

In-Process Monitoring of Part Quality in Laser Powder Bed Fusion Additive Manufacturing Process using Acoustic Emission Sensors

Benjamin D. Bevans^{*1,2}, Alex Riensche^{1,2}, Antonio Carrington Jr.², Kaustubh Deshmukh³, Mihir Darji², Yuri Plotnikov⁴, John Sions⁴, Kyle Snyder⁴, Derek Hass², Prahalada Rao^{2,3}

¹School of Industrial and Systems Engineering, University of Oklahoma, Norman, OK

²Industrial and Systems Engineering, Virginia Polytechnical Institute, Blacksburg, VA, USA

³Mechanical Engineering, Virginia Polytechnical Institute, Blacksburg, VA, USA

⁴Commonwealth Center for Advanced Manufacturing, Disputanta, VA.

**Corresponding author, email(s): benjamin.bevans@ou.edu; benbevans@vt.edu*

Abstract

In this work, we used in-situ acoustic emission sensors for online monitoring of part quality in laser powder bed fusion (LPBF) additive manufacturing process. Currently, sensors such as thermo-optical imaging cameras and photodiodes are used to observe the laser-material interactions on the top surface of the powder bed. Data from these sensors is subsequently analyzed to detect onset of incipient flaws, e.g., porosity. However, a drawback of these existing sensing modalities is that they are unable to penetrate beyond the top surface of the powder bed. It is important to detect process phenomena within the bulk volume of the part buried under the powder, because these sub-surface phenomena are linked to such flaws as support failures, poor surface finish, microstructure heterogeneity, among others. To address this existing gap, four passive acoustic emission (AE) sensors were installed in the build plate of an EOS M290 LPBF system. Acoustic emission data was acquired during processing of stainless steel 316L samples under differing parameter settings and part design variations. The AE signals were decomposed using wavelet transforms. Subsequently, to localize the origin of AE signals to specific part features, they were spatially synchronized with infrared thermal images. The resulting spatially localized AE signatures were statistically correlated ($R^2 > 85\%$) to multi-scale aspects of part quality, such as thermal-induced part failures, surface roughness, and solidified microstructure (primary dendritic arm spacing). This work takes a critical step toward in-situ, non-destructive evaluation of multi-scale part quality aspects using AE sensors.

Keywords: Laser powder bed fusion; Acoustic emission; wavelet analysis; microstructure; support failures; surface finish.

1 Introduction

1.1 Objective and Motivation

The objective of this work is to monitor and detect incipient flaw formation in the laser powder bed fusion (LPBF) additive manufacturing process using data acquired from an in-situ acoustic emission sensor array. As shown in Figure 1, in LPBF metal powder is raked across a build plate and selectively melted layer-by-layer using a laser [1]. The LPBF process is favored in industries, such as aerospace, automotive, and biomedical, due to its ability to manufacture geometrically complex parts, reduce lead times, eliminate sub-components, and minimize weight [2, 3].

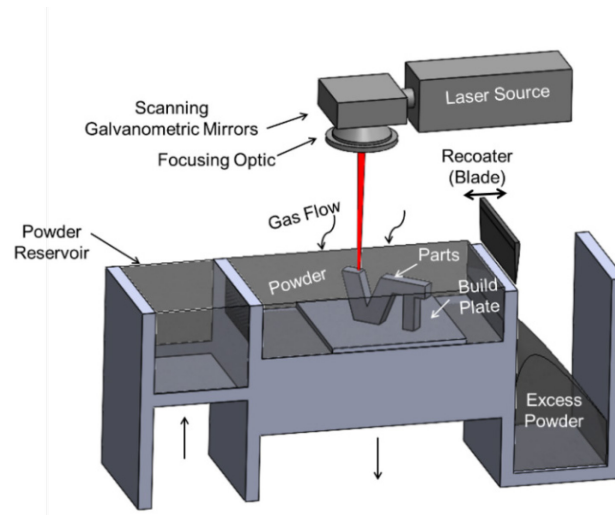


Figure 1: A schematic of the laser powder bed fusion (LPBF) additive manufacturing process.

However, despite empirical optimization, LPBF-processed parts are often afflicted by flaws such as porosity, thermal-induced distortion, poor surface finish, and microstructure heterogeneity, among others [4-7]. Such flaws cause large part-to-part variation in functional properties that are detrimental to safety-critical applications. Therefore, to ensure adherence to functional specifications, LPBF parts are currently inspected post-process through non-destructive evaluation techniques and destructive metallurgical characterization, which are expensive and cumbersome [8-10].

A popular non-destructive evaluation approach is X-ray computed tomography (X-ray CT), which requires several hours to complete for aerospace industry-relevant materials, such as stainless steel and Inconel [11]. Another emerging non-destructive evaluation approach is ultrasonic testing [12, 13]. In active ultrasound-based inspection, transducers transmit ultrasonic signals through the sample, typically in a liquid medium such as water. The intensity and velocity of the ultrasound signal is analyzed after it is reflected from the manufactured sample. Ultrasound evaluation has been shown to detect porosity and variation in grain size in metal additively manufactured parts [14, 15]. However, to the best of our knowledge, in-situ ultrasound-based monitoring of the LPBF process remains to be realized.

To mitigate post-process characterization, and facilitate future closed-loop process control in LPBF, there is immense ongoing research focused on sensor-based in-process monitoring and prediction of incipient flaw formation [16-18]. Researchers have used thermo-optical cameras, photodiodes, and imaging pyrometers, among other sensing techniques, to capture process phenomena such as the shape and temperature of the meltpool, viz., the molten pool of material caused by the laser-material interaction, spatter characteristics, surface temperature, etc. [19, 20]. The sensor data are often coupled with machine learning algorithms to predict incipient flaws, e.g., porosity and warping [21-25].

A major limitation with existing sensor-based process quality monitoring approaches is that they capture phenomena on the surface of the powder bed, and thereby exclude observation of the rest of the part which is progressively buried inside the powder with the deposition of each new layer. In other words, current sensor-based monitoring approaches in LPBF are largely incapable of detecting flaws that occur on account of thermal phenomena active in the bulk volume of the part buried underneath the surface of the powder bed.

To explain further, in the LPBF process the laser typically penetrates and remelts 2-4 layers (~ 40 to $120\ \mu\text{m}$) deep into the previously deposited material [26, 27]. The partial re-melting of solidified microstructure is one the main causes for flaw formation across multiple scales [28]. For example, microstructure heterogeneity, inter-granular cracking and hot tears occur due to complex thermal-fluid phenomena at the micro-scale [29, 30]; deterioration in surface finish and geometric integrity of overhang and thin-wall features are caused on account of heat accumulation at the meso-scale [31]; and distortion and support failures arise due to thermal-induced residual stresses at the macro-scale [32]. Therefore, from a process monitoring and defect mitigation perspective, there is an urgent need to capture sub-surface LPBF process phenomena. While in-situ X-ray synchrotron imaging has been leveraged to understand the behavior of the meltpool below the powder bed surface, these studies have been restricted to deposition of single tracks [33]. Moreover, X-ray synchrotron imaging is challenging to scale to practice, albeit, nascent efforts are ongoing to incorporate X-ray imaging within LPBF machines [34-36].

Eddy current monitoring is another non-destructive technique that has been used to detect surface and sub-surface LPBF defects, such as porosity [37, 38]. Eddy currents are excited inside the sample by a magnetic field that varies in time and excitation frequencies [39]. By monitoring the resulting current, voltage, and resistance of the eddy current signal, various forms of sub-surface defects such as large pores and cracks are detected [40]. However, eddy currents are capable of penetrating ~ 2 -3 mm of material. Further, eddy current-based monitoring has been demonstrated for detecting relatively large sub-surface flaws exceeding $200\ \mu\text{m}$ in size [41]. The implementation of eddy currents for online monitoring of LPBF is currently limited to measurements post-deposition of a layer rather than continuously capturing stochastic variations and flaw formation.

This work utilizes acoustic emission (AE) sensors that, unlike existing sensors, are capable of monitoring the sub-surface phenomena in-situ [42]. The aim is to correlate abnormalities, such as a drift in input energy, thermal-induced build failures, variation in surface finish, and microstructure heterogeneity, to changes in the AE waveform from its nominal state. AE sensors have been used in monitoring of manufacturing processes for over three decades [43-45]. During manufacturing, changes in internal stress of the part can result from a variety of events, such as formation of cracks, material phase transformations, dislocations, material deformation, and thermal-induced defects, among others [46, 47]. Ultimately, elastic waves released from these internal stress-related events reach the surface of the part, where they cause evanescent transient surface displacements that range from nanoseconds to milliseconds in time scale, and typically, 10 kHz to 10 MHz in frequency [48]. These surface displacements may be detected with a piezoelectric transducer, or non-contact means, such as a laser interferometry [49].

We underscore that AE signals are distinctive from acoustic signals captured with a microphone; AE-based sensing is related to the detection of elastic waves in a solid medium, whereas, in acoustic sensing a microphone or transducer is used for detection of acoustic waveforms traveling through a non-solid medium such as air [50]. We also note that numerous papers in the literature confound AE and acoustic sensing [51-53]. For example, in Ref. [52, 53] an acoustic microphone is used to detect keyhole and lack-of-fusion porosity in LPBF of stainless steel 316L through analysis of the acquired data with machine learning. However, the sensing approach described in Ref. [52, 53] is not AE-based, although it has been (erroneously) described as such. This is because the acoustic signals are detected by a microphone after translating through air in place of measuring vibrations translating through a solid medium.

As discussed by Dornfeld *et. al.* [54], one of the earliest uses of contact-based AE sensors in manufacturing was for monitoring of machining process. In machining, piezoelectric AE transducers are typically attached to the surface of the specimen or cutting tool to capture elastic waveforms in the 10 kHz –2 MHz frequency [55]. Elastic energy released due to events, such as tool failure, micro-cracking, plastic deformation, and regenerative chatter during surface generation manifests as AE signatures [45]. Particularly, AE-based sensing was found to be sensitive to evanescent sub-micrometer scale phenomena, such as intergranular micro-fracture and material dislocation, inherent to ultraprecision micro- and nano-machining, where the material removal length scale ranges from 10 μm to 1 nm [56, 57].

In Figure 2 we conceptualize the use of AE sensors for process monitoring in LPBF. The interaction of the laser and material at the surface would generate high frequency acoustic waveforms. These waveforms on propagating through the solid part (marked in black) are captured by an array of AE sensors embedded in the build plate. When the acoustic wave interacts with a flaw, such as a void or crack, its spatiotemporal morphology would change. This change in characteristics of the acoustic signal, as schematically illustrated in Figure 2(b), results from wave interference due to differences in acoustic impedance and variations of the wave propagation speed in the non-metallic media, such as voids. Additionally, as shown in Figure 2(c), such failures as broken supporting struts may also alter the nature of wave propagation due to multiple reflections, thus causing temporal amplitude changes in the AE signal.

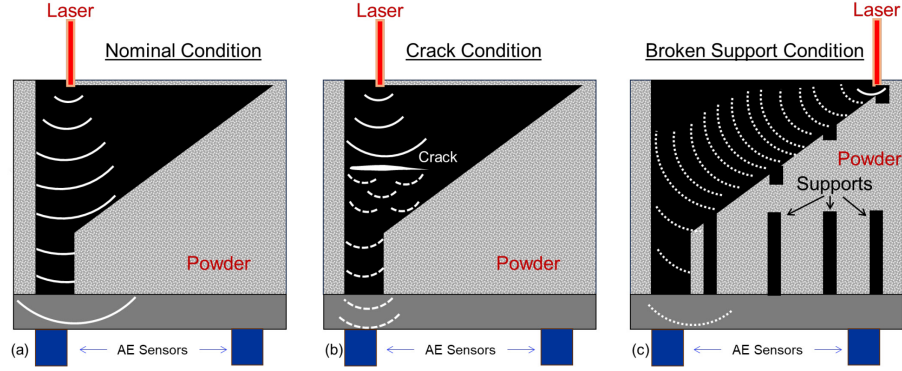


Figure 2: Conceptual effect of part flaws on the AE wave. The transient, high-frequency elastic waveforms generated by surface-level laser-material interactions travel through the part and are captured by the AE sensors. The spatiotemporal morphology of the AE signal is influenced by flaw formation and build failures.

1.2 Prior Work in AE-based sensing in additive manufacturing – Gaps and Challenges

Researchers are actively exploring avenues to use both acoustic and AE-based approaches to perform online, non-destructive monitoring of additively manufactured parts [58-60]. In a recent article Prem *et. al.* [61] evaluated 115 acoustic and AE-based monitoring papers across multiple additive manufacturing processes. Of these 115 papers, 9 used acoustic monitoring with a microphone, and only 3 used contact AE-based sensing for process monitoring in LPBF. The remaining 103 papers focused on other additive manufacturing technologies, such as fused filament fabrication, directed energy deposition, etc. Likewise, AbouelNour and Gupta [17] provide a comprehensive review of various sensing modalities, including AE, for process monitoring in AM. In what follows, we provide a focused review of both contact and non-contact AE-based techniques in LPBF.

As will become evident from the forthcoming summary, the majority of the existing AE-based LPBF process monitoring research is restricted to detection of flaws, such as porosity and cracking. Investigations into correlation of AE signatures with solidified microstructure and surface finish remains to be explored. By contrast, this work correlates AE signals with multi-scale part quality

aspects encompassing solidified microstructure (grain size), surface finish, build failures, and cracking.

Mohammadi *et. al.* [62, 63] used AE sensors placed at the bottom of the LPBF build plate. The data was subsequently analyzed to extract statistical time-domain features. These features were used within machine learning models to detect flaws such as porosity and cracking. Similarly, Eschner *et. al.* [64] used an AE sensor placed underneath the build plate, and analyzed the data with a Fourier transform spectrogram and convolutional neural networks to classify the level of porosity. They achieved a classification accuracy of 85% (F-score). Recently, Plotnikov *et. al.* [65], embedded three passive AE piezoelectric sensors at the bottom of the build plate. They correlated the AE signature to extreme processing conditions that induced various levels of porosity. Kononenko *et. al.* [66], used contact-based AE sensors to detect the onset of crack formation with a statistical accuracy of 99% by coupling principal component analysis of the frequency space with simple machine learning models, such as support vector classifiers and logistic regression.

There are two challenges with using AE-based sensing for process monitoring in LPBF. First, as summarized in the context of Figure 2, owing to the complex path and time dependencies, the AE signal is inherently nonlinear and non-stationary, and the interaction with flaws results in evanescent signatures [67]. Additionally, the AE waveforms do not travel in a linear path but can reverberate inside of the sample. The reverberations and extraneous process events, such as recoater motion, machine elements, among others, causes substantial background noise that must be identified and removed from the AE signal [68]. Conventional statistical signal processing and linear frequency analysis, such as Fourier transforms are ill-suited to accommodate the non-stationary and nonlinear aspects inherent to AE signatures [69]. Second, AE signals are 1D time

series signatures; spatial information regarding the origin of the AE signature from a specific area of a part and layer is not accessible. Therefore, during the LPBF process where multiple parts are melted at the same time on a layer, it is difficult, if not impossible, to localize the origin of the AE signal to a specific spatial location on a part.

As an example of non-contact AE sensing in LPBF, Shevchik *et. al.* [70] placed a fiber Bragg grating sensor in the build chamber 200 mm away from the laser melting region. They analyzed the acoustic signature captured by the sensor with spectral convolutional neural networks and reinforced machine learning methods, and classified the level of porosity within the sample with an accuracy ranging from 78-90% [71, 72]. Spatially resolved acoustic spectroscopy (SRAS) is another example of non-contact AE sensing in which a laser generates the acoustic signature and a separate laser is used to detect the resulting elastic waveform [73]. The SRAS approach, pioneered by Smith and co-workers [73-75], has been used to detect microstructural characteristics such as grain size and orientation, as well as porosity. However, similar to the limitation with eddy current-based inspection, the effectiveness of SRAS is currently restricted to near-surface defects.

1.3 Approach, Novelty, and Limitations

In this work, we have used the following two-step approach, shown in Figure 3, to overcome the foregoing challenges in AE-based monitoring of LPBF, and consequently, correlate AE signals with grain size, surface finish, build failures, and cracking.

- Multi-spectral wavelet decomposition of the AE signal: To address its nonlinear and non-stationary nature, a discrete wavelet transform is used to denoise and decompose the raw AE signal into eight frequency levels (octaves). The spectrally deconvolved AE signal is analyzed and a feature called spectral energy (E_s) is extracted. The spectral energy (E_s) which is the squared magnitude of the deconvolved AE signal averaged over a specific time window.

- Signal localization: The AE waveforms do not travel in a linear path but can reverberate inside of the sample and through other geometries. Therefore, localizing the AE signature is essential for effective process monitoring.

