

## Predictive Qualification of Laser Powder Bed Fusion: Leveraging Multi-Modal InSitu Monitoring and Real-Time Control for Part Qualification

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### **Abstract**

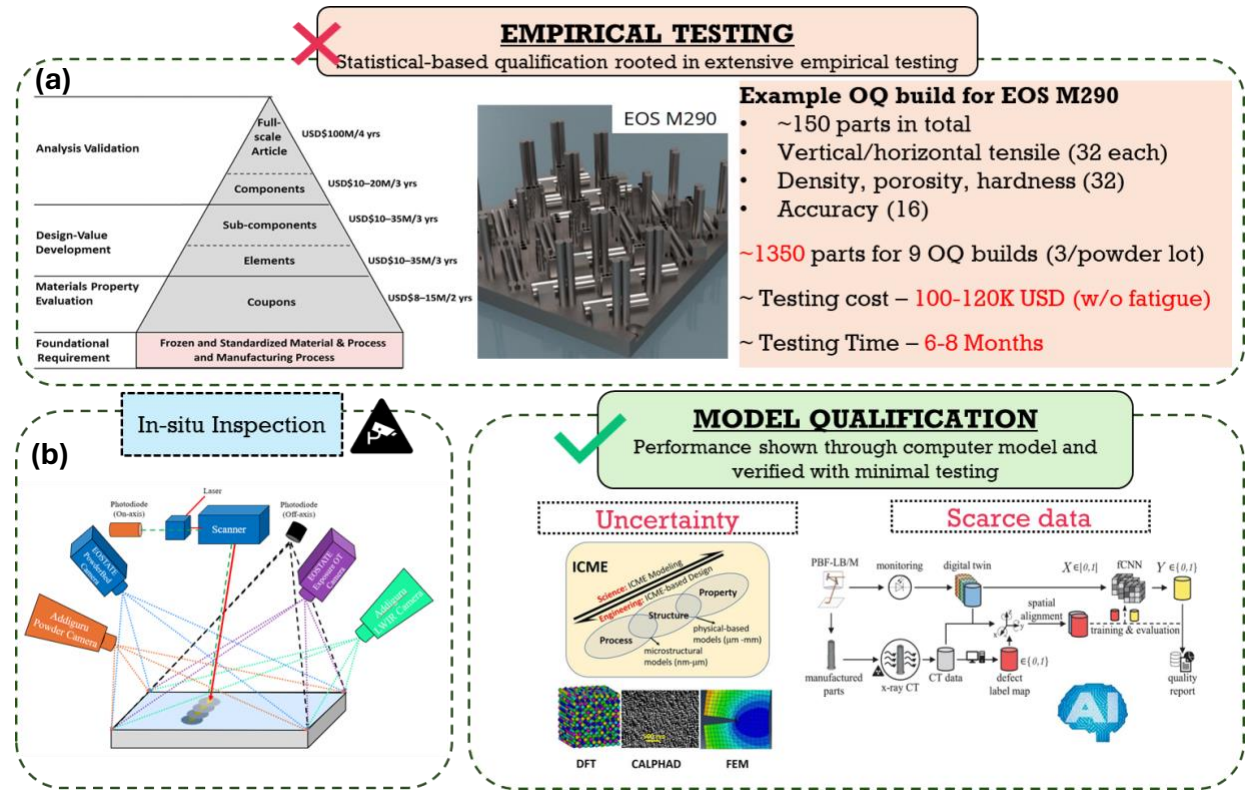
Laser powder bed fusion (LPBF) adoption faces hurdles from repeatability issues and slow, costly traditional qualification methods. In-situ process monitoring (ISPM) using multiple high-resolution sensors like Optical Tomography (OT), Melt Pool Monitoring (MPM), photodiodes, and IR cameras offers a path to faster, model-based qualification. This research utilizes multi-modal ISPM data to detect process anomalies and variations and predict final part quality. Strong correlations were found between OT signals and defect formation, which enables a data-driven framework to detect abnormalities that lie outside the defined thresholds of Grey Values (GV). Furthermore, these real-time signals facilitate closed-loop control, enabling active adjustments to process parameters during the build, such as laser power. This integrated monitoring, prediction, and control approach significantly accelerates qualification, reduces testing burdens, and enhances LPBF reliability for industrial applications.

