additionally, for post-analysis and data visualization, Volume Graphics VGStudio Max software was used along with myVGL viewer.

4. Melt Pool Monitoring (MPM)

Due to the limitations of destructive and non-destructive post-processing techniques in additively manufactured components, Melt Pool Monitoring (MPM) systems have emerged as an in-situ non-destructive testing (NDT) solution capable of overcoming the complexity, cost, preparation, and time constraints associated with traditional inspection methods. In this way, in-situ process monitoring approaches may play an important role in detection and identification

of defects while having a positive impact in economic and environmental terms regarding time and usage of resources (Alberts et al. 2017; Uhlmann et al. 2025). In-situ monitoring enables early detection and removal of defective parts during production, reducing overall manufacturing time (Alberts et al. 2017). By correlating process parameters with real-time data, MPM enables early detection and removal of defective parts, it can support closed-loop control for corrective actions (Grasso and Colosimo 2017) but also provide information on beam-material interactions, thermal behaviour and by-product formation (Colosimo and Grasso 2020). Several in-situ monitoring techniques have been incorporated into PBF-LB/M systems, including photodiode-based monitoring Low Coherence Interferometry (LCI), Infrared thermography, and Optical imaging via Charged-Coupled Device (CCD cameras) (Alberts et al. 2017). These methods are used to track down parameters such as laser power and process signatures like powder bed condition and part deformation that may be traced back to the key process indicators which determine the quality of the process regarding the delivered density, dimensional accuracy, surface finish, residual stresses, and mechanical properties (Artzt et al. 2020; Engelhardt, Wegener, and Niendorf 2024a). Melt pool monitoring approaches based on photodiodes have gained increasing popularity in recent years. By using a combination of two photodiodes to track thermal emissions during the build, MPM provides detailed process documentation and may support part quality and certification in regulated industries. This process monitoring and real-time process control systems can be implemented in PBF-LB/M to measure various key process parameters and process signatures linked to different types of defects. This enables localized, detailed analysis of the manufactured parts, ultimately improving the quality and repeatability of the components produced (Engelhardt, Wegener, and Niendorf 2024b). Moreover, machine learning (ML) models may also be developed to identify layers with hotspots at global and local scales (Yadav et al. 2021, 2022), enhancing the in-situ quality control of the PBF-LB/M process. In this work, InfiniAM from Renishaw was used for MPM since it offers a process monitoring approach that can be combined with conventional PBF-LB/M systems. Thermal emissions were measured during the manufacturing process using two photodiodes (PD) with a frequency of 100 kHz and a resolution of 12 bit. While melt pool PD is able to capture lower emissions in the infrared (IR) region ranging from 1090 nm to 1700 nm with a field of view of $\varnothing$ 2.6 mm, plasma PD is able to track higher emissions from 700 nm to 1040 nm with a field of view of $\varnothing$ 6.3 mm. This makes the IR PD more suitable for detecting LOF defects, while plasma PD is preferred for KH type of defects. Emissions can be processed and visualized using InfiniAM Spectral at a macro-level or by Matlab using the data recorded by the machine which gives a better resolution, preferred for a micro-level detection of defects.

4.1. Proposed methodology

With this in mind, the proposed methodology involved developing a MATLAB script to extract emission data for each layer. In the first step, data from the entire build process were retrieved. Subsequently, the emissions corresponding to the specimen under analysis were isolated, and the coordinate system from the MPM dataset was aligned with the μ CT reference frame. This alignment enabled the localization of defects within the MPM data and allowed an attempt to correlate emission intensity with the presence of such defects. From the total emission data of the specimen, the layers containing defects were identified. For each defect, a small region of $400 \times 400 \mu\text{m}$ was selected, with the defect centroid positioned at the centre of this area. This procedure was performed for the defect layer as well as for the layers immediately above and below it, ensuring that the defect region was fully captured. Two additional defect-free (reference) areas were then defined within the same three layers. Finally, histograms of emission intensity were obtained for each layer, and the average emission values from both the defect and reference areas were compared across the histograms to identify differences in emission behaviour associated with the presence of defects. This approach was performed for the KH and OP specimens since the LOF specimen presented a high number of defects which hindered the selection of defect free areas within the area where defects were found.