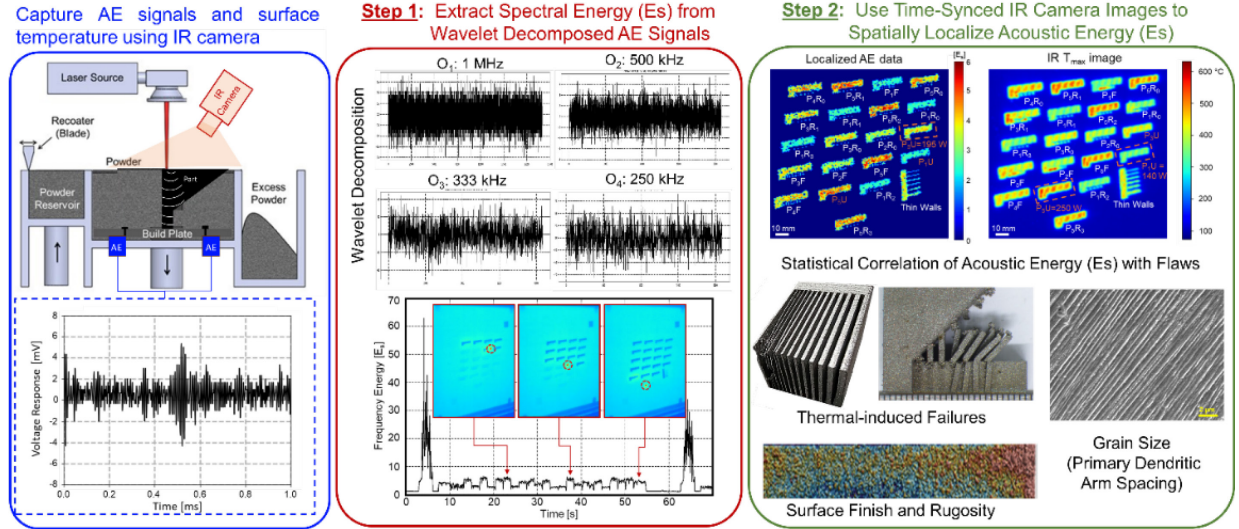


Figure 3: Overview of the two-step approach used in this work to detect flaws. In-situ AE and IR data are acquired during the build. Step 1: Extract spectral energy from wavelet-based decomposition, Step 2: Spatially locate source of AE spectral energy (E_s) using time-synced IR camera, and correlate to flaws.

The main novelty of this work is in synchronizing the AE signal with 2D IR imaging data. Consequently, the AE signal can be tagged to a specific location on the part surface, which in turn enables pinpointing areas on the build plate with incipient part defects. Specifically, the AE spectral energy (E_s) is synchronized with 2-dimensional IR data to locate each AE data point to a specific instant of laser interaction and spatial coordinate on the build plate. Further, to demonstrate a causal relationship between the acoustic energy (E_s) generated at the laser-material interface and part quality we leverage experimentally verified, computational thermal simulation models [76]. Thermal simulations for similar shapes are reported in our previously published work; details of the thermal simulation model are eschewed in this paper for brevity [27, 76, 77].

The resolution of defects detected by the AE-based process monitoring approach is limited to $> 50 \mu\text{m}$ on account of the limited spatial resolution of the IR camera used to localize the AE signatures. In this work we demonstrate that the approach detects flaws in thin-wall sections as small as $200 \mu\text{m}$. The resolution of defect detection with AE sensors can be significantly improved by using alternate imaging sources, such as optical tomography and high-speed imaging for signal localization in lieu of infrared imaging. Indeed, if the laser location can be tracked in time and synchronized with the collection of the AE signal, it is possible to eliminate the need for an imaging sensor for localizing the AE signal and produce higher resolution results than discussed in this work.

We reckon that the proposed approach would not be conducive for monitoring the status of extreme overhang geometries with minimal solid material connecting the part to the substrate where the AE sensors are embedded. This is of minor practical concern because industry best practice recommends against printing such geometries. We note that overhang angles up to 80° have produced identifiable AE signals in our ongoing works.

The scope of this work is restricted to correlation of AE signatures with specific defects; the AE signatures are not used to predict the onset of defects due to limited availability of characterization data. We are currently devising machine learning models which couple process simulations and AE signatures to predict multi-scale material characteristics.

The rest of this paper is organized as follows. Sec. 2 describes the experimental setup, design of experiments, and sample data. Sec. 3 details the methodology for wavelet decomposition and monitoring of AE signatures. Sec. 4 reports the results, wherein we demonstrate the effectiveness of the AE signatures toward detection of cracking, support failures, surface finish, microstructure, and porosity. Conclusions and avenues for further research are summarized in Sec. 5.

2 Methodology

2.1 Experimental Setup

A multi-sensor suite was installed on an EOS M290 LPBF machine. The sensors used were: (i) optical imaging camera; (ii) long wavelength infrared (LWIR) thermal imaging camera; and (iii) four piezoelectric AE sensors attached to the bottom of the substrate. The sensor specifications are detailed in Table 1 and a schematic is provided in Figure 4. All sensors were interfaced via LabView and each data point was time-stamped within a resolution of 1 ms using the same clock [78]. The precise synchronization of thermal imaging and AE data is critical to this work as it enables localization of AE signatures to specific coordinates on the powder bed and features on individual parts. We note that imaging modalities, such as optical topography cameras, can also be used in lieu of IR imaging, as long as the image has sufficient resolution to track the laser position and is isochronous with the acquisition of AE signal.

The off-axis optical camera acquires an image of the powder bed after the melting of each layer. The IR thermal camera operates continuously at a frame rate of 33 frames per second and captures the top surface temperature of each of the parts at the longwave infrared wavelength range from 7.5 μm to 13.5 μm . The IR thermal camera measurements were calibrated to the absolute temperature scale using an industry standard procedure described in our prior works [76]. The thermal images are used for spatial localization of AE signatures.

The four AE sensors were seated in a square formation on a sensor plate, as shown in Figure 5. The AE sensors demarcated as AE-1 and AE-4 were tuned for a high frequency response of 150-850 kHz, and AE sensors AE-2 and AE-3 were tuned for a lower frequency response of 50-400 kHz. These two types of AE sensors are used to monitor a wider range of frequency responses in-situ. The build plate was placed on top of the AE sensor plate and bolted on with equal torque

(~25 N·m) on all four corners. The AE sensors were mechanically coupled to the build plate using vacuum grease. The signals from the four AE sensors were synchronously digitized at a rate of 1 MHz and calibrated using a waveform generator.

Table 1: Sensors used in this work to monitor the LPBF process.

Sensor Type	Model	Resolution	Spatial Resolution	Sampling Frequency	Observation
Optical Imaging Camera	Basler DFK AFU420-CCS	42 Megapixels	290 pixels per mm ²	1 image per layer	Top surface of the powder bed
Infrared Thermal Imaging Camera	FLIR A65	640 × 512 7.5-13.5 μm	2 pixels per mm ²	30 Hz	Relative temperature of the top surface of the powder bed
Acoustic Emission	AE ISR WDCA-HT	150-850 kHz	N/A	1 MHz	Acoustic energy through the sample
	AE ISR 15CA-HT	50-400 kHz			

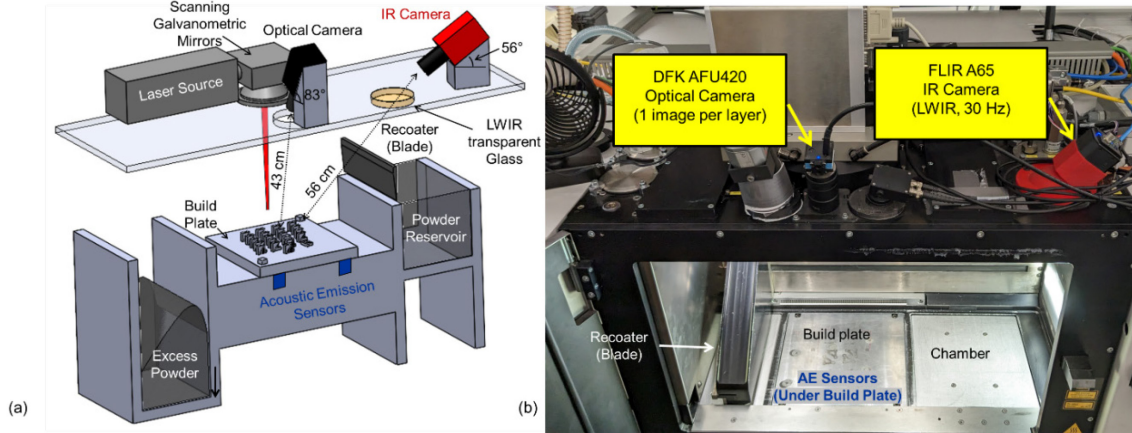


Figure 4: The sensor setup consisted of an optical camera, a FLIR long wavelength IR camera, and 4 Acoustic emission sensors installed on an EOS M290 LPBF machine.

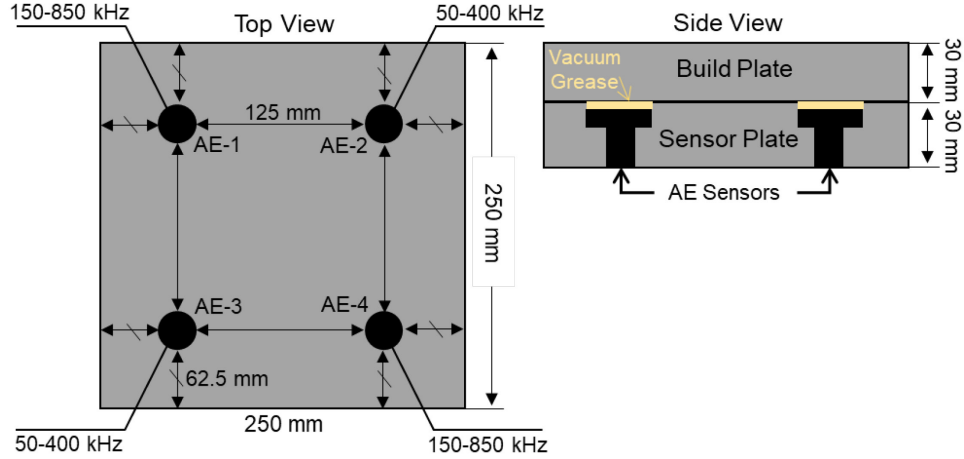


Figure 5: Four AE sensors are installed below the build plate. The build plate is placed on top of the sensor plate with the four AE sensors and coupled with vacuum grease.

2.2 Experiments

Twenty overhang geometries (Figure 6) were manufactured under varying processing parameter settings and part design conditions. The nominal processing parameters suggested by the machine manufacturer are listed in Table 2. The parts are 20 mm tall, and consist of 1000 layers, each 20 μm thick. The stainless steel 316L (SS 316L) powder feedstock has a mean particle diameter of 30 μm and standard deviation of 15 μm . The material used, SS 316L, is a single phase austenitic grade stainless steel that is known for its corrosion resistant properties [79]. In addition to the 20 overhang geometries, a thin-wall part and two $10 \times 10 \times 6 \text{ mm}^3$ cuboid geometries are also processed on the same build plate. These are used for sensor calibration and as fiducials for localizing the sensor data and are not further studied in this work.

Table 2: Table of nominal processing parameters and material properties used in this work.

Process Parameter [Units]	Values
Nominal Laser Power, P [W]	195
Scanning Velocity, V [$\text{mm}\cdot\text{s}^{-1}$]	1083
Hatch Spacing, H [mm]	0.09
Layer Thickness, T [mm]	0.02
Volumetric Global Energy Density E_v [J/mm^3]	100
Build Atmosphere	Argon
Build Plate Preheat Temperature [$^{\circ}\text{C}$]	70
Recoater Cycle Time [sec]	10
Recoater Blade Type	Metal

Auxiliary Process Parameters [Units]	Values
Upskin Laser Power, P_u [W]	135
Upskin Scanning Velocity, V_u [mm·s ⁻¹]	800
Downskin Laser Power, P_d [W]	80
Downskin Scanning Velocity, V_d [mm·s ⁻¹]	1000
Support Strut Laser Power, P_s [W]	100
Support Strut Scanning Velocity, V_s [mm·s ⁻¹]	675
Scan Strategy	67° rotation, random hatch
Powder Material Properties	Values
Material Type	Stainless Steel 316L
Material Manufacturer	Oerlikon
Powder Size Range [μ m]	15 – 45 (D10 – D90)

The three types of sample overhang geometries manufactured in this work are shown in Figure 6. These geometries, which have been studied extensively in our previous works, were chosen because the overhang region tends to accumulate varying levels of heat contingent on the processing parameters and nature of support structures [27, 76, 77]. The complex interaction of part design, processing parameters, and thermal history, influence multi-scale part quality aspects ranging from microstructure (grain size), surface finish, and thermal-induced distortion and failure of support structures [27, 76, 77].

The three variations of the overhang geometry, as noted in Figure 6(top), are as follows: (i) parts without support, labeled U ; (ii) parts with full supports, labeled F ; and (iii) parts with reduced supports, labeled R . The as-built parts are depicted in Figure 6(bottom), all three unsupported overhang geometries (U) were manufactured successfully without any visually evident flaws. However, it is observed that certain reduced (R) and full (F) supported overhang geometries experienced varying degree of support failures. These failures, as will be explained shortly, are a result of plastic deformation and recoater contact on account of excessive heat retention in the overhang region. In Figure 6(bottom), some of the as-built parts do not have supporting struts as they were cancelled during the process to avoid catastrophic failure of entire build. Detailed explanations of each of the overhang sample geometries, U , F , and R , are discussed herewith.

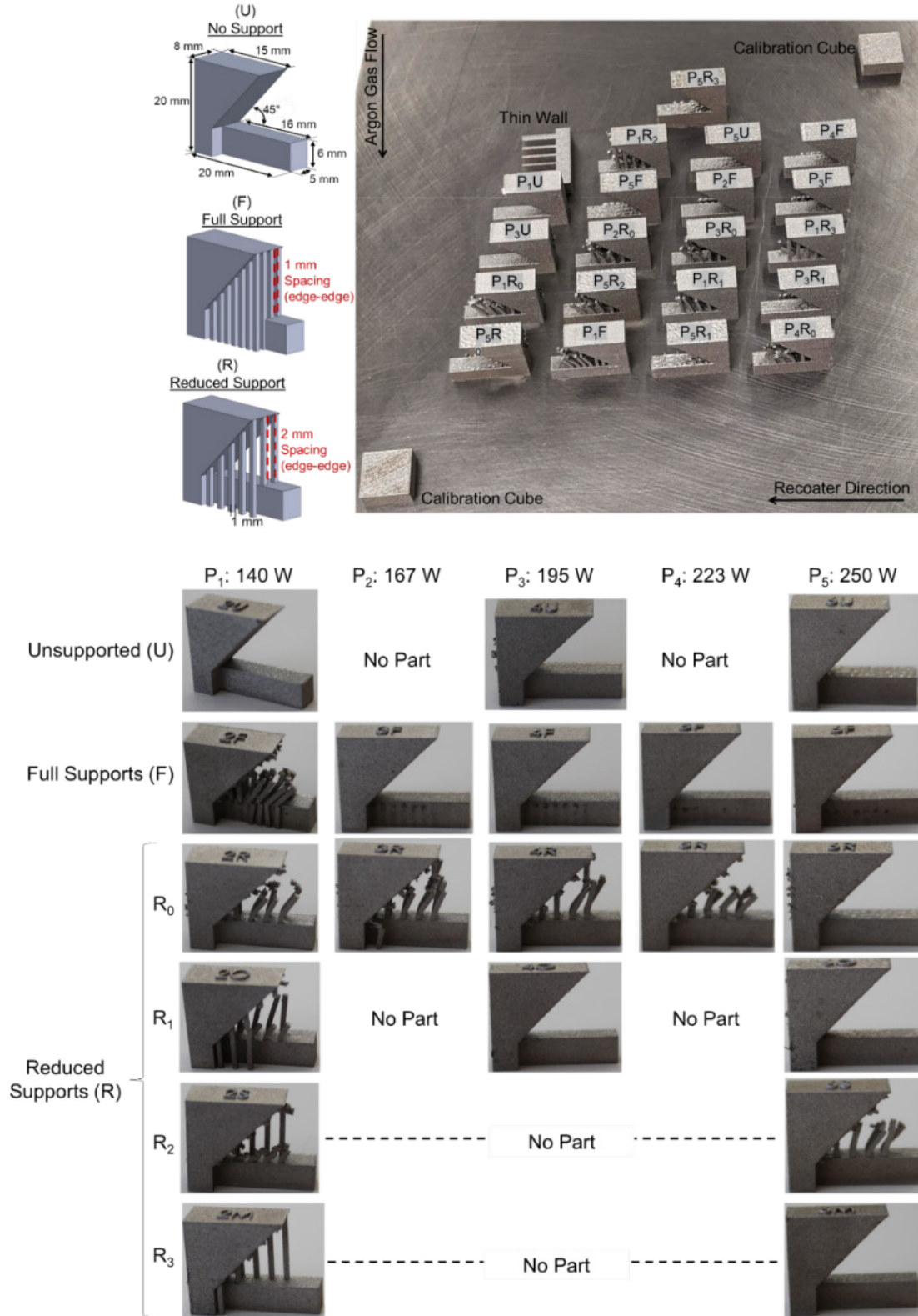


Figure 6: (Top) Exemplar geometries and layout of the build plate used in this work. (Bottom) Unsupported (U), full support material (F), and reduced support material (R) overhang geometries, and their support struts.