### **Introduction**

Metal Additive Manufacturing (AM) has emerged as a preferred manufacturing technique due to its inherent design freedom, customization capabilities, and potential for near-net-shape production. Over the past few decades, significant advancements have been made in the development of highly printable alloys, optimized scan strategies, build techniques, and powder production methods, making Laser Powder Bed Fusion (LPBF) a highly versatile and adaptable metal AM process. Despite these advancements, standardization and part qualification remain significant challenges, primarily due to the complex and variable thermal histories involved in layer-wise fabrication<sup>1,2</sup>. Since defects can form dynamically, there is a need for real-time, high-resolution process monitoring. The past years have seen rapid progress in the development and integration of advanced sensor technologies aimed at enabling instantaneous data capture and process feedback, laying the groundwork for data-driven process control and digital qualification<sup>3</sup>.

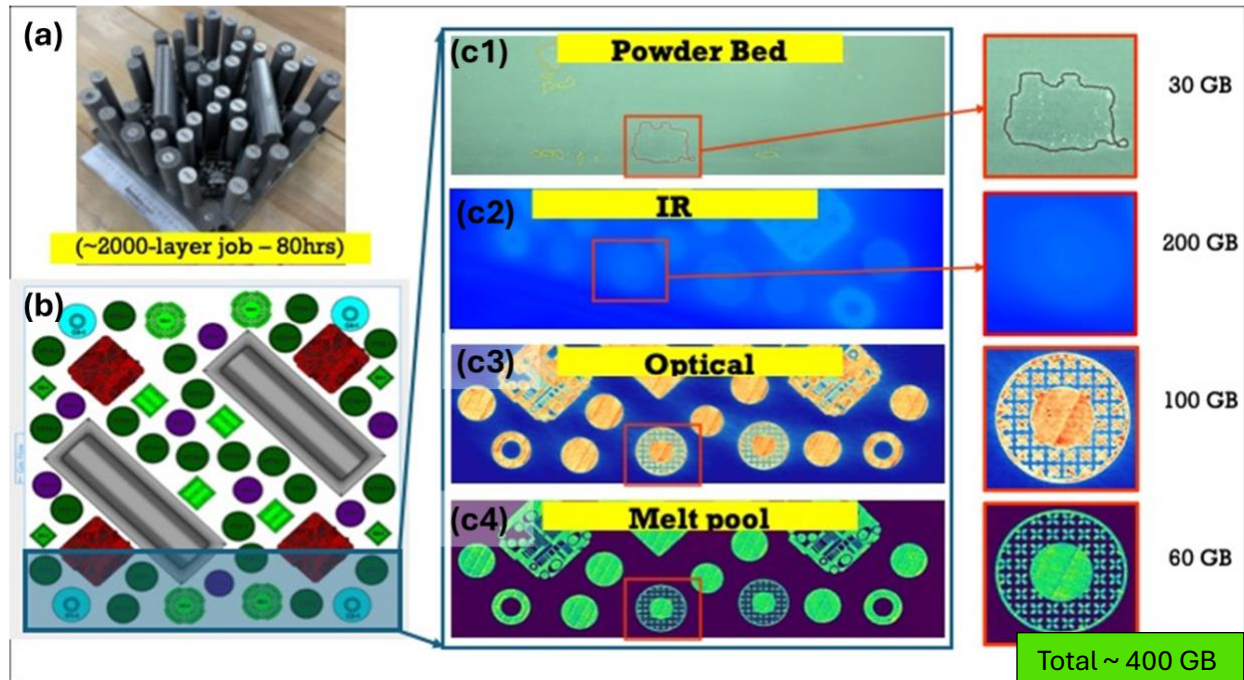
Empirical testing has long been the widely accepted method for part qualification in traditional casting processes, owing to its efficiency, low cost, and the relatively limited number of process variables involved<sup>4</sup>. However, over several decades, casting workflows have made empirical validation both feasible and reliable. LPBF introduces a vast processing space with highly customizable parameters, resulting in significant part-to-part variability. As each part may

exhibit unique thermal histories and microstructures, empirical testing becomes increasingly time-consuming and cost-prohibitive when applied to every individual build (Figure 1 (a)).