5. Analysis of the Experimental Results

In this section, the results of the μ CT analysis are presented, and the effect of defects on the failure mechanisms of the different samples is analysed. As previously mentioned, three specimens were printed using different scan speeds to generate distinct defect scenarios, namely, KH, OP, and LOF. These specimens were tested to evaluate the severity of the various defects on the mechanical performance of AM components. The corresponding samples were identified as KH, OP, and LOF, consistent with the types of defects that were intended to be induced. Figure 3 (a), (b), and (c)

show the failure locations and the positions of the defects identified in these samples, respectively. Sample KH resulted in an uneven distribution of small sized pores ranging from 0.15 to $0.45 \cdot 10^5 \mu\text{m}^3$. From Fig. 3 (a), it can be said that fracture might have been promoted by a cluster of small sized defects of 0.15 and $0.45 \cdot 10^5 \mu\text{m}^3$ with $\varnothing 38$ and $\varnothing 45 \mu\text{m}$, respectively. Sample OP contained a greater number of defects when compared to the KH sample. These defects were evenly distributed across the specimen with low to moderate volume and diameter sizes of 0.2 to $16.3 \cdot 10^5 \mu\text{m}^3$ with $\varnothing 40$ to $\varnothing 300 \mu\text{m}$, respectively. As illustrated in Fig. 3 (b), fracture might have been influenced by a cluster of a high density of small medium and high sized defects. Finally, from Figure 3 (c), it can be observed that the sample LOF contained several irregularly shaped defects, distributed in clusters across the specimen. These defects presented medium to large volumes from 3.5 to $620 \cdot 10^5 \mu\text{m}^3$, and diameters ranging from 60 to $1800 \mu\text{m}$. In addition, fracture of LOF sample occurred in a non-uniform manner, suggesting that it propagated along paths of clustered defects, which suggests that higher defects concentrations acted as preferential fracture site, Fig. 3 (c).