2.2.1 *Unsupported Overhang Geometries (U)*

Three unsupported part geometries were manufactured as shown in Figure 6 under laser power settings, annotated as $P_{1U} = 140$ W, $P_{3U} = 195$ W, and $P_{5U} = 250$ W. These laser power ranges represent $\pm 30\%$ from the nominal laser power setting $P_{3U} = 195$ W, and were chosen from literature to minimize the formation of lack-of-fusion and keyhole porosity [80]. All three unsupported parts were manufactured with no visible flaw formation.

2.2.2 *Full Support Overhang Geometries (F)*

Five overhang geometries were built with supporting struts underneath the overhang section. These struts were $1\text{ mm} \times 1\text{ mm}$ in cross-section and were located with edge-to-edge spacing of 1 mm. The parts were manufactured at five laser power conditions ranging $\pm 30\%$ of the nominal value of 195 W, in intervals of 15% (~ 28 W). The parts are labeled P_{1F} – P_{5F} and processed under the following laser power conditions: $P_{1F} = 140$ W, $P_{2F} = 167$ W, $P_{3F} = 195$ W, $P_{4F} = 223$ W, and $P_{5F} = 250$ W, with the rest of the processing conditions maintained constant, as detailed in Table 2. In these geometries, both the support struts and bulk regions of the part were manufactured under identical processing conditions.

As observed from Figure 6(bottom), the lowest laser power sample (P_{1F}) experienced significant recoater interactions. The contact with the recoater caused the support struts to fail due to plastic deformation, however, the bulk volume of the parts finished to completion. The support structures of samples P_{2F} – P_{5F} were cancelled in the first 300 layers (6 mm) due to excessive recoater interactions that occur on account of thermal-induced deformation. These recoater interactions resulted in material debris that could potentially jeopardize the entire build.

2.2.3 Reduced Support Overhang Geometries (R)

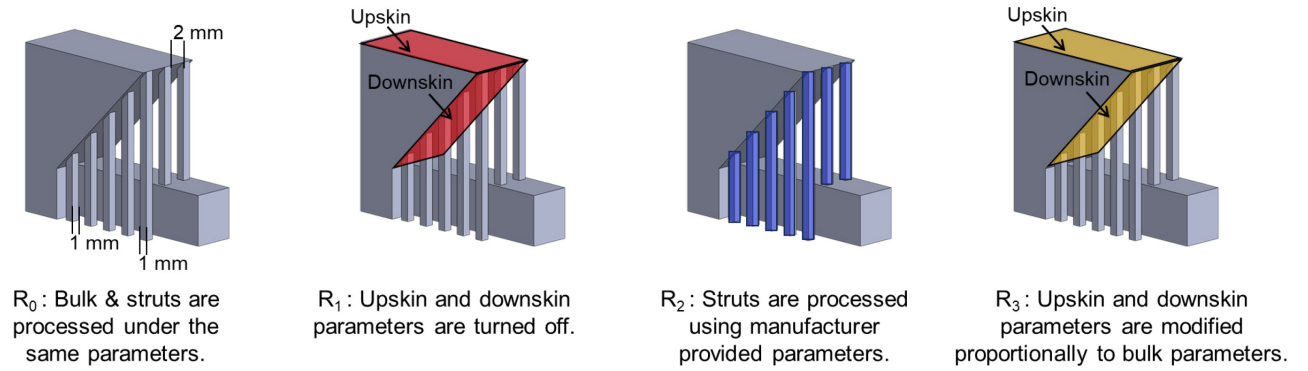


Figure 7: Schematic of build parameters for the reduced support parts. R_0 & R_1 – no upskin and downskin parameters; R_2 – manufacturer recommended support parameters; and R_3 – modified upskin and downskin parameters.

Twelve reduced support parts (R) were built with 2 mm edge-to-edge spacing between the support struts under the following four processing condition and parameter variations, labeled as R_0 , R_1 , R_2 , and R_3 , as noted in Figure 7.

- R_0 : Five parts were built at five laser power settings, ranging from $P_{1R_0} = 140$ W to $P_{5R_0} = 250$ W, viz., $\pm 30\%$ of the nominal laser power setting of 195 W, similar to the full support samples (F). For these five parts, the bulk areas and support struts were processed at the same laser power. Four samples $P_{1R_0} - P_{4R_0}$ experienced support failures. The support struts for sample P_{5R_0} processed at $P = 250$ W were cancelled in the first 300 layers due to excessive recoater interactions.
- R_1 : The bulk and supporting struts of the part were processed at power settings $P_{1R_1} = 140$ W, $P_{3R_1} = 195$ W, and $P_{5R_1} = 250$ W. The three parts were produced with the upskin and downskin parameters turned off. As demarcated in Figure 7, upskin surfaces are those regions where unmelted powder exists above a layer, conversely, downskin surface have unmelted powder below. Typically, as reported in Table 2, upskin and downskin boundaries in LPBF are processed at a reduced power and velocity compared to the bulk to improve surface finish

[81]. The supports of sample P₁R₁ failed due to deformation, while the bulk part was printed successfully. Samples P₃R₁ and P₅R₁ had the support struts cancelled in the first 300 layers due to severe recoater interactions.

- R₂: Two parts, labelled P₁R₂ and P₅R₂, were produced using manufacturer recommended parameters for support materials ($P_s = 100 \text{ W}$, $V_s = 675 \text{ mm} \cdot \text{s}^{-1}$) while maintaining the bulk overhang laser power at P₁R₂ = 140 W and P₅R₂ = 250 W. While the support struts failed to build due to plastic distortion, the bulk parts were successfully completed. The upskin and downskin parameters were maintained at manufacturer recommended settings. For SS 316L the manufacturer recommended upskin parameters are $P_u = 135 \text{ W}$ and $V_u = 800 \text{ mm} \cdot \text{s}^{-1}$; and downskin parameters are $P_d = 80 \text{ W}$ and $V_d = 1000 \text{ mm} \cdot \text{s}^{-1}$.
- R₃: Two parts labeled, P₁R₃ and P₅R₃, are printed with laser power 140 W and 250 W respectively. However, as shown in Figure 7, in contrast to R₂, the manufacturer recommended parameters for upskin & downskin were altered, to create differences in the surface finish and microstructure. The modified upskin and downskin parameters were proportional to the laser power of the bulk material at P₁R₃ = 140 W and P₅R₃ = 250 W. Sample P₁R₃ had an upskin laser power $P_u = 95 \text{ W}$ and a downskin laser power $P_d = 55 \text{ W}$. Whereas, sample P₅R₃ had an upskin laser power $P_u = 175 \text{ W}$ and a downskin laser power $P_d = 105 \text{ W}$. Scan velocity was not altered from the manufacturer recommended settings to minimize confounding variables.

The supporting struts of P₁R₃ failed on account of plastic deformation, while the supports for the high laser power sample (P₅R₃) had the support struts cancelled in the first 300 layers to prevent build failure.

2.2.4 Validation Experiments

To affirm the transferability of the approach to different part shapes another build plate was printed, as shown in Figure 8. During this build the IR camera and the four AE sensors captured data under identical conditions discussed in Sec. 2.1. The geometries of interest are two thin-wall parts, with thin-wall thickness ranging from 0.1–1.5 mm which fail to build. Specifically, walls of thickness less than 0.2 mm experience severe thermal-induced deformation. In our future work we intend to validate the approach with Inconel 718 LPBF parts.

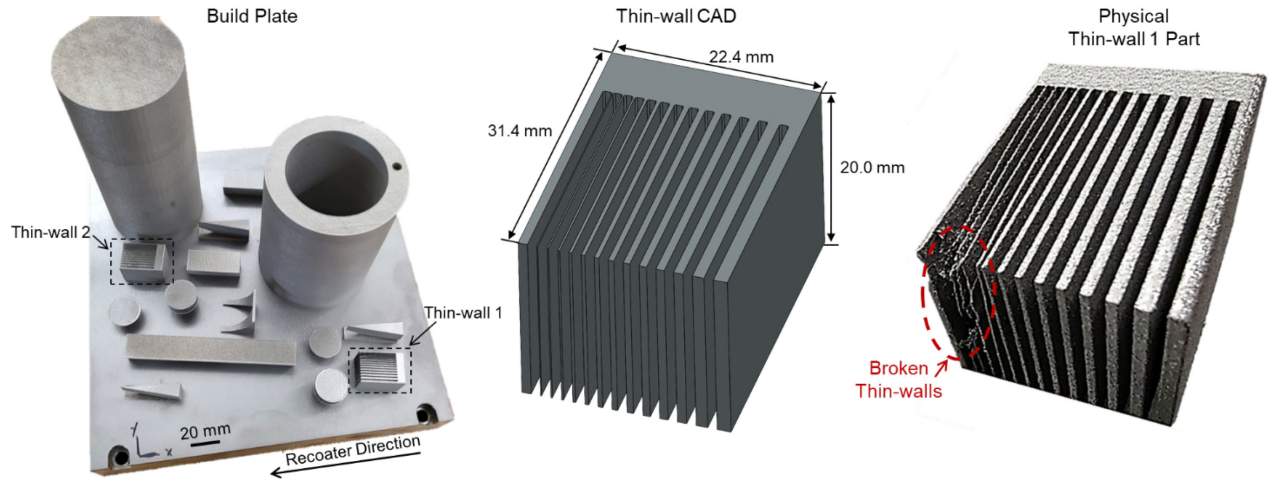


Figure 8: A validation build plate manufactured with identical sensor setup and material (SS 316L) on the same machine (EOS M290).

2.3 Materials Characterization

The 20 overhang samples were characterized post-process using both non-destructive and destructive metallurgical analyses. First, each sample was analyzed using X-ray computed tomography (X-ray CT, North Star Imaging X3000 system) at a voxel resolution of $\sim 16 \mu\text{m}$. No lack-of-fusion porosity was observed in the X-ray CT images. This was affirmed with optical microscopy and scanning electron microscopy (SEM). The absence of lack-of-fusion porosity is to be expected as the processing parameters were specifically selected to avoid porosity.

Surface roughness and primary dendritic arm spacing (PDAS, λ_1), analogous to grain size, was measured for select samples using confocal laser microscopy and SEM, respectively. The PDAS has a significant effect on mechanical properties, such as microhardness, tensile strength, and fatigue life [82-84]. The foregoing functional properties are typically inversely proportional to the PDAS [85]. The PDAS measurements were obtained from the SEM images using the bounding box procedure detailed in our previous works [27].

In preparation for SEM analysis, samples were ground and polished to surface roughness $R_a \sim 5 \text{ nm}$. Subsequently, the samples were etched using aqua regia (3 HCl:1 HNO₃) and examined using SEM at 7000x magnification with a beam accelerating voltage of 5 kV. Surface roughness measurements of the top surface for all 20 samples, along with the underskin of 11 samples with no support struts, were acquired using a Keyence VK-X3000 3D surface profilometer and confocal microscope. Poor surface quality in LPBF samples can generate crack propagation points that reduce fatigue life in high stress applications [86].

3 Process Monitoring

3.1 Sample Data

3.1.1 Acoustic Emission

Depicted in Figure 9(a) is the as-received AE time signal, after +40 dB amplification in the range of 10 – 1,000 kHz, for a 1 ms time window when the laser is turned off. During the laser off condition, the AE voltage response oscillates between ± 1 mV with a resolution of ~ 0.5 mV. Shown in Figure 9(b) is the voltage response for a 1 ms time window when the laser power is set to its lowest level of 140 W. Under this processing condition, the voltage response typically oscillates between ± 2 mV. Shown in Figure 9(c) is the AE response at the highest input power of 250 W, the voltage response from the AE sensor typically oscillates between ± 3 mV and occasionally increases up to 6 mV.

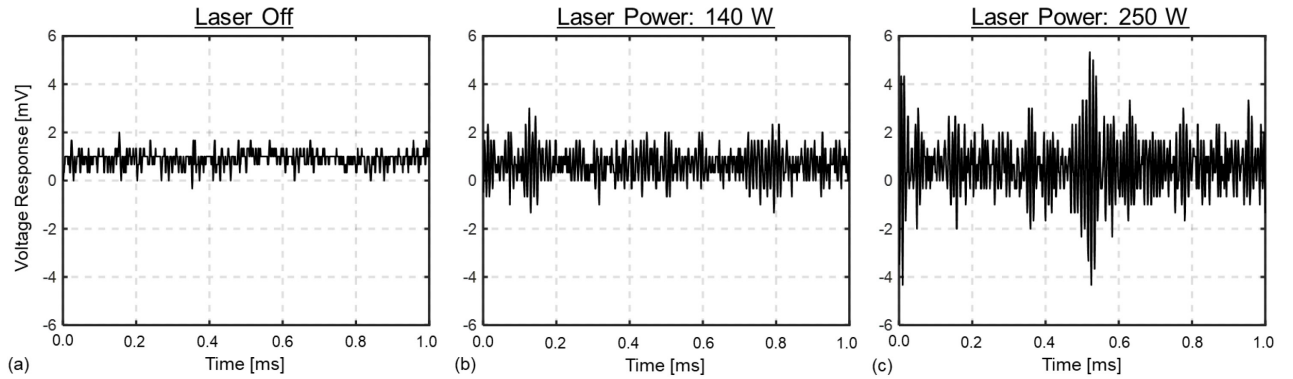


Figure 9: Example of the as-received AE signal acquired when the (a) laser is off, (b) at a low laser power of 140 W, and (c) at a high laser power of 250 W.

While prominent changes in processing conditions result in visually discernable differences in the AE signature, subtle flaw formation phenomena, such as variation in surface finish, are not apparent due to extraneous noise and the evanescent nature of the signal. Accordingly, this work uses wavelet decomposition to analyze the AE data from all four sensors at multiple time-frequency scales. The wavelet multispectral analyses are particularly suited for non-stationary and

non-linear AE waveforms traveling through the metallic medium [87]. Moreover, wavelet transformation preserves both time and frequency information. In contrast, the Fourier transform only captures the frequency domain information, and is ill-suited for analyses of AE signals with inherent non-stationary characteristics with sharp evanescent peaks [69]. After wavelet analysis, the 1D AE signatures are localized to specific part locations through synchronization with infrared thermal imaging data. The wavelet analysis and data fusion with infrared thermal imaging are discussed in depth in Sec. 3.3.

3.1.2 Infrared Thermal Imaging

Data from the infrared thermal imaging camera was continuously acquired at a rate of 30 frames per second. A total of 988,010 images were captured throughout the printing process. A typical layer has ~1,000 images. The peak temperature of each pixel recorded by the thermal camera is synchronized to the position of the laser on the build plate.

Exemplified in Figure 10(top) is the procedure by which the peak (maximum) temperature observed at each image pixel is composited for an entire layer. The pixel-by-pixel peak temperature consolidated for an entire layer is termed $T_{\max}$ and is the maximum temperature captured by the thermal camera within its dynamic range. Shown in Figure 10 (bottom) are $T_{\max}$ images for layers 10, 600, and 900. From Figure 10(bottom), it is observed that the $T_{\max}$ images not only correlate with the set laser power throughout all layers of deposition, but also detect hot spots generated during the process. These hot spots correspond to severe recoater interaction events.