**Figure 1:** (a) Example of a typical Operational Qualification (OQ) build for the EOS M290 platform and cost/time implications of using empirical testing approach (b) Advantages of using in-situ inspection and model qualification approaches for expedited LPBF qualification.

First of all, destructive tests are both highly costly and time-intensive and hinder the adoption of AM for large-scale production. Second, the existing non-destructive testing methods, such as X-Ray CT (XCT) and X-Ray diffraction (XRD), which are carried out post-printing, are advantageous over destructive ones since they save the parts but are extremely slow, require highly technical labs, and sophisticated equipment. To address this challenge, a shift toward in-situ inspection (Figure 1 (b)) methodologies has emerged<sup>5</sup>. These involved the integration of multiple process monitoring sensors, such as Long-Wave Infrared (LWIR) cameras, Optical Tomography (OT), Melt Pool Monitoring (MPM) systems, and powder bed cameras. Coupled with model-based qualification approaches, these systems enable real-time detection of process anomalies and defect prediction. This fusion of sensing technologies and data-driven models offers a scalable, non-destructive alternative to empirical testing, facilitating faster and more cost-effective qualification in LPBF<sup>6-12</sup> (Figure 2).



**Figure 2:** (a) Example OQ build done on EOS M290 (b) Highlighted region (top-view) of OQ build job layout consisting of various geometries (c1-c4) Powder Bed (PB) monitoring evaluates recoating quality, Optical Tomography (OT) captures thermal signatures across the entire build plane, Long Wavelength Infrared camera captures temperature variation (LWIR) and Melt Pool Monitoring (MPM) tracks localized melt pool dynamics.

This study focuses on the digital qualification of LPBF builds using in-situ process monitoring techniques. A layout containing multiple sample geometries was printed to assess the influence of selected process variables on build quality. A procedure for determining an acceptable signal range, establishing upper and lower bounds, is discussed. Analysis of OT data by applying these limits revealed that it successfully captured instantaneous fluctuations during the build, which correlated with defects observed through ex-situ characterization—establishing a positive relationship between OT signals and defect formation.. Although many of these modalities had been around for a while, establishing coherence between the data from the different modalities had been a great challenge owing to the volume of data, thereby making it difficult to extract the anomalies. To address this, in addition to the multimodalities, we propose a threshold-based, sensor and material-agnostic approach that normalizes in-situ signals and flags real-time deviations. Consequently, the approach serves as a rapid screening tool that complements NDE/destructive sampling, to enable mass-production use. However, this methodology is designed to detect the deviations customized for a given machine SI#, and any changes to it would require re-establishing the threshold limits. Overall, this study proposes a unique signature-based qualification framework to address scalability beyond low-volume/high-mix production requirements by establishing composite multi-modal threshold limits and correlating them to defect detection.

In the future, after establishing the limits, closed-loop control<sup>7-10</sup> can be applied to improve both process stability and microstructural uniformity. Also, this framework can be extended by using machine learning (ML) algorithms to train models capable of predicting and classifying defects directly from real-time process signals, enabling scalable, automated qualification.

### **Materials and Methods**

The experiments were conducted on Electro Optical Systems (EOS GmbH) M290 system using Ti-6Al-4V (Grade 5) powder feedstock (Table 1) using processing parameters (Table 2)<sup>13</sup>.