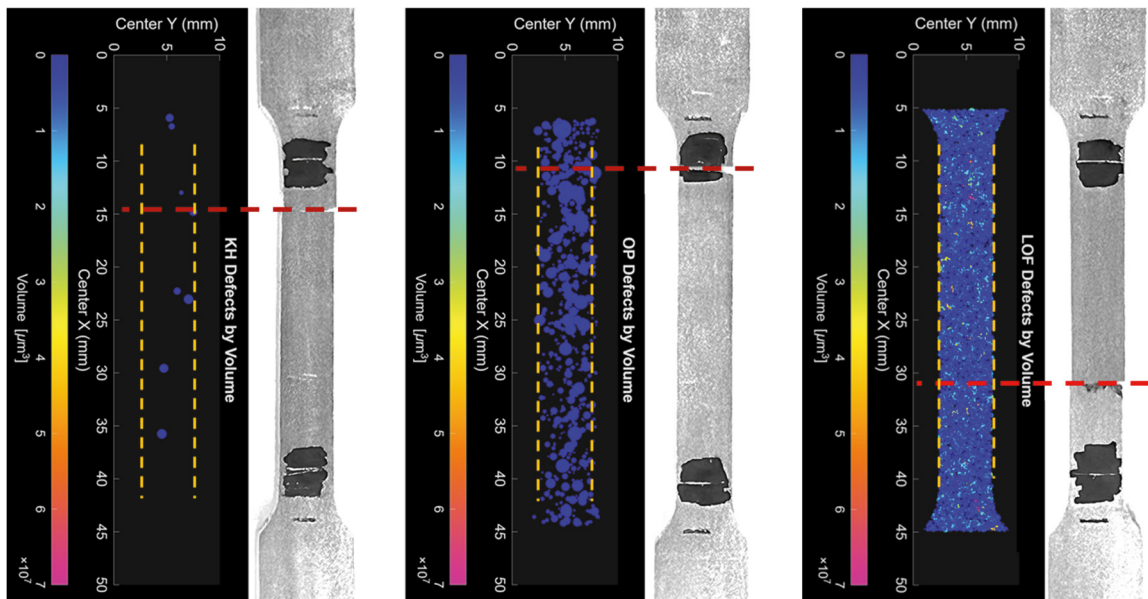


Fig. 3. Location and mapping of defects, and failure location after tensile testing of specimens KH (a), OP (b), and LOF (c).

Complementary μCT analyses for all samples are presented in Figure 4. For each sample, sphericity and compactness were plotted against the BB factor, represented by the color scale. The defect diameter, $\varnothing$, is shown by the size of each data point found in the Figures. The combined application of sphericity, Ψ , compactness, Ω , and BB factor can be used to characterize the shape of a pore (Aboulkhair et al. 2019; Nudelis and Mayr 2022a), as discussed in section 3. Pores satisfying the criteria for spherical morphology can only appear in the top-right quadrant, as depicted in Fig. 4. In contrast, irregular pores can occupy all quadrants and to avoid misclassification, the BB factor can be used. Considering diameter, pores between 50 to $200 \mu\text{m}$ correspond to KH defects, whereas those between 200 to $400 \mu\text{m}$ are typical of LOF defects. Hydrogen-induced pores, below $10 \mu\text{m}$, lie below the μCT resolution and were therefore omitted from the analysis.

As shown in Figure 4, the majority of defects in sample KH meet the morphological criteria for spherical pores, with most located in the upper-right quadrant. These pores exhibit diameters between 60 and $120 \mu\text{m}$, which aligns with the typical size range of KH defects. Further supporting the existence of KH defects is the fact that the largest defects in terms of volume are also localized in this area, with BB factor values close to the unit. In contrast, the LOF specimen exhibited the largest defects which primarily concentrated in the bottom left quadrant, with diameters up to $1800 \mu\text{m}$, in the LOF range. These defects showed low sphericity, compactness, and BB factor values, further supporting their classification as LOF-type defects. Sample OP appears to be an intermediate scenario, displaying defects with a wide range of sphericity and compactness values. Higher BB factor values were observed in the top-right quadrant compared to the bottom-left quadrant which was a trend also found in the LOF sample. The diameter

of defects ranged from 40 to 300 μm , indicating the presence of both small spherical and small irregular pores, which can be a result from the combined effect of scan speed and other printing parameters. These observations suggest a changing mechanism between keyholing and lack of fusion as the scan speed increases from 1500 to 3500 mm/s. The LOF condition represents the most severe case since it is characterized by large, irregular pores caused by using higher scan speeds reducing the energy input. Conversely, the KH sample exhibited only eight keyhole-type defects which can be attributed to excessive energy input resulting from the lower scan speed.

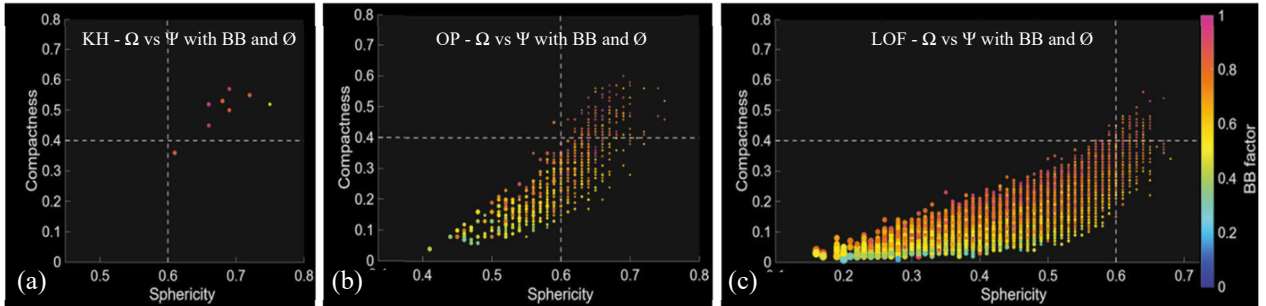


Fig. 4. Sphericity, Ψ , and compactness, Ω , plotted against the BB factor and diameter, Φ , for samples KH (a), OP (b), and LOF (c).