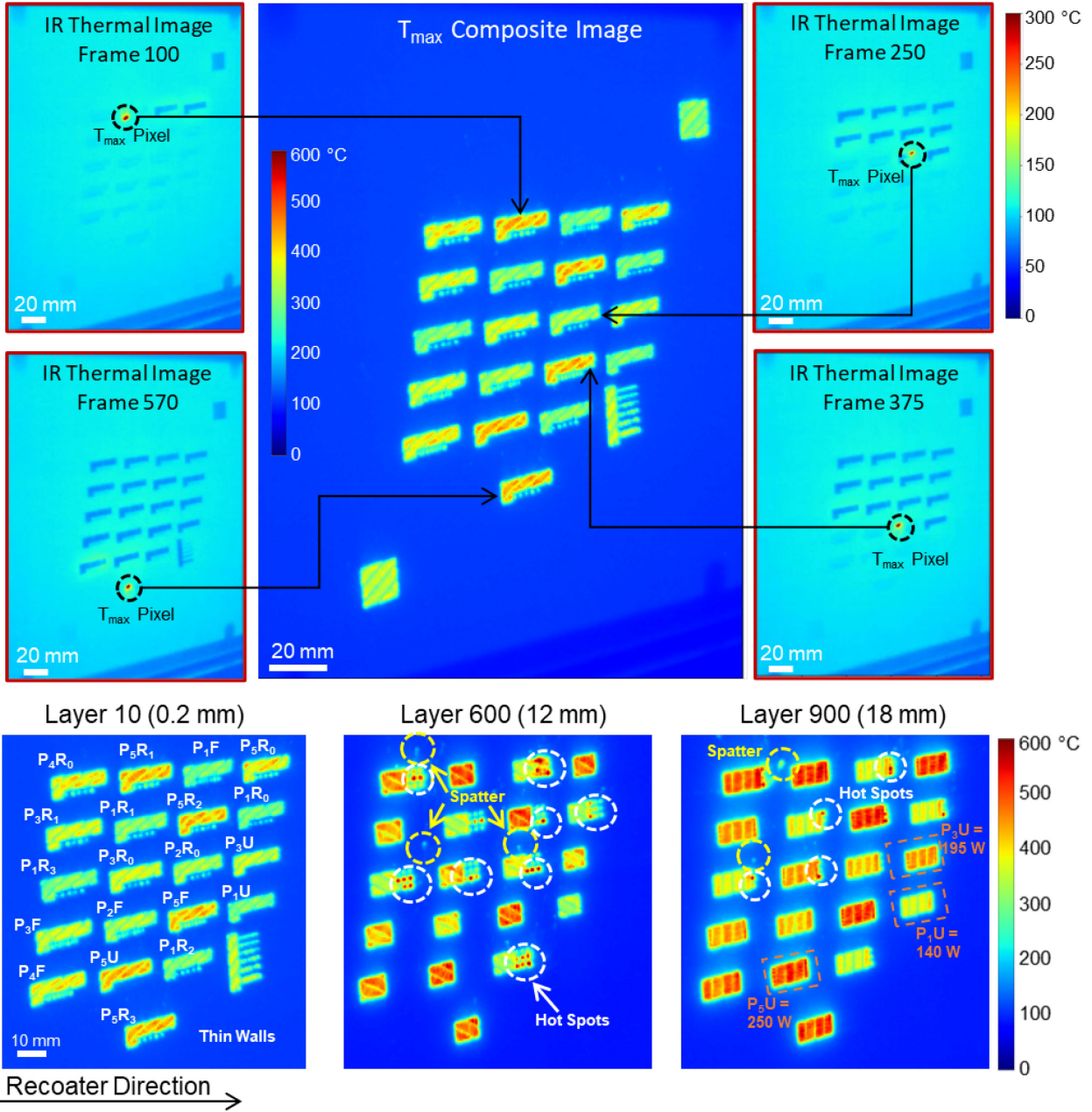


Figure 10: (Top) The peak temperature captured by the thermal camera are consolidated for an entire layer, resulting in a $T_{\max}$ image for an entire layer. (Bottom) $T_{\max}$ images for representative layers 10, 600, and 900. Note the hotspots and spatter events.

3.1.3 Optical Imaging

The optical camera captures an image of a layer post-melting. Representative optical images for three layers are shown in Figure 11. Catastrophic build failures and recoater interactions are evident, after they occur, by analyzing the intensity variations in the optical image.

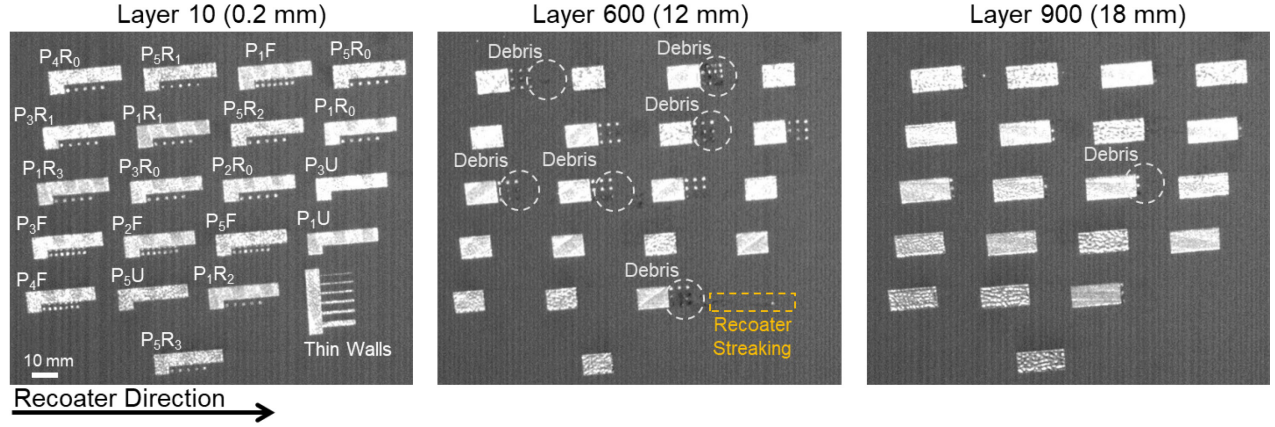


Figure 11: Example optical data acquired for three different layers. Note the occurrence of failures and recoater interactions from the optical images.

3.2 Signal Decomposition

As summarized in Figure 12, the discrete wavelet transform is used to decompose the raw AE signal into multiple time-frequency scales [88]. The multispectral wavelet decomposition of the as-received AE signal S is described through Eqn. (1).

$$W(2^i, 2^i) \triangleq \frac{1}{\sqrt{2^i}} \sum_{d=1}^{d=N} \bar{\psi}\left(\frac{d}{2^i} - 1\right) S(d) \quad (1)$$

Where W is the deconstructed wavelet signal of the frequency level (octave) i ; d is the discrete data point of the N number of total data points in the as-received AE signal S ; and $\bar{\psi}$ is the deconstruction wavelet. The discrete wavelet transform is applied to a 33 ms window of AE data acquired from each of the four AE sensors consisting of 33,000 data points; each sensor data stream from each of the four AE sensors was deconstructed separately. Approximately 10^7 data points are

acquired and analyzed per layer by one AE sensor. A 33 ms window is chosen as it corresponds to the frame rate of the IR camera, which will be used for synchronization with the AE signals.

A biorthogonal 3.3 function ($\bar{\psi}$, basis wavelet) is used for signal deconstruction. The biorthogonal 3.3 wavelet was chosen via empirical testing and based on our prior work with acoustic signals in additive manufacturing [89]. As shown in Figure 12, due to wavelet decomposition, each of the four AE signal streams are deconstructed into its 8 base frequencies (octaves) labeled O_1 through O_8 .

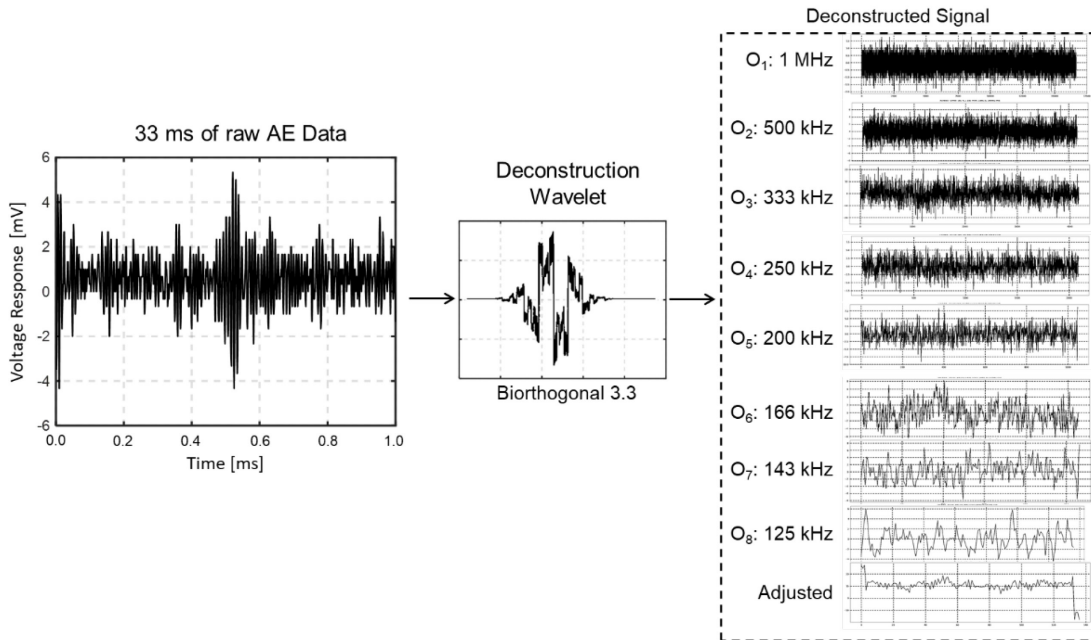


Figure 12: Each 33 ms window of AE data is deconstructed into its 8 base frequencies (octaves O_1 - O_8), and the adjusted signal using a biorthogonal wavelet transform.

With each 33 ms of AE data deconstructed into eight octaves, the relative spectral energy of each octave ensemble was calculated using the following root mean square equation:

$$E_{i,t} = \sqrt{\frac{\sum_{d=1}^{d=n} W_{i,t,d}^2}{n}} \quad (2)$$

Where $E_{i,t}$ is the spectral energy of octave i for every 33 ms window of the deconstructed signal W . Where d is a discrete data point, and n is the total number of discrete data points in each

deconstructed signal window. This process of extracting the spectral energy for every 33 ms long window was repeated for the entire duration of a layer being deposited, and across all layers. For each octave, there are $\sim 1,000$ spectral energy statistics per layer per AE sensor.

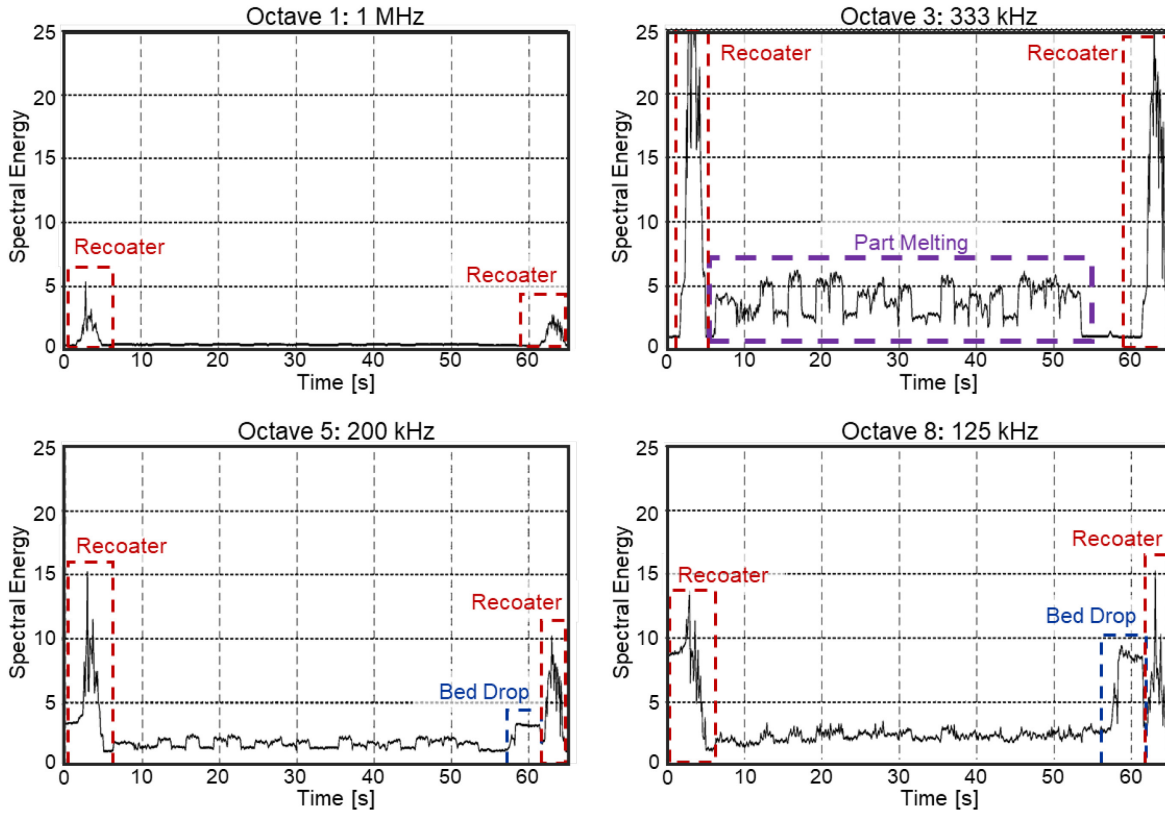


Figure 13: The spectral energy $E_{i,t}$ for octaves $i = 1, 3, 5$, and 8 . Octave 3 contains the most consequential events correlated with meltpool interactions.

Figure 13 visualizes the spectral energy $E_{i,t}$ extracted for the entirety of the first layer of the build for octaves $i = 1, 3, 5$, and 8 from sensor AE-1. A large frequency response is observed at the start and end of every layer, demarcated in red. These spikes correlate to the recoater motion of the blade as it rakes a new layer of powder over the build plate. The increase in acoustic energy is a result of subtle displacements from the motion of the recoater blade. In between these recoater-related spikes are the AE signatures resulting from the laser melting of the parts on the build plate. These signatures are most prominent in octave O_3 . In the lower frequency octaves, e.g., O_5 , events corresponding to the build plate being lowered can be observed, demarcated in blue.

3.3 Signal Localization

In Figure 14(top), we further examine the characteristics of octave O_3 (333 kHz) for layer 1. Henceforth, the energy contained in octave O_3 after wavelet decomposition is referred as the AE signature (E_s). To correlate the AE data with specific flaw formation related events, we first linked E_s to the spatial infrared thermal images frame-by-frame in the manner summarized in Figure 14(top).

The IR camera captures an image every 33 ms, this resolution is identical to the signal length over which the AE signal is analyzed, and for which E_s is extracted. From the data time stamps, the position of the laser strike can be extracted for every 33 ms time step by tracking individual pixels within the IR camera with the highest intensity, which represents the X-Y position of the laser on the powder bed. The location of the laser strike is then linked to each data point in the AE signature (E_s) using the synced time stamp. This linking of every 33 ms of AE data to a specific X-Y position on the build plate is repeated for the entire layer. The result, as depicted in Figure 14(bottom), is a spatial representation of the AE signature (E_s) over the entire layer of the build,. The color bars on the AE heat map correspond to the magnitude of the acoustic energy (E_s). This generation of the AE heat map is the justification for using a 33 ms window size when analyzing the raw AE signal, as this is the finest resolution achievable with the given set-up. In Sec. 4.1, the differences in the acoustic heat map are correlated to process events and part quality.