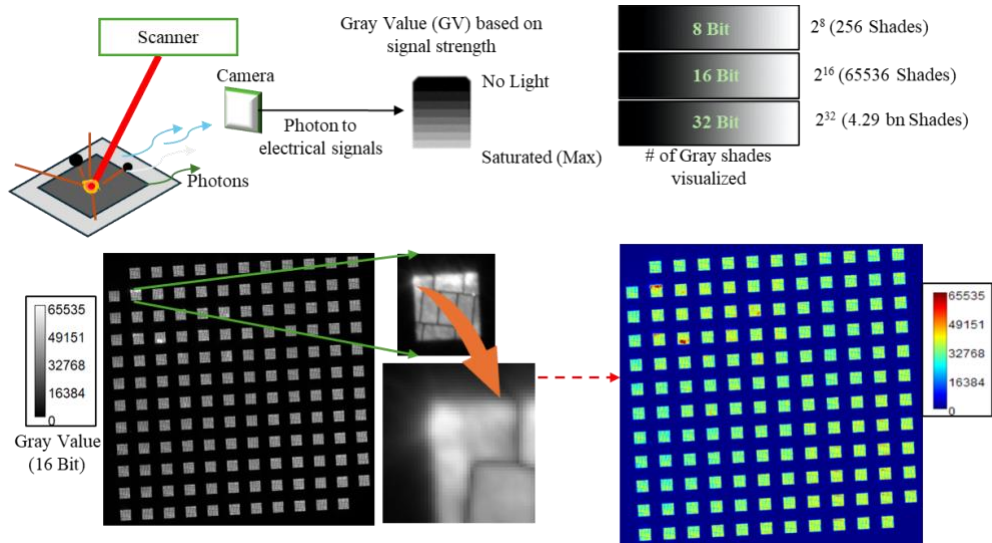
**Table 1:** Chemical composition of Ti-6Al-4V (Grade 5) powder as per EOS specifications.

	Ti	Al	V	O	N	C	Fe
Ti-6Al-4V	Bal.	6.5	4.05	0.16	0.018	0.015	0.20

**Table 2:** EOS M290 process parameters used to fabricate Ti-6Al-4V samples.

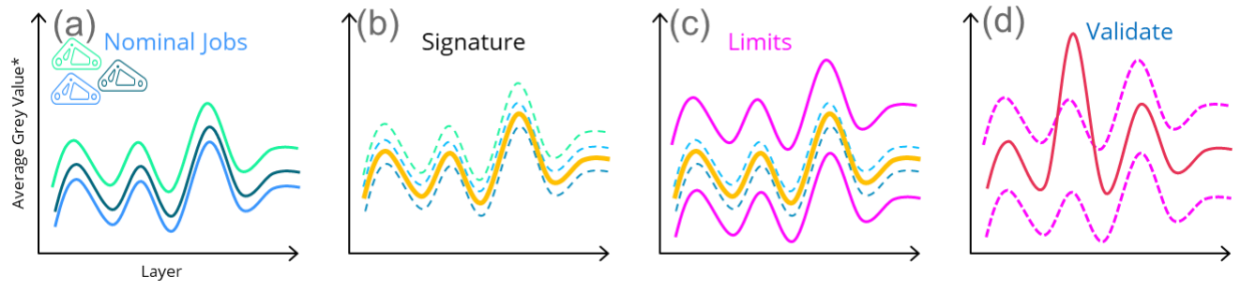
Laser Power (W)	Scan Speed (mm/s)	Hatch Distance (μm)	Layer Thickness (μm)	VED (J/mm <sup>3</sup> )
340	1250	120	60	38

Optical Tomography (OT) was used to collect layer-by-layer thermal data (Figure 3). The OT camera intensity is measured using the Grey Value (GV). The higher the intensity, the higher the gray value. The Mean of Mean Grey Value ( $Mean \overline{GV}$ ) and standard deviation of the Mean Grey Value ( $Std \overline{GV}$ ) within the gauge region were analyzed as indicators of net heat input and process variability, respectively.