6. MPM information

As explained in Section 4.1, the histograms of emissions were generated for the layer where the defects were found, as well as for the immediately adjacent layers above and below. Additionally, three different areas of $400 \times 400 \mu\text{m}$ were defined within the aforementioned layers. One of these areas was centered on the defect coordinates, while the other two were located in regions where no defects were found, as shown in Fig. 5. For each area and for the entire layer, the average emission value was computed, and these values were overlaid in the histograms of the respective layers. Figure 5 presents the histograms for layer 252, where the defect was identified. The defect in consideration has a diameter of 63.94 μm and a volume of $0.72 \cdot 10^5 \mu\text{m}^3$ and it was found in the KH sample.

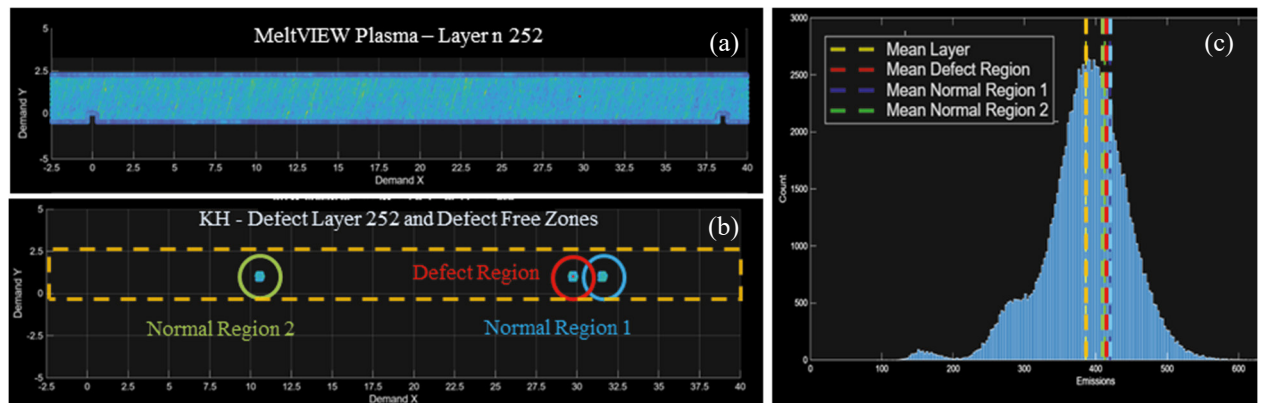


Fig. 5. Layer 252 of KH sample (a), location of the defect and non-affected regions 1 and 2, (b), and the corresponding histogram of the whole layer and showing the average emissions of each region, (c).

From the analysis of the histogram of the layer where the largest defect was found in sample KH, it is possible to observe that the emission value with the highest count was 375, which also corresponded to the average value obtained for the entire layer. Regarding the three defined areas (defect region, normal region 1, and 2), the average emission values are slightly higher than the average emission value found for the entirety of the layer. However, the average values for these regions are very similar to each other. This indicates that, for this specific defect, its presence had no

significant influence on local emission behaviour. A reason behind that fact resides on the fact that defects may only be detected when they are comprised within two scan tracks and is larger than the hatch distance. Otherwise, emissions might be masked with neighboring scan track emissions. Since the largest defect diameter ($63.94\text{ }\mu\text{m}$) in this instance, was smaller than the hatch distance ($90\text{ }\mu\text{m}$) utilized during the production the sample, the defect was likely masked by the adjacent scan tracks, preventing its detection using the MPM data available.