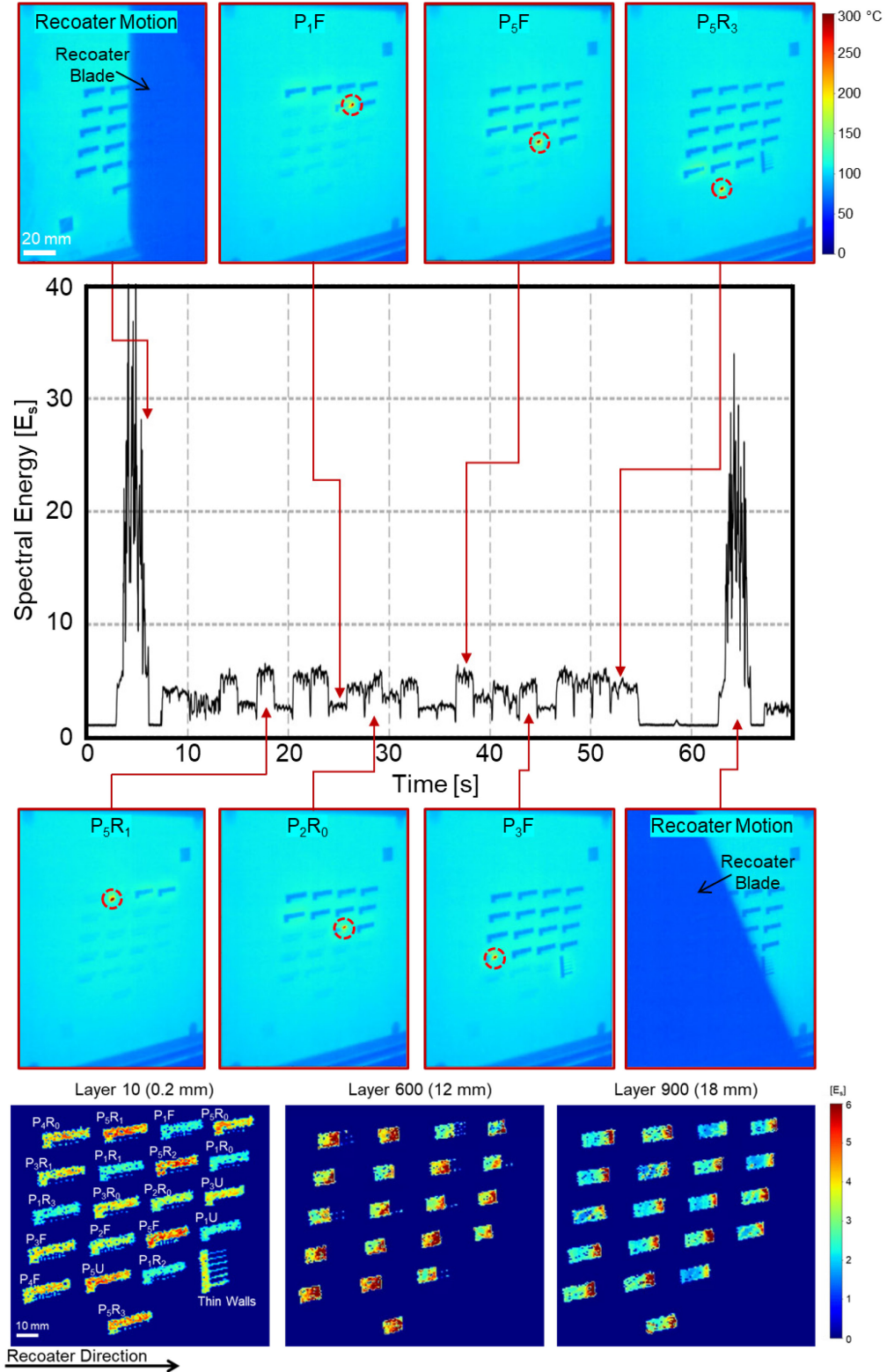


Figure 14: (Top) The IR camera images are fused to track the laser position at every 33 ms. (Bottom) The localized AE energy heat map for three representative layers throughout the build.

Finally, the AE heat map images generated from each of the four AE sensors were averaged. By averaging the AE heat map signatures the minor positional effects from the sensors are mitigated. The AE energy heat maps generated for three select layers are depicted in Figure 14(bottom). As an example, in Figure 15, the AE heat map for layer 10 is compared to the $T_{\max}$ images from the thermal camera. When the layer temperature for a particular sample is high the corresponding AE frequency energy for the third octave (E_s) is also high. This is apparent, for example, when comparing the images for the laser power conditions of $P = 140, 195$, and 250 W for U -type samples without support struts (P_1U , P_3U , and P_5U).

In Figure 15 it is observed that at the low laser power of $P_1U = 140$ W, the magnitude of the AE signal of ~ 2 units (E_s) correlates with the $T_{\max}$ layer temperature of ~ 300 °C, while at the nominal laser power $P_3U = 195$ W, the magnitude of AE signal increases to ~ 4 units (E_s), and correlates with the $T_{\max}$ layer temperature of ~ 400 °C. Likewise, at the highest laser power $P_5U = 250$ W, the magnitude of the AE signature increases to ~ 6 units (E_s), and correlates with a $T_{\max}$ layer temperature of ~ 500 °C. The local variations in AE signature observed in these 2D heat map are statistically correlated with various aspects of part quality in the forthcoming Sec. 4.

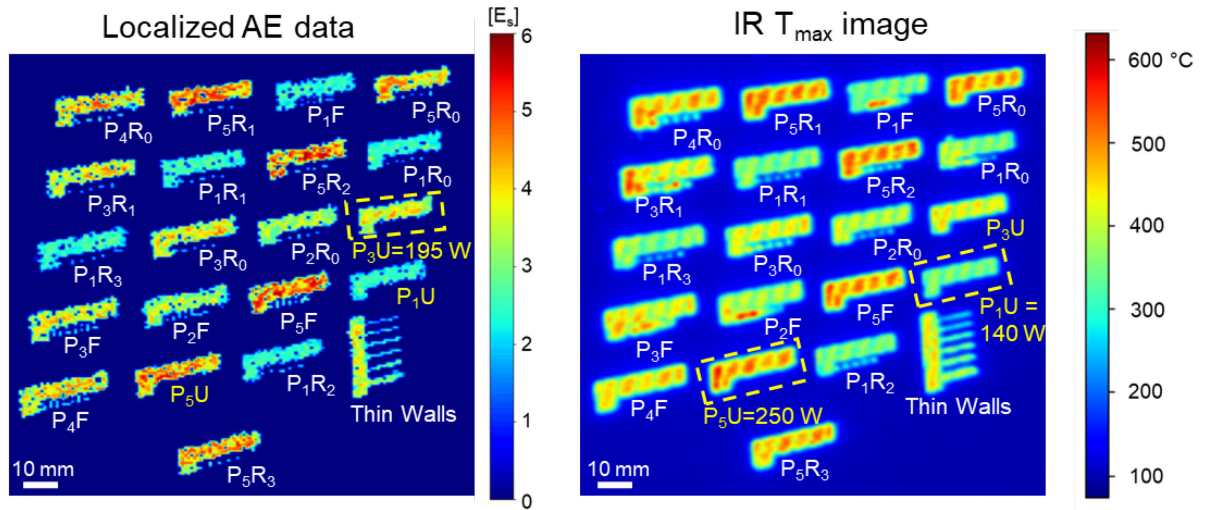


Figure 15: Comparison of localized AE heat map data to the $T_{\max}$ image from the IR camera. A prominent correlation between $T_{\max}$ and the AE signature (E_s) heat map is evident.

4 Results

In this section we correlate the AE signature (E_s) with the following four LPBF part quality-related aspects: (i) variation in laser energy density; (ii) build failures including distortion and collapse of supports due to recoater contact; (iii) variation in surface roughness; and (iv) variation in microstructure (grain size).

4.1 Case 1 – Using AE signatures to detect deviations in input energy

This study demonstrates the ability of AE signatures to detect deviations in input energy at the laser-material interface. In LPBF, although the processing parameters are monitored and controlled in the machine, the actual input energy at the laser-material interface may vary on account several factors, such as variation in gas flow rates; deviation in laser focus height due to accumulation of soot and solid byproducts on the optical lens; non-uniform build height; and scan path errors [90, 91]. In other words, the actual energy delivered at the laser-material interface can potentially deviate from the machine settings, resulting in flaw formation. These variations in input energy density are currently not corrected in commercial machines by the machine controller, as their occurrence is extraneous to the laser optical chain.

For example, in a recent article, Bevans *et. al.* [91] describe part failures on account of excessive heat accumulation and distortion, despite successful completion of the same parts in previous iterations under identical conditions. The reason for these failures was attributed to uneven gas flow across the powder bed, which resulted in heat retention and warpage in certain parts. Bevans *et. al.* [91] also demonstrate the occurrence of over melting flaw formation in lattice parts due to a machine-related inaccuracies in tracing the programmed complex scan path. Gaikwad *et. al.* [19] reported the occurrence of lack-of-fusion porosity due to variation of the laser focus height during processing of Stainless Steel 316L.

In Figure 16(bottom), the localized AE data (E_s), averaged from all four sensors, is stacked as a layer-averaged composite image in the X-Z direction for three representative unsupported (U) geometries (P_1U , P_3U , and P_5U). Figure 16(top) shows a composite image stack of the corresponding $T_{\max}$ data. Results from part-scale thermal simulations implemented for each of the processing conditions is depicted in Figure 16(middle). The overhang regions tend to retain heat due to the poor conductivity of the powder. These thermal simulations for a similar shape have been experimentally validated and published in our previous work [27, 76, 77].

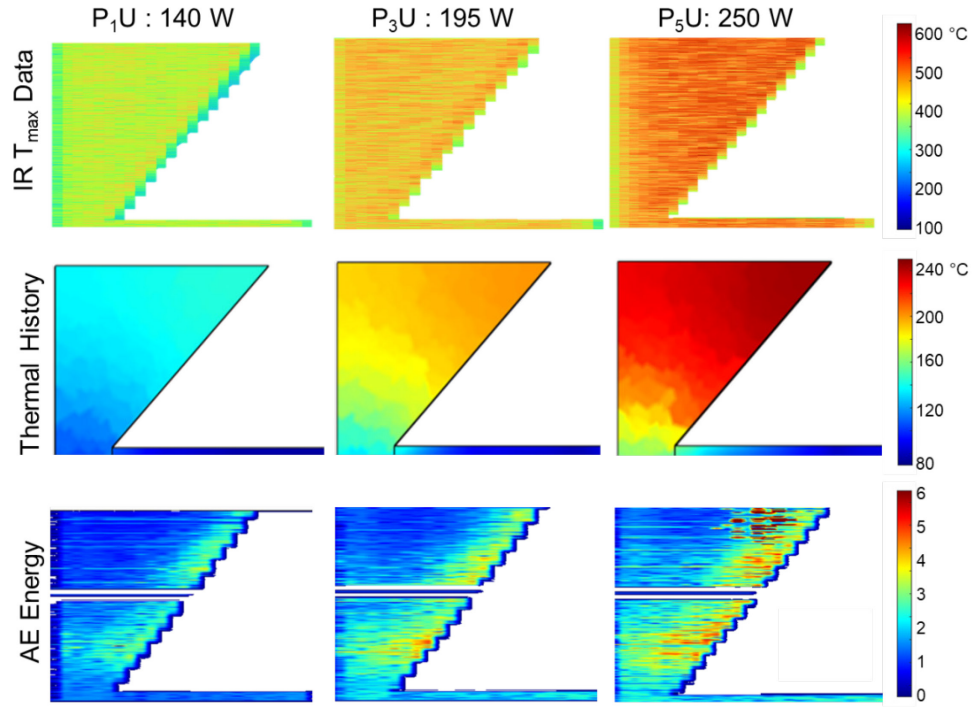


Figure 16: Layer-wise effect of input laser power for sample P_1U , P_3U , and P_5U on (Top) $T_{\max}$ measured (middle) thermal history from simulations, (bottom) AE Energy (E_s) heat map.

As the input energy increases, the heat retention in the part increases proportionally, corresponding to an increase in magnitude of the AE signature (E_s). Additionally, it was observed that intensity of the AE signature was higher in the overhang region of the part, compared to the bulk section, which corresponds to the heat retention predicted by the simulation model. A data collection error in the AE signal between layers 630 and 667 resulted in lack of information therein.

In contrast to the AE signals, the thermal image ($T_{\max}$), shown in Figure 16(middle), fails to capture the local variations in thermal history predicted in the thermal simulations. This is because infrared cameras cannot penetrate beyond the top surface of the powder bed. Next, the AE spectral energy (E_s) is quantitatively correlated to the energy density, $E_V = \frac{P}{V \cdot H \cdot T}$ [$\text{J} \cdot \text{mm}^{-3}$] for the first 10 layers for all 20 overhang geometries. The first 10 layers of the overhang samples were chosen for the analysis to avoid the confounding effect of heat retention from the latter overhang region, and possible variation in signal due to variations in the surface texture.

The magnitude of the AE spectral energy (E_s) averaged over the first 10 layers is mapped against the input laser power (P) in Figure 17. Approximately 10 minutes of AE data amounting to $\sim 10^6$ data points and 1,000 AE energy (E_s) measurements is represented in Figure 17; the error bars are ± 1 standard deviation. A nearly linear correlation ($R^2 \sim 99\%$) is observed between E_s and the input laser power (P). Thus, the AE signatures (E_s) are sensitive to both the local variations in thermal history, as well as input energy density (E_V), consistent with recently published results by Plotnikov *et al.* [78]. The observed local variation in E_s is assumed to be from stochastic aspects, such as gas flow behavior, and not from local variations in the input energy (E_V).

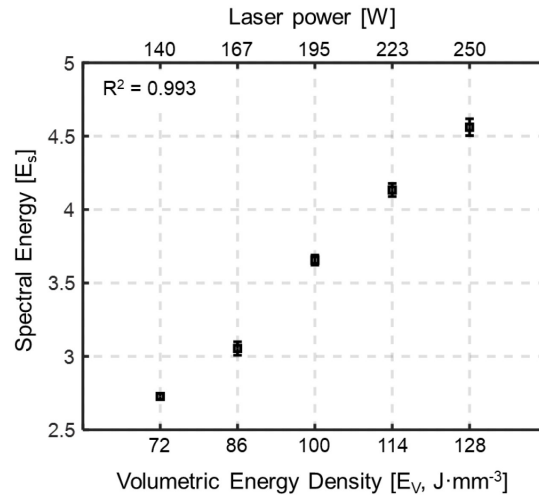


Figure 17: The spectral energy (E_s) increases proportionally to energy density (E_V) ($R^2 \sim 99\%$).

4.2 Case 2 - Detecting build failures due to thermal-induced distortion

The aim of this study is to detect incipient build failures on account of collapse of support struts, recoater contact events, and warping using data acquired from the AE signatures. Pertinently, these events were detected by the AE signal before they cascaded into catastrophic failures. In contrast, the $T_{\max}$ parameter derived from the IR thermal camera, did not detect impending failures until after they occurred.

Heat retention and uneven part temperature distribution causes the part to deform during processing [77, 92]. The top surface of the part may protrude above the powder bed, a phenomena called superelevation, and interfere with the recoater motion, resulting in damage to both the part and recoater [92]. Indeed, an entire build is often lost following a recoater crash, as the debris from the collision interference with other parts on the build plate. A deformation of greater than 40 μm in the z-direction, viz., the typical clearance between the recoater and top of the powder bed, is liable to cause a recoater crash. Approximately 70% of build failures in LPBF are attributed to recoater contact and support failures [93]. Thus, early detection of incipient recoater crash events and support failures are valuable, since an operator can halt printing of an at-risk part while continuing with processing of the other parts on the build plate.

As explained previously in the context of Figure 6 (Sec. 2.2), all the samples with reduced (R) and full support struts (F) experienced failures leading up to a recoater crash. The occurrence of recoater crash events is evident from examination of the in-situ optical imaging camera in Figure 18. The recoater interferes with the supporting struts and plastically dislocates them out of situ resulting in a condition termed *bare powder melting*. In the present case, bare powder melting occurs when the laser melts the area above a plastically deformed strut, however the melted powder does not have bulk material underneath upon which to fuse.

As a consequence of, the melted material agglomerates and adheres to the recoater blade. The adhered material is subsequently dragged by the recoater disturbing the top surface of the powder bed (recoater streaking), thus endangering the integrity of the rest of the parts along its path. The high temperature regions (hot spots) in the infrared $T_{\max}$ images in Figure 18 are symptomatic of bare powder sintering. These hotspots are also witnessed in the heat map of the AE signature (E_s).