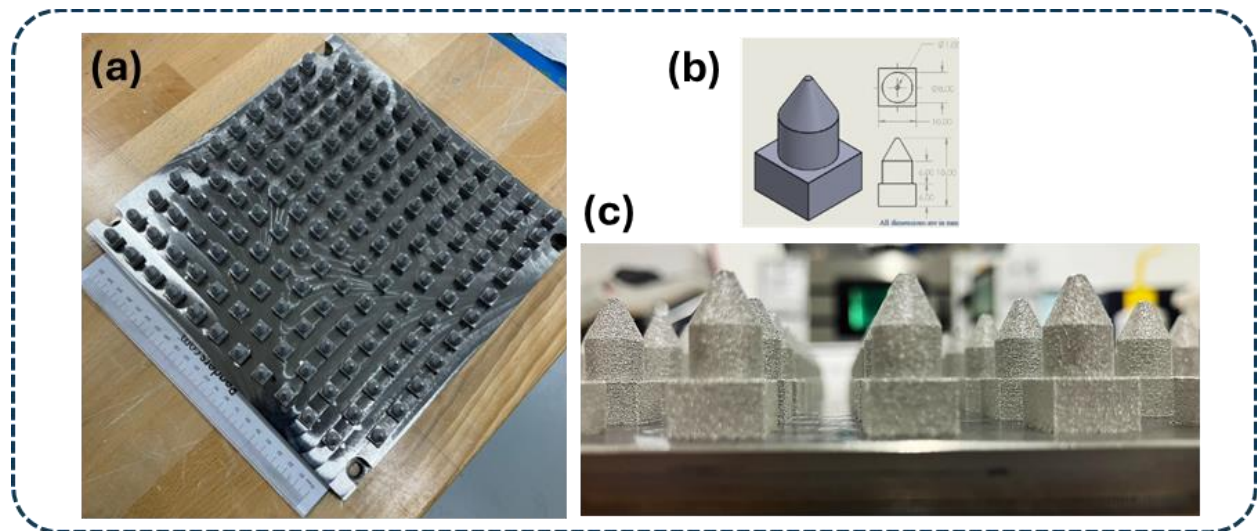
**Figure 3:** A typical schematic of a grey value collected by the EOS Smart Monitoring suite (Exposure OT, Melt Pool Monitoring, or Powder Bed) in 8 and 16 Bit GV.

Based on these OT values, a procedure for part qualification is defined in Figure 4. It shows the stepwise method of determining a qualification procedure. First, several nominal jobs are run to collect signatures, establishing upper and lower bounds of acceptable GVs. Next, the signatures from the newer runs are validated based on these upper and lower bounds.



**Figure 4:** (a) A procedure of validating and qualification by running multiple nominal jobs (b) Nominal signatures achieved (c) Based on these signatures, upper and lower bounds are defined (d) Based on these bounds, data is validated

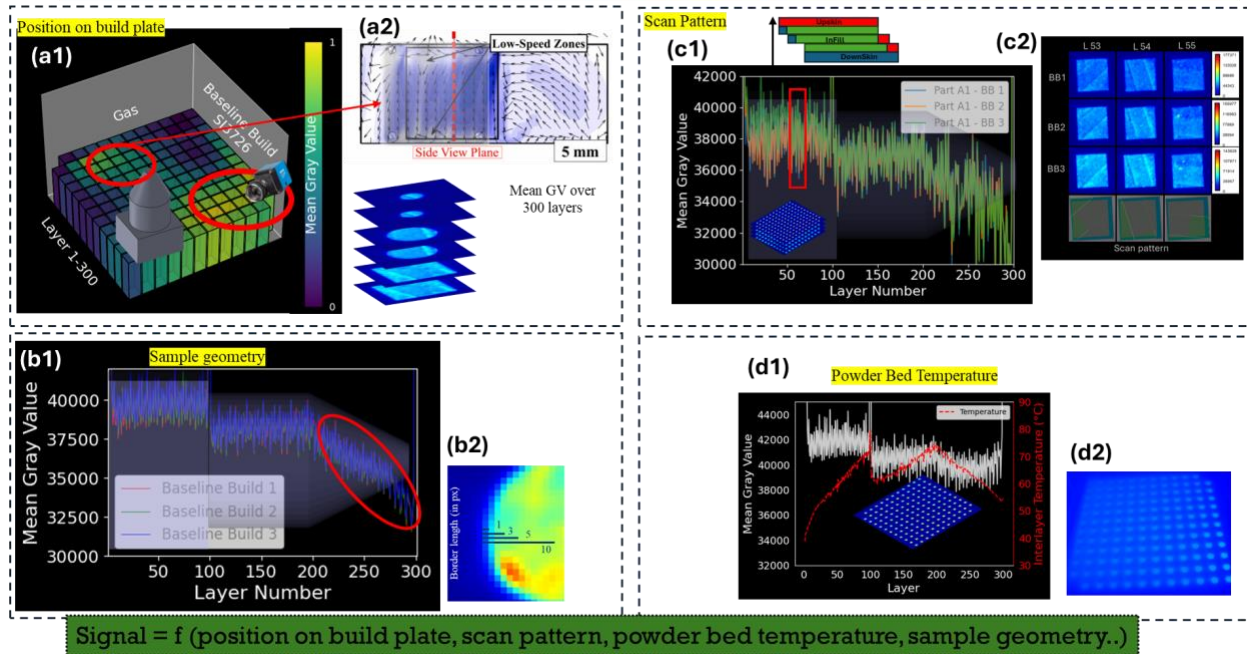
A layout having 142 units of bullet-shaped samples was chosen for this study, shown in Figure 5 (a-c). Figure 5 (b) shows the dimensions and the printed layout of all these units within the baseline builds. The sample geometry was chosen such that the variation in OT signals across variations in sample geometries (cuboidal, cylindrical, conical) can be recorded.