7. Conclusions

Dogbone specimens manufactured via PBF-LBM technology and AlSi10Mg alloy were produced with different printing parameters and different thicknesses. All printing parameters were set constant with the exception of scan speed which was varied by 40% regarding the optimum printing parameters suggested by the manufacturer. This strategy was used to induce keyhole and lack of fusion defects. Samples were printed following three different regimes: KH, OP and LOF. The methodology of this work consisted in validating whether the information of MPM can be used as reliable pass/fail assessment of the suitability of a given component, thereby simplifying the complex process of certification and qualification of AM components in the industry. According to the histogram results, the emissions found for the defected area were not distinctive enough from the emission correspondent to defect-free areas. Similarly, the average emission values found in the regions containing defects were indistinguishable compared to those in both defect-free regions and the overall layer average. This trend was consistent not only for the layer containing the defect but also for the adjacent layers. Several factors may explain the absence of a distinctive emission signature in the defective regions. For instance, in the KH sample, the largest defect exhibited a diameter of $63.94\text{ }\mu\text{m}$ and a volume of $0.72 \times 10^5\text{ }\mu\text{m}^3$. Defects are typically detectable only when they extend across two or more scan tracks and exceed the hatch distance. Otherwise, the emission signals associated with such defects can be masked by those from neighbouring scan tracks. In this case, the largest defect diameter ($63.94\text{ }\mu\text{m}$) was smaller than the hatch distance ($90\text{ }\mu\text{m}$) used in the sample fabrication, which might prevent its detection through MPM data.

Additional information obtained from μCT suggests that:

- A changing mechanism between keyholing and lack of fusion defects can be noted, when changing the scan speed from 1500 mm/s to 3500 mm/s while using a power of 500 W , for a fixed thickness of 3 mm .
- Defects in sample KH comply with the spherical pore criteria and KH morphology due to the use of a reduced scan speed. It was found a low amount of defects unevenly distributed with low volume and diameter. The fracture might have been affected by a cluster of small sized defects of 0.15 and $0.45 \cdot 10^5\text{ }\mu\text{m}^3$ with $\varnothing 38$ and $\varnothing 45\text{ }\mu\text{m}$, respectively.
- OP shows a higher amount of defects (compared to the KH scenario) evenly distributed across the specimen with low to moderate volume and diameter sizes of 0.2 to $16.3 \cdot 10^5\text{ }\mu\text{m}^3$ with $\varnothing 40$ to $\varnothing 300\text{ }\mu\text{m}$, respectively. The fracture might have been affected by a cluster of a high density of small, medium, and high sized defects.
- LOF resulted in the worst-case scenario of defects, where defects were promoted by the higher scan speed. This decreased the energy delivered to the part thus originating larger and irregular LOF defects. Several irregular defects are found evenly distributed in clusters across the specimen with medium to high Volume and Diameter sizes of 3.5 to $620 \cdot 10^5\text{ }\mu\text{m}^3$ and $\varnothing 60$ to $\varnothing 1800\text{ }\mu\text{m}$, respectively. This is accompanied by low values of sphericity, compactness, and BB factor for the majority of defects. Results suggest that the failure mechanism occurs in an irregular way suggesting that it propagates through a path of defects. Higher concentrations of defects might have promoted fracture in the identified region.

In light of these results, it may be said that:

- The KH condition exhibited the fewest defects among the three induced defect scenarios, whereas the LOF condition showed the highest defect density and largest defect sizes.
- A spherical pore classification criterion can effectively be applied to filter defects based on their morphology, using three key descriptors: sphericity, compactness, and BB factor. 40%

- MPM systems, such as InfiniAM, have the potential to be integrated with μ CT analysis to streamline the certification and qualification of additive manufacturing (AM) processes. However, this integration is not straightforward, as the recorded emissions are influenced by factors such as the size and position of the defects.

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