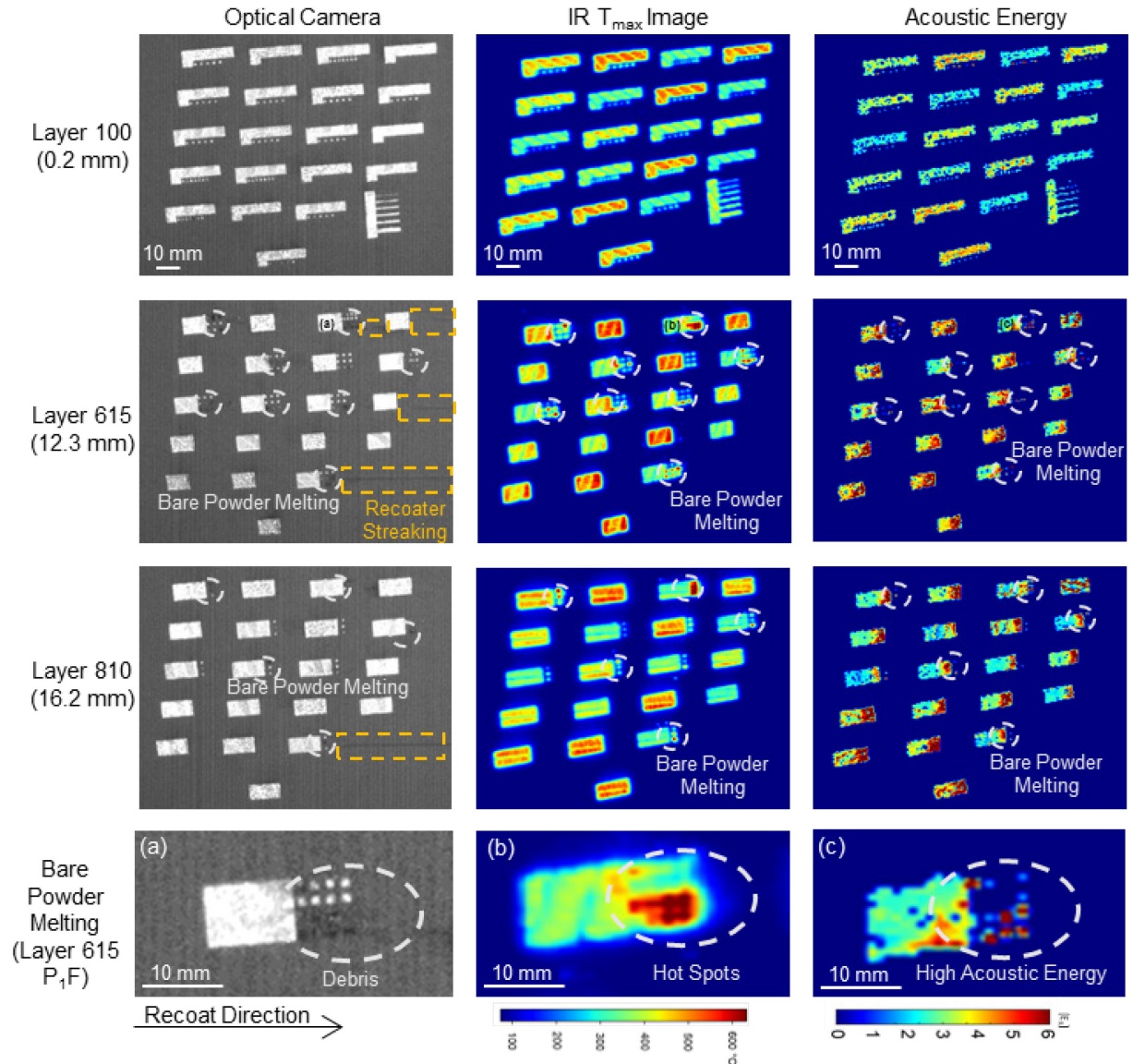


Figure 18: Example in-situ optical, $T_{\max}$, and AE heatmap images captured. These images show that the process was initially stable, but after layer 600, there are several instances of recoater streaking and bare powder melting following plastic deformation of struts.

In Figure 19(middle), the spatial layer-wise AE heat map signature for two representative parts (P₁F and P₅R₂), which experienced recoater events and collapse of supports, are compared alongside the IR $T_{\max}$ images and the actual as-built part. In the AE heat map for the foregoing samples distinct regions of high-magnitude AE energy (E_s) were observed during processing of the supporting struts. These regions correlate to physical locations where a row of struts merge with the overhang region approximately at layer 600 (Figure 19(bottom)). From the AE heat map image in Figure 19(middle), it is evident that AE signal detects the onset of incipient strut failure before they cascade to catastrophic recoater contact event at layer 600 (12 mm). For example, prominent hotspots in the AE signature are evident in layer ~400 (8 mm) of sample P₁F, due to bare powder melting resulting from relatively minor dislocations in the support struts. In contrast, hotspots are detected in the IR $T_{\max}$ signature in Figure 19(top) after layer 600 following a significant recoater interference and collapse of supports.

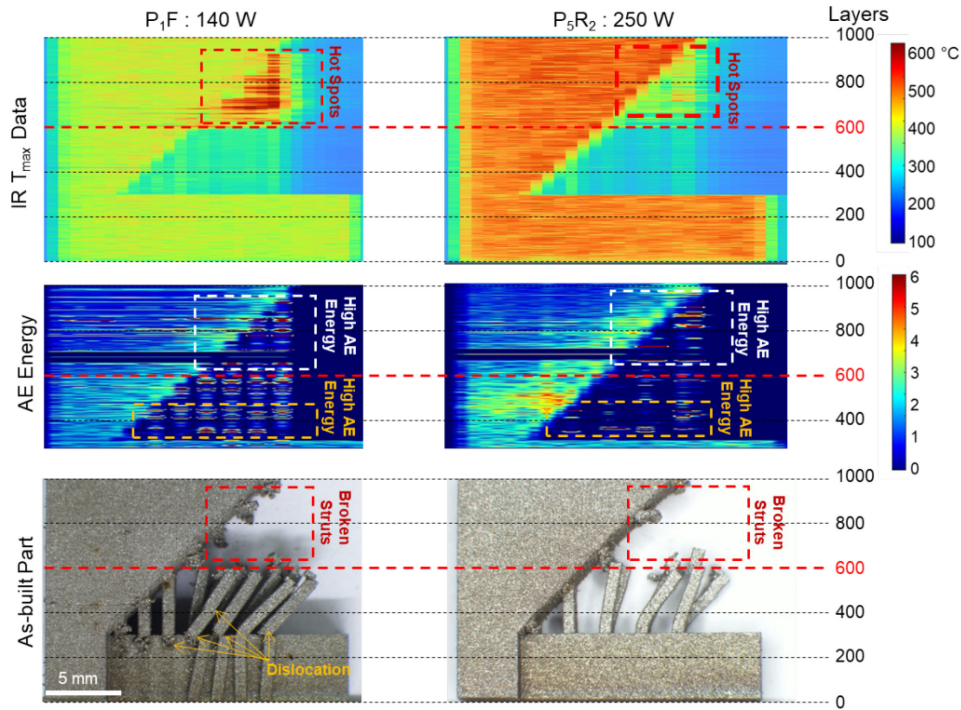


Figure 19: (Top) IR $T_{\max}$ images for two representative samples, P₁F and P₅R₂. (Middle) corresponding AE heatmaps, (Bottom) actual as-built part. AE heat maps depict regions of high energy content corresponding to impending failure of supports.

Continuing with the analysis and to test the robustness of the method, the AE signatures from the validation build plate (Sec. 2.2.4) were used to detect failures of the two thin-wall build parts. As evident from the heat map of the AE energy (E_s) in Figure 20 no AE signal is acquired in the failed regions of the thin-wall part, as there is lack of material under the melted area for the elastic acoustic waves to travel through to the build plate. The superior geometric resolution of the AE sensor, compared to the thermal camera, allows visual identification of flaws that occur within specific regions of a layer, as well as between layer flaws. Thus, an operator can leverage the AE information to visually identify and terminate an at-risk part and save the rest of the build.

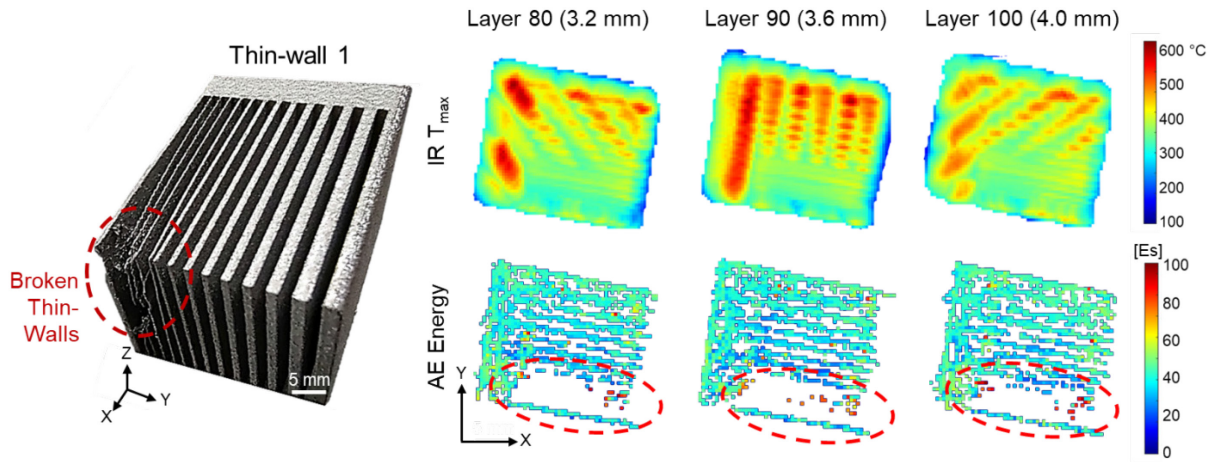


Figure 20: The thin-walls fail around the 2-4 mm of build height due to thermal induced distortion. This failure is difficult to recognize from the thermal images but readily evident in the AE data.

4.3 Case 3- Detecting variation in surface finish and surface related flaws

The aim of this study is to correlate the AE signature (E_s) to surface-related aspects of part quality. Referring to Figure 21, the AE signature were correlated to the surface finish of underskin surface measured at the overhang regions of 11 samples. The samples considered are the three *U*-type overhang geometries without support material – P_1U , P_3U , and P_5U , as well as those *F*- and *R*-type parts whose supports were terminated during the process, namely, P_2F - P_5F , P_5R_0 , P_3R_1 , P_5R_1 , and P_5R_3 . The undersurface of the overhang region was chosen for measurement of surface

finish as the prominent heat retention therein is likely to undermine its surface integrity [81, 94]. For example, in the thermal simulations and IR signatures for parts P₁U-P₅U visualized previously in the context of Figure 16, the surface roughness of the underskin areas increase proportionally with the laser power due to increased heat retention.

The areal surface finish (S_a) of the underskin was measured using confocal microscopy. Results for representative samples P₁U-P₅U, and P₄F are shown in Figure 21. The magnitude of AE signature (E_s) is correlated to the resulting surface roughness of the underskin region. The farther regions of the underskin are observed to have the largest variation in the surface roughness in accordance with the larger heat retention. The higher heat retention causes partial melting of the surrounding powder, which consequently adheres to the underskin surface of the overhang part, resulting in poor surface finish [76].

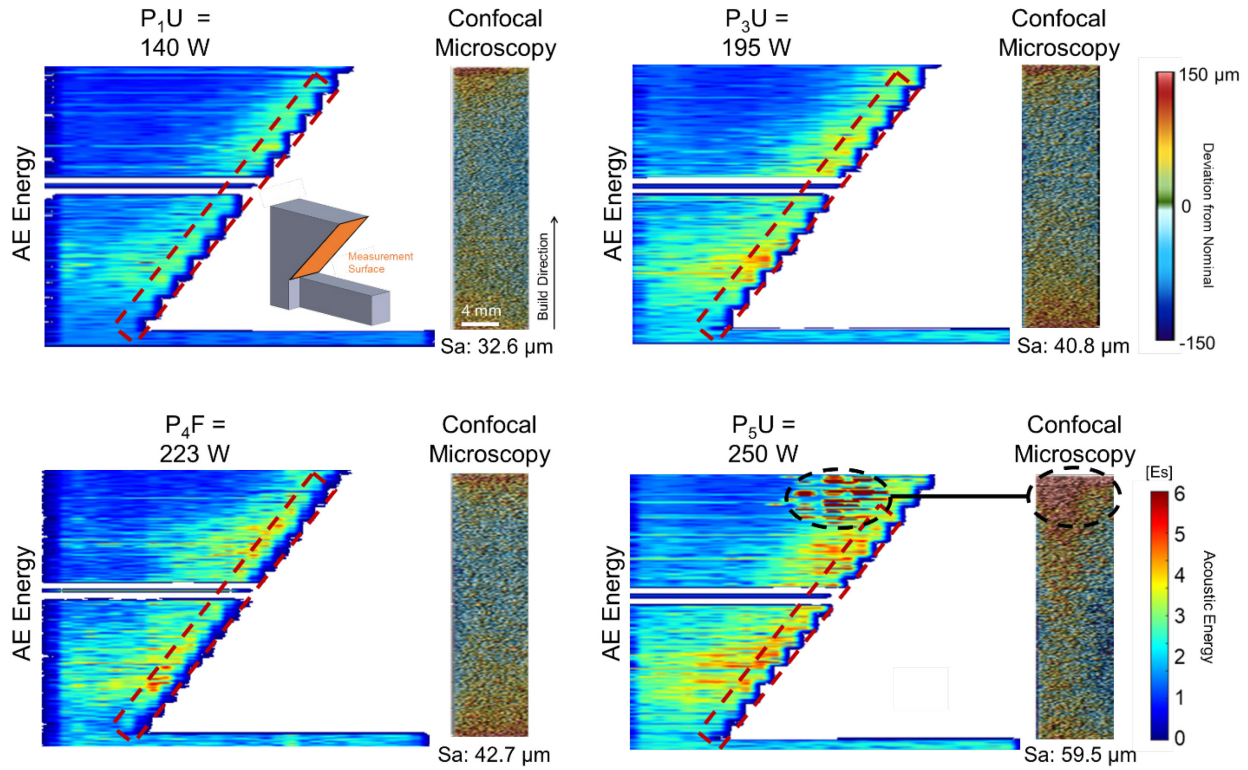


Figure 21: The higher magnitude of AE energy in the overhang region is correlated to deterioration in surface finish.

Next, the AE signature is quantitatively correlated to the surface finish (Sa). In Figure 22(a), the average areal surface roughness (Sa) of the underskin surface is plotted as a function of the average AE energy (E_s) within 1 mm of the underskin for the 11 samples. A nearly linear correlation ($R^2 \sim 87\%$) between Sa and E_s is evident in Figure 22(a). However, in Figure 22(b), when Sa of the underskin is plotted as a function of the input laser power (P), the correlation deteriorates to $R^2 \sim 79\%$. The AE signature has a higher correlation with Sa as it implicitly captures the heat retention within the overhang region. This aspect of the thermal history of the process is not encapsulated by the process parameters or surface-level thermal phenomena captured by the IR camera.

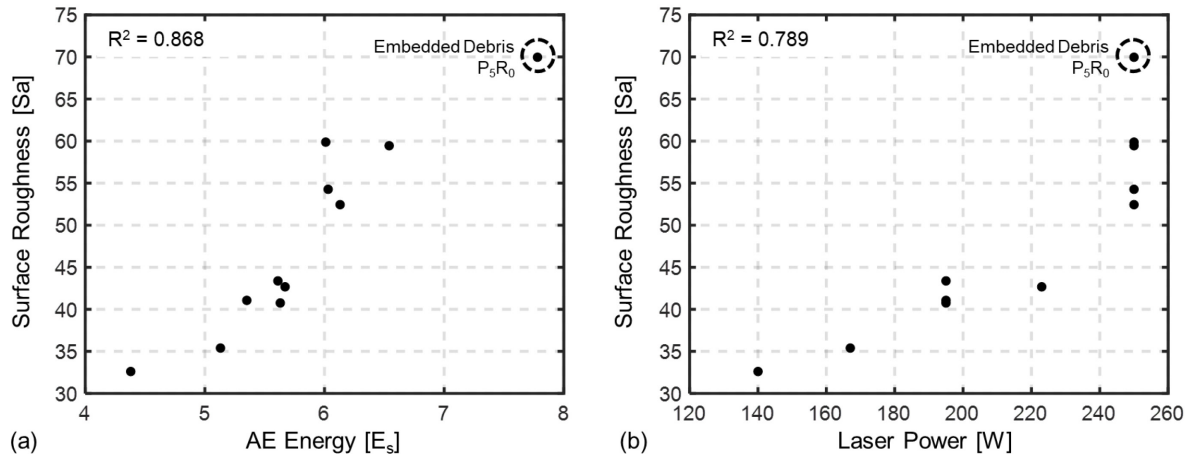


Figure 22: (a) A linear trend is apparent ($R^2 \sim 87\%$) between the AE signature and surface roughness (Sa) of the underskin region. (b) The correlation reduces to $R^2 \sim 79\%$ when Sa is plotted as a function of laser power.

Next, the AE signature is correlated to locations of debris material adhered to other samples after being dragged across the powder bed by the recoater following failure for a support strut. For example, Figure 23 the overhang region of sample P₅R₀ was observed to have a large surface roughness due to partially melted material adhered at two locations on the underskin surface, as well as debris from recoater events. Since sample P₅R₀ was downstream of the recoater path, material from failed struts were embedded in its back-end. These artifacts are demarcated in the

X-ray CT image of the part in Figure 23(b). The AE energy heat map in Figure 23(a) manifests two high magnitude regions corresponding to the build height location (layer) at which the partially melted materials are adhered. Thus, the foregoing results demonstrates the ability of the AE signature to detect stochastic flow formation and instabilities detrimental to part quality.