**Figure 5:** (a) Layout of baseline build, (b) Dimensions and projections of each unit, (c) Magnified view of each unit.

## Results and Discussion

To understand the variations in OT signals due to changes in build envelope conditions, we investigated the effects of several parameters in Figure 6. It presents a comprehensive overview of the experimental layout and variation in OT signals due to various build process variables. Figure 6 (b-e) captures the variation in OT signal as a function of (a) position within the build plate, (b) build geometry, (c) scan pattern, (d) temperature of the powder-bed.



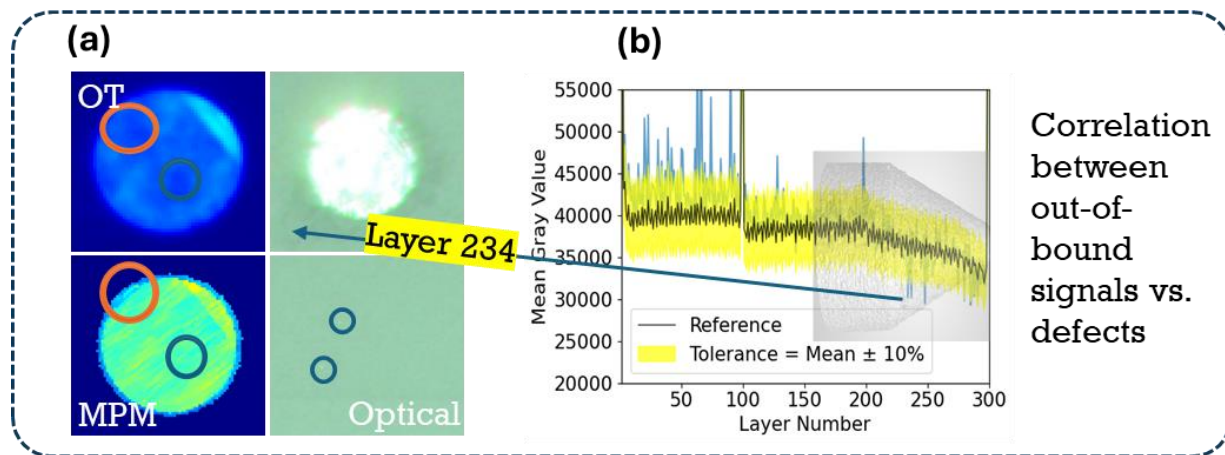
**Figure 6:** (a) Baseline builds with bullet-like specimens printed on M290. Variations in mean  $\overline{GV}$  due to (c1-c2) Build geometry (d1-d2) Scan pattern (e1-e2) Powder bed temperature

Figure 6 (a) shows that the OT signal varies across the build plate due to two primary factors: (a1) the position of the OT camera and (a2) the behavior of the gas flow. A small region with elevated OT signal values near the grid nozzle corresponds to a low-speed zone. This reduced flow speed leads to ineffective plume removal, resulting in increased signal variation and a higher mean OT signal. In contrast, more consistent OT signals are observed farther away from the grid nozzle. However, the mean OT signal tends to be higher in this region because the camera is positioned directly above the hose sample. The influence of the camera's position becomes more pronounced due to the smaller cross-sections of the bullet-shaped coupons.