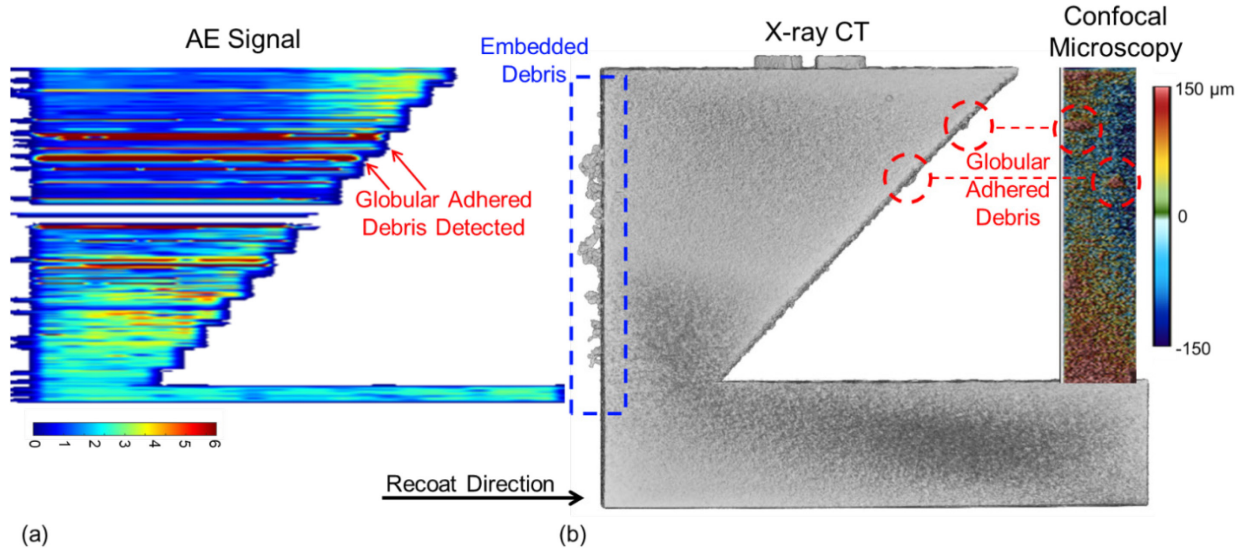


Figure 23: High magnitude of AE signature is correlated to debris and partially melted material

In addition to the underskin surface roughness, the top surface of all 20 samples was also analyzed. Representative results concerning the three unsupported (*U*) samples, P₁U, P₃U, and P₅U; and two fully supported (*F*) samples, P₂F and P₄F, are shown in Figure 24. Juxtaposed are the laser confocal microscopy image of the top surface, composite T_{max} image from the IR data, and stacked images of the AE signature (E_s). In Figure 24(bottom), the regions of high E_s magnitude are visually correlated to degraded surface characteristics in Figure 24(top). The surface rugosity is progressively degraded with increasing input laser power likely due to meltpool instability [95, 96]. For instance, in Figure 24(top), the surface roughness (*Sa*) of the top surface of P₅U is almost twice as that for samples P₁U. In sample P₅U significant instances of surface instability are detected in the AE heat map near the boundary of the part compared to the bulk

owing to exacerbated heat retention. These surface instabilities and subtle distortions often result in catastrophic recoater crash events. By contrast the IR thermal images in Figure 24(middle) do not detect local temperature variations symptomatic of surface instabilities.

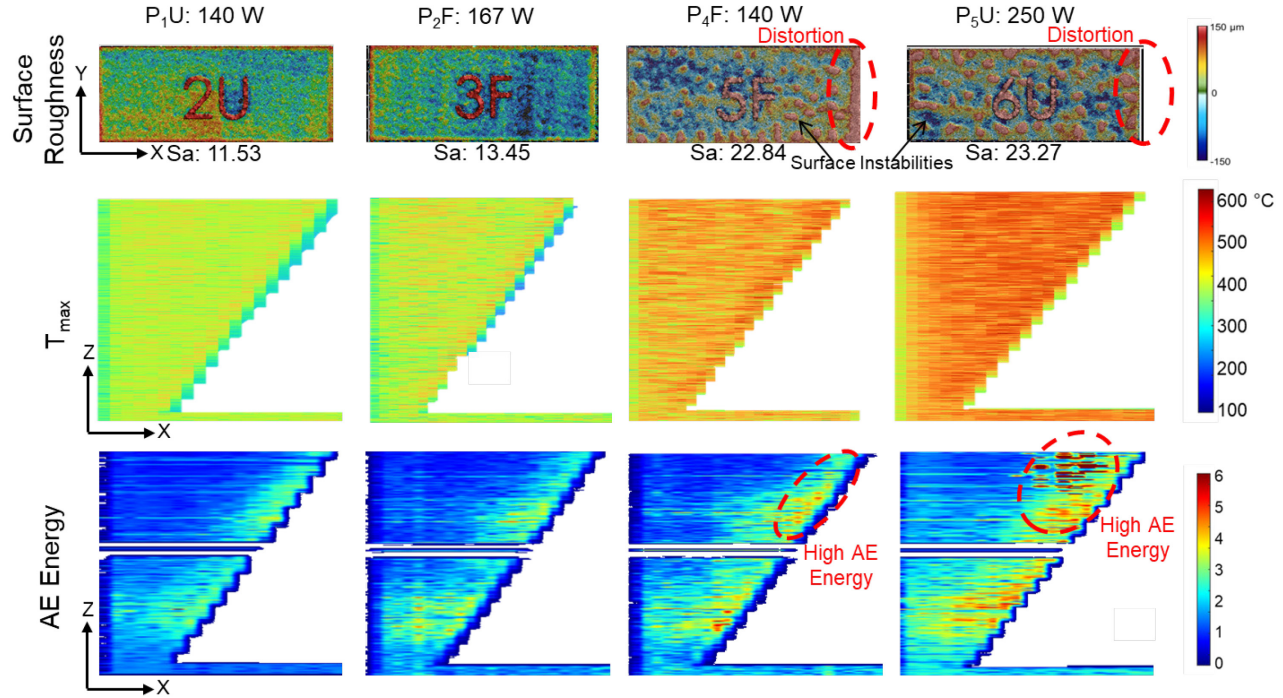


Figure 24: (Top) The confocal microscopy images of the top surface of representative samples with increasing laser energy. (Middle) Infrared thermal imaging T_{max} signatures. (Bottom) AE energy (E_s) composite images. The IR images fail to capture the local variation systematic of degraded surface finish.

4.4 Case 4 - Detecting variation in microstructure (grain size)

This case correlates the AE signatures to the solidified microstructure in terms of the primary dendritic arm spacing, analogous to the grain size. In LPBF of stainless steel 316L a dendritic-type microstructure is typically evolved [97]. Such a dendritic microstructure is evident from the SEM image shown in Figure 25(a) for part P₁U. The size of dendrites is characterized in terms of the primary dendritic arm spacing (PDAS, λ_1), which is measured from SEM images. The measurement of PDAS involves several hours of cumbersome post-process metallographic characterization followed by manual analysis of SEM images. Consequently, the rapid, in-situ and

non-destructive evaluation PDAS based on AE data would be valuable from a process monitoring perspective. In our previous works, the PDAS for a similar part geometry was linked to the processing parameters and thermal history of the part [27]. A larger heat retention has been related to grain coarsening and concomitant increase in the PDAS [27, 98]. The PDAS, in turn, is inversely proportional to microhardness and the tensile strength of the part [99].

As shown in Figure 25(a), the PDAS was measured at five regions from SEM images using the bounding box procedure [27]. These regions are in the interior of the part, and thus not confounded with previous observations. At each location, four SEM measurements were acquired to account for stochastic variations in the grain size. The average PDAS across all five locations for five representative overhang geometries – three *U*-type parts without supports P_1U , P_3U , and P_5U , and two *F*-type parts with full-supports P_2F and P_4F are shown in Figure 25. It is observed that as the input energy increases, the PDAS also increases (grain coarsening) due to increased heat retention. The PDAS is less than $0.5 \mu\text{m}$ for samples P_1U and P_2F , which are produced at laser power $P = 140 \text{ W}$ and $P = 167 \text{ W}$, respectively. By contrast, the PDAS for P_3U , P_4F , and P_5U produced at laser power $P \geq 195 \text{ W}$ exceeds $0.5 \mu\text{m}$.

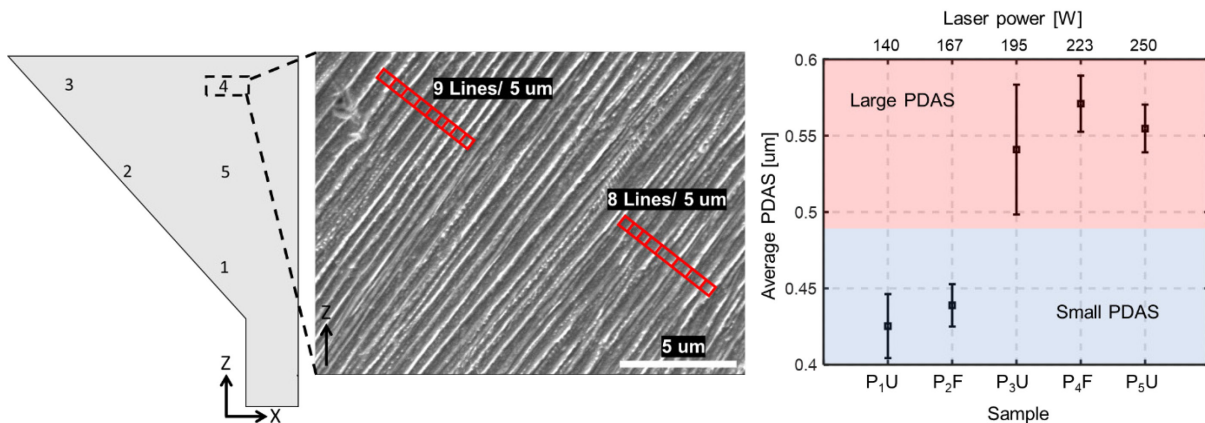


Figure 25: Five measurement locations were analyzed with SEM to measure the primary dendritic arm spacing (PDAS) with ± 1 standard deviation. Lower volumetric energy density samples had significantly smaller PDAS than sample processed with higher energy density.

The correlation of PDAS, AE signature, and part thermal history is investigated further in Figure 26. Depicted in Figure 26 are the thermal distributions predicted from simulations, AE energy, and SEM images at two representative locations in the bulk region of samples P₁U, P₃U, and P₅U. In Figure 26(a), the thermal simulations predict that heat retention within the part, especially the overhang region, is exacerbated with increasing laser power. Representative SEM micrographs at two locations shown in Figure 26(c) affirm that as the heat retention increases, the PDAS (λ_1) in general increases. This increase in thermal energy that results in grain coarsening is captured by the AE signatures in Figure 26(b); the magnitude of AE energy (E_s) is proportional to the grain size.

To statistically quantify the relationship between the AE signature and the grain size, in Figure 27 we correlated the PDAS measured at five locations shown in Figure 25(a) to the corresponding AE energy (E_s). Noting that four PDAS measurements were acquired at each of the five sampled locations, Figure 27(a) maps the mean and one standard deviation of E_s to the average location-specific PDAS for the five samples P₁U – P₅U. A linear trend is evident from this region-specific analysis of PDAS, and mean and standard deviation of E_s . This trend is confirmed in Figure 27(b) when the PDAS is stratified into two-levels, namely, $\lambda_1 < 0.5 \mu\text{m}$ and $\lambda_1 > 0.5 \mu\text{m}$. The separation boundary of $\lambda_1 = 0.5 \mu\text{m}$ is rationalized based on the natural clustering of PDAS first observed in Figure 25(b). Thus, the PDAS related grain size of an as-built sample can be classified non-destructively via the use of in-situ AE sensor signatures, thereby eschewing post-process destructive metallographically analyses.

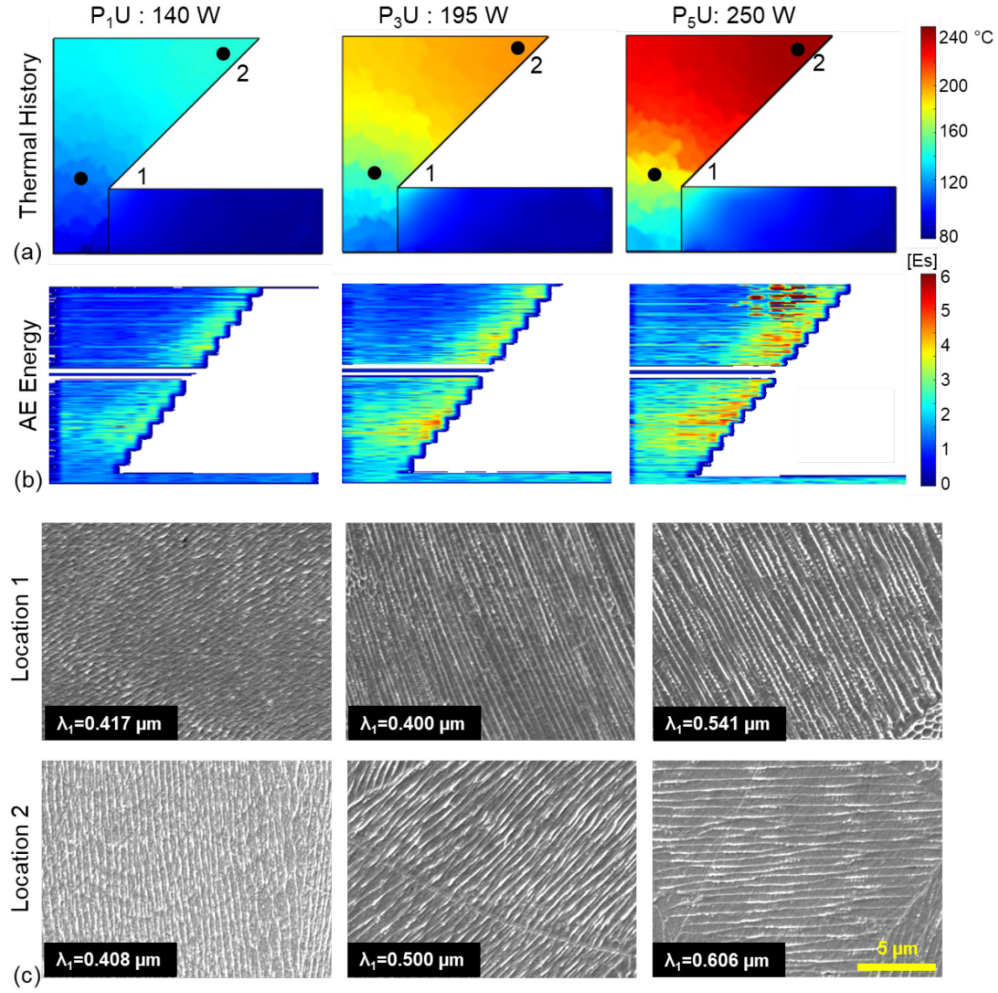


Figure 26: (a) Thermal history prediction for three representative parts P_1U , P_3U , and P_5U . (b) AE energy heatmaps for the three samples. (c) SEM images at two locations. Heat accumulation in the samples leads to grain coarsening (larger λ_1). The grain coarsening is correlated to the increased magnitude of AE Signatures (E_s).

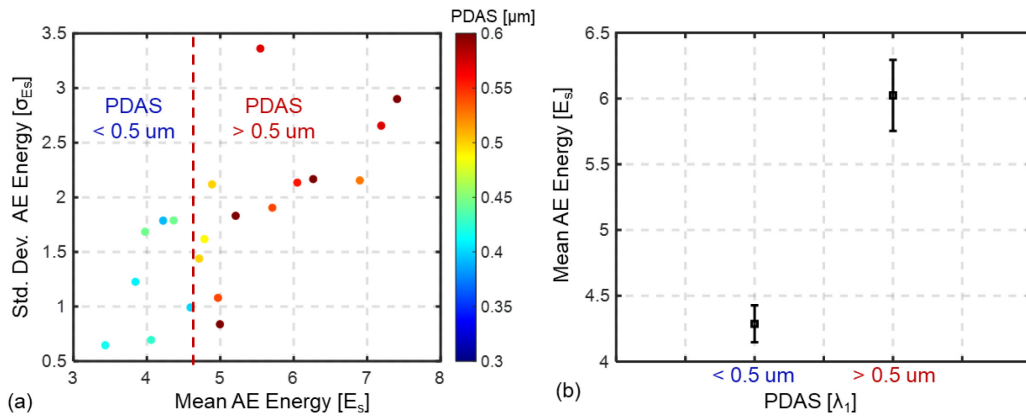


Figure 27: (a) The mean and standard deviation of the AE frequency energy for each PDAS measurement. (b) The AE data clusters prominently between large and small grain sizes.