Figure 6 (b1-b2) shows the variation of Mean OT Values with changes in Geometry. The observed drop in OT signal values is primarily due to the increase in powder bed temperature, which is influenced by the printed cross-sectional area. Notably, a significant decrease in OT signals is seen in the conical region. This is attributed to the lower laser power used for contour scanning compared to bulk scanning. As the cross-sectional area decreases, the effect of contour pixels in mean GV calculation increases, making their influence on the mean OT signal more

significant. If contour pixels are excluded from the calculation, the OT signal appears relatively consistent across varying geometries. The OT signal varies with the scan pattern due to changes in the direction of plume ejection and melt pool orientation, which directly affects the grayscale value (GV). As a result, fluctuations in GV are observed depending on the scan pattern used. (If a fixed scan angle is maintained throughout), the GV remains relatively constant. Figure 6 (c1-c2) visually demonstrates the variation in GV corresponding to different scan angles for three different sets of prints. The slight variation in the OT signal can be correlated with the bed temperature determined by the IR camera, as can be seen in Figure 6 (d1-d2).

Figure 7 illustrates the variation in OT signal leading to mean  $\overline{GV}$  variation across all 142 bullet-shaped specimens for each printed layer, ranging from the bottom to the top. The anomalous OT signals were cross-verified with other in-situ monitoring modalities, such as melt pool monitoring (MPM) and powder bed imaging, further supporting the presence of anomalies. The reference OT signal is established by calculating the mean grayscale value (GV) for each layer across 142 specimens. A tolerance band of  $\pm 10\%$  is applied to account for variations due to scan patterns defining the upper and lower thresholds. Any signal falling outside this range is considered indicative of a potential anomaly. Applying this strategy to the baseline build, the OT signal variation is shown over 300 layers for a single unit.



**Figure 7:** (a) Defect detection using the EOS Smart Monitoring suite (Exposure OT, Melt Pool Monitoring, and Powder bed camera) for detecting (b) out-of-bound signals corresponding to the signal deviation.

This layer-wise analysis of data fluctuation shows that deviation in ISPM data from the mean correlates with the detection of defects. Layer 234, which exhibited a mean  $\overline{GV}$  signal deviations outside these bounds showed variation in the MPM signal (Figure 7 (a)), as well, for the same layer as shown in Figure 7 (b). These evaluations confirmed that the deviations corresponded to porosity within the specimen. The variation from this target value shown in Figure 7 (b) was used to establish the acceptable upper and lower bounds.

## **Conclusion**

This study demonstrates the capability of in-situ process monitoring (ISPM) modalities to accurately capture signal deviations that are indicative of defect formation during L-PBF. First, the study confirms that ISPM systems such as Optical Tomography (OT) are effective in recording real-time signal fluctuations that arise from variations in process parameters like scan strategy, energy input, or geometry. Second, after establishing thresholds for acceptable signal ranges, out-of-bound OT signals were shown to reliably correlate with the presence of defects identified during ex-situ microstructural analysis. These deviations served as early indicators of process instability and potential defect-prone regions. Our future work will focus on identifying and integrating these threshold limits into a Closed-Loop Control (CLC) framework, which would enable the system to dynamically adjust the process parameters to maintain grey value (GV) limits within the optimal range. As a result, thermal fluctuations that typically lead to local defects such as porosity or microstructural inconsistencies are likely to be reduced.

### **Credit authorship contribution statement:**

**Y. Parikh:** Supervision, Formal Analysis, Methodology, Writing, Review — original draft. **Y. Mundada:** Data curation, Analysis, Writing, Editing **A. Roy:** Data curation, Writing — original draft., Writing — review and editing. The authors gratefully acknowledge Ryan Smith and Bharath Bhusan Ravichander for their contributions.

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