5 Conclusions and Future Work

We used in-situ passive acoustic emission (AE) sensors for online monitoring of part quality in laser powder bed fusion (LPBF) additive manufacturing. Extensive research is being conducted on sensor-based monitoring of part quality in LPBF using approaches, such as infrared thermal imaging and meltpool pyrometry. However, these existing sensing modalities have limited ability to capture sub-surface process phenomena that cause flaws such as cracking, distortion, degradation in surface integrity, and microstructure heterogeneity, among others.

By contrast, this work uses AE sensors embedded within the substrate to acquire elastic waves that travel through the part, and thus capture the sub-surface process phenomena. The AE signatures were analyzed using multi-spectral wavelet transforms. A key innovation that enabled multi-scale flaw monitoring is the spatial localization of the 1D AE signals to specific part locations through synchronization with surface temperature data obtained using an infrared thermal camera.

The spatially localized AE signatures were statistically correlated to input energy density ($R^2 > 99\%$), incipient part failures, surface finish deterioration ($R^2 > 87\%$), and microstructure heterogeneity. This correlation between the processed AE signature and part quality was not readily identifiable using traditional IR thermal imaging or thermal modeling, especially with the identification of grain size. Specific outcomes from this work are as follows.

1. A total of 20 stainless steel 316L parts were manufactured using EOS M290 LPBF system under various process parameters, part design, and support combinations. These processing conditions resulted in a variety of flaws, ranging from recoater crashes, support failures, variation in surface finish, and microstructure heterogeneity. The degree and severity of flaw

formation was ascertained using materials characterization techniques such as X-ray CT, confocal, optical, and scanning electron microscopy.

2. During the process, AE signatures were obtained by embedding four passive piezoelectric sensors in the substrate (build plate) tuned to acquire different signal frequencies at a sampling rate of 1 MHz. These AE signatures were analyzed using wavelet transforms for decomposition into multiple time-frequency ensembles. From wavelet analyses it was determined that the AE signal corresponding to a specific frequency of 333 kHz was correlated to consequential aspects of the process. Concurrently with the AE signatures, the top surface temperature was measured using an infrared thermal camera. The 1D AE signatures were synchronized pixel-by-pixel with thermal images to generate spatially localized 2D AE signatures.
3. The spectral AE energy (E_s) contained in the 333 kHz frequency regime was correlated, both visually and statistically, to various process phenomena spanning across macro-, meso-, and micro-scales. For example, impending macro-scale part distortion, support failures, and recoater crashes, were detected before they occurred from analysis of the AE signatures. In comparison, these failures were only evident post-hoc using thermal imaging. The magnitude of AE energy E_s was also statistically correlated ($R^2 > 85\%$) with the meso-scale surface finish (Sa), and the micro-scale primary dendritic arm spacing (PDAS).

Thus, this work takes the first step toward in-situ qualification of multi-scale part quality aspects in LPBF. Whilst this work is limited to correlating the AE signature to part quality for stainless steel 316L, our ongoing efforts are directed toward using AE signatures within machine learning models for predicting specific part quality aspects with increasing robustness. We will further endeavor to extend AE-based process monitoring to additional materials, such as Inconel 718 and 17-4 PH stainless steel, and more complex part shapes.

References

- [1] W.J. Sames, F.A. List, S. Pannala, R.R. Dehoff, S.S. Babu, The metallurgy and processing science of metal additive manufacturing, *International Materials Reviews* 61(5) (2016) 315-360.<https://doi.org/10.1080/09506608.2015.1116649>
- [2] B. Blakey-Milner, P. Gradl, G. Snedden, M. Brooks, J. Pitot, E. Lopez, M. Leary, F. Berto, A. du Plessis, Metal additive manufacturing in aerospace: A review, *Materials & Design* 209 (2021) 110008.<https://doi.org/10.1016/j.matdes.2021.110008>
- [3] G.R. Kumar, M. Sathishkumar, M. Vignesh, M. Manikandan, G. Rajyalakshmi, R. Ramanujam, N. Arivazhagan, Metal additive manufacturing of commercial aerospace components – A comprehensive review, *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering* (2022) 09544089221104070.<https://doi.org/10.1177/09544089221104070>
- [4] A. Mostafaei, C. Zhao, Y. He, S. Reza Ghiaasiaan, B. Shi, S. Shao, N. Shamsaei, Z. Wu, N. Kouraytem, T. Sun, J. Pauza, J.V. Gordon, B. Webler, N.D. Parab, M. Asherloo, Q. Guo, L. Chen, A.D. Rollett, Defects and anomalies in powder bed fusion metal additive manufacturing, *Current Opinion in Solid State and Materials Science* 26(2) (2022) 100974.<https://doi.org/10.1016/j.cossms.2021.100974>
- [5] P.R. Gradl, D.C. Tinker, J. Ivester, S.W. Skinner, T. Teasley, J.L. Bili, Geometric feature reproducibility for laser powder bed fusion (L-PBF) additive manufacturing with Inconel 718, *Additive Manufacturing* 47 (2021) 102305.<https://doi.org/10.1016/j.addma.2021.102305>
- [6] J.V. Gordon, S.P. Narra, R.W. Cunningham, H. Liu, H. Chen, R.M. Suter, J.L. Beuth, A.D. Rollett, Defect structure process maps for laser powder bed fusion additive manufacturing, *Additive Manufacturing* 36 (2020) 101552.<https://doi.org/10.1016/j.addma.2020.101552>
- [7] S.R. Narasimharaju, W. Zeng, T.L. See, Z. Zhu, P. Scott, X. Jiang, S. Lou, A comprehensive review on laser powder bed fusion of steels: Processing, microstructure, defects and control methods, mechanical properties, current challenges and future trends, *Journal of Manufacturing Processes* 75 (2022) 375-414.<https://doi.org/10.1016/j.jmapro.2021.12.033>
- [8] S. Sanchez, P. Smith, Z. Xu, G. Gaspard, C.J. Hyde, W.W. Wits, I.A. Ashcroft, H. Chen, A.T. Clare, Powder Bed Fusion of nickel-based superalloys: A review, *International Journal of Machine Tools and Manufacture* 165 (2021) 103729.<https://doi.org/10.1016/j.ijmachtools.2021.103729>
- [9] M. Seifi, M. Gorelik, J. Waller, N. Hrabe, N. Shamsaei, S. Daniewicz, J.J. Lewandowski, Progress Towards Metal Additive Manufacturing Standardization to Support Qualification and Certification, *JOM* 69(3) (2017) 439-455.<https://doi.org/10.1007/s11837-017-2265-2>
- [10] R. Russell, D. Wells, J. Waller, B. Poorganji, E. Ott, T. Nakagawa, H. Sandoval, N. Shamsaei, M. Seifi, 3 - Qualification and certification of metal additive manufactured hardware for aerospace applications, in: F. Froes, R. Boyer (Eds.), *Additive Manufacturing for the Aerospace Industry*, Elsevier 2019, pp. 33-66.<https://doi.org/10.1016/B978-0-12-814062-8.00003-0>
- [11] A. Du Plessis, S.G. le Roux, J. Waller, P. Sperling, N. Achilles, A. Beerlink, J.-F. Métayer, M. Sinico, G. Probst, W. Dewulf, Laboratory X-ray tomography for metal additive manufacturing: Round robin test, *Additive Manufacturing* 30 (2019) 100837.<https://doi.org/10.1016/j.addma.2019.100837>
- [12] F. Honarvar, S. Patel, M. Vlasea, H. Amini, A. Varvani-Farahani, Nondestructive Characterization of Laser Powder Bed Fusion Components Using High-Frequency Phased Array Ultrasonic Testing, *Journal of Materials Engineering and Performance* 30(9) (2021) 6766-6776.<https://doi.org/10.1007/s11665-021-05988-7>

- [13] F. Honarvar, A. Varvani-Farahani, A review of ultrasonic testing applications in additive manufacturing: Defect evaluation, material characterization, and process control, *Ultrasonics* 108 (2020) 106227. <https://doi.org/10.1016/j.ultras.2020.106227>
- [14] N. Huang, O.J. Cook, R.L.W. Smithson, C.M. Kube, A.P. Argüelles, A.M. Beese, Use of ultrasound to identify microstructure-property relationships in 316 stainless steel fabricated with binder jet additive manufacturing, *Additive Manufacturing* 51 (2022) 102591. <https://doi.org/10.1016/j.addma.2021.102591>
- [15] Z. Smoqi, L.D. Sotelo, A. Gaikwad, J.A. Turner, P. Rao, Ultrasonic nondestructive evaluation of additively manufactured wear coatings, *NDT & E International* 133 (2023) 102754. <https://doi.org/10.1016/j.ndteint.2022.102754>
- [16] P. Wang, Y. Yang, N.S. Moghaddam, Process modeling in laser powder bed fusion towards defect detection and quality control via machine learning: The state-of-the-art and research challenges, *Journal of Manufacturing Processes* 73 (2022) 961-984. <https://doi.org/10.1016/j.jmapro.2021.11.037>
- [17] Y. AbouelNour, N. Gupta, In-situ monitoring of sub-surface and internal defects in additive manufacturing: A review, *Materials & Design* 222 (2022) 111063. <https://doi.org/10.1016/j.matdes.2022.111063>
- [18] M. Grasso, A. Remani, A. Dickins, B.M. Colosimo, R.K. Leach, In-situ measurement and monitoring methods for metal powder bed fusion: an updated review, *Measurement Science and Technology* 32(11) (2021) 112001. <https://dx.doi.org/10.1088/1361-6501/ac0b6b>
- [19] A. Gaikwad, R.J. Williams, H. de Winton, B.D. Bevans, Z. Smoqi, P. Rao, P.A. Hooper, Multi phenomena melt pool sensor data fusion for enhanced process monitoring of laser powder bed fusion additive manufacturing, *Materials & Design* 221 (2022) 110919. <https://doi.org/10.1016/j.matdes.2022.110919>
- [20] T.G. Spears, S.A. Gold, In-process sensing in selective laser melting (SLM) additive manufacturing, *Integrating Materials and Manufacturing Innovation* 5(1) (2016) 16-40. <https://doi.org/10.1186/s40192-016-0045-4>
- [21] Z. Smoqi, A. Gaikwad, B. Bevans, M.H. Kobir, J. Craig, A. Abul-Haj, A. Peralta, P. Rao, Monitoring and prediction of porosity in laser powder bed fusion using physics-informed melt pool signatures and machine learning, *Journal of Materials Processing Technology* 304 (2022) 117550. <https://doi.org/10.1016/j.jmatprotec.2022.117550>
- [22] M.A. Ansari, A. Crampton, S. Parkinson, A Layer-Wise Surface Deformation Defect Detection by Convolutional Neural Networks in Laser Powder-Bed Fusion Images, *Materials* 15(20) (2022) 7166
- [23] C. Wang, X.P. Tan, S.B. Tor, C.S. Lim, Machine learning in additive manufacturing: State-of-the-art and perspectives, *Additive Manufacturing* 36 (2020) 101538. <https://doi.org/10.1016/j.addma.2020.101538>
- [24] C. Schwerz, L. Nyborg, Linking In Situ Melt Pool Monitoring to Melt Pool Size Distributions and Internal Flaws in Laser Powder Bed Fusion, *Metals* 11(11) (2021) 1856. <https://www.mdpi.com/2075-4701/11/11/1856>
- [25] D. Mahmoud, M. Magolon, J. Boer, M.A. Elbestawi, M.G. Mohammadi, Applications of Machine Learning in Process Monitoring and Controls of L-PBF Additive Manufacturing: A Review, *Applied Sciences* 11(24) (2021) 11910. <https://www.mdpi.com/2076-3417/11/24/11910>
- [26] J. Kim, S. Lee, J.-K. Hong, N. Kang, Y.S. Choi, Calibration of Laser Penetration Depth and Absorptivity in Finite Element Method Based Modeling of Powder Bed Fusion Melt Pools, *Metals and Materials International* 26(6) (2020) 891-902. <https://doi.org/10.1007/s12540-019-00599-3>

- [27] A.R. Riensche, B.D. Bevans, G. King, A. Krishnan, K.D. Cole, P. Rao, Predicting melt pool depth and primary dendritic arm spacing in laser powder bed fusion additive manufacturing using physics-based machine learning, *Materials & Design* 237 (2024) 112540. <https://doi.org/10.1016/j.matdes.2023.112540>
- [28] Z. Snow, A.R. Nassar, E.W. Reutzel, Invited Review Article: Review of the formation and impact of flaws in powder bed fusion additive manufacturing, *Additive Manufacturing* 36 (2020) 101457. <https://doi.org/10.1016/j.addma.2020.101457>
- [29] E. Li, Z. Zhou, L. Wang, R. Zou, A. Yu, Numerical studies of melt pool and gas bubble dynamics in laser powder bed fusion process, *Additive Manufacturing* 56 (2022) 102913. <https://doi.org/10.1016/j.addma.2022.102913>
- [30] H. Chen, S. Patel, M. Vlasea, Y. Zou, Enhanced tensile ductility of an additively manufactured AlSi10Mg alloy by reducing the density of melt pool boundaries, *Scripta Materialia* 221 (2022) 114954. <https://doi.org/10.1016/j.scriptamat.2022.114954>
- [31] A. Keshavarzkermani, E. Marzbanrad, R. Esmaeilizadeh, Y. Mahmoodkhani, U. Ali, P.D. Enrique, N.Y. Zhou, A. Bonakdar, E. Toyserkani, An investigation into the effect of process parameters on melt pool geometry, cell spacing, and grain refinement during laser powder bed fusion, *Optics & Laser Technology* 116 (2019) 83-91. <https://doi.org/10.1016/j.optlastec.2019.03.012>
- [32] W.L. Smith, J.D. Roehling, M. Strantza, R.K. Ganeriwala, A.S. Ashby, B. Vrancken, B. Clausen, G.M. Guss, D.W. Brown, J.T. McKeown, M.R. Hill, M.J. Matthews, Residual stress analysis of in situ surface layer heating effects on laser powder bed fusion of 316L stainless steel, *Additive Manufacturing* 47 (2021) 102252. <https://doi.org/10.1016/j.addma.2021.102252>
- [33] C. Ioannidou, H.-H. König, N. Semjatov, U. Ackelid, P. Staron, C. Körner, P. Hedström, G. Lindwall, In-situ synchrotron X-ray analysis of metal Additive Manufacturing: Current state, opportunities and challenges, *Materials & Design* 219 (2022) 110790. <https://doi.org/10.1016/j.matdes.2022.110790>
- [34] R. Wang, D. Garcia, R.R. Kamath, C. Dou, X. Ma, B. Shen, H. Choo, K. Fezzaa, H.Z. Yu, Z. Kong, In situ melt pool measurements for laser powder bed fusion using multi sensing and correlation analysis, *Scientific Reports* 12(1) (2022) 13716. <https://doi.org/10.1038/s41598-022-18096-w>
- [35] Z. Ren, L. Gao, S.J. Clark, K. Fezzaa, P. Shevchenko, A. Choi, W. Everhart, A.D. Rollett, L. Chen, T. Sun, Machine learning-aided real-time detection of keyhole pore generation in laser powder bed fusion, *Science* 379(6627) (2023) 89-94. <https://doi.org/10.1126/science.add4667>
- [36] H.-H. König, N. Semjatov, G. Spartacus, P. Bidola, C. Ioannidou, J. Ye, J. Renner, U. Lienert, G.A. Faria, B. Wahlmann, M. Wildheim, U. Ackelid, F. Beckmann, P. Staron, P. Hedström, C. Körner, G. Lindwall, MiniMelt: An instrument for real-time tracking of electron beam additive manufacturing using synchrotron x-ray techniques, *Review of Scientific Instruments* 94(12) (2023) 125103. <https://doi.org/10.1063/5.0177255>
- [37] M.P. Blodgett, P.B. Nagy, Eddy Current Assessment of Near-Surface Residual Stress in Shot-Peened Nickel-Base Superalloys, *Journal of Nondestructive Evaluation* 23(3) (2004) 107-123. <https://doi.org/10.1023/B:JONE.0000048866.40648.fe>
- [38] J. Petrich, Z. Snow, D. Corbin, E.W. Reutzel, Multi-modal sensor fusion with machine learning for data-driven process monitoring for additive manufacturing, *Additive Manufacturing* 48 (2021) 102364. <https://doi.org/10.1016/j.addma.2021.102364>
- [39] W. Du, Q. Bai, Y. Wang, B. Zhang, Eddy current detection of subsurface defects for additive/subtractive hybrid manufacturing, *The International Journal of Advanced Manufacturing Technology* 95(9) (2018) 3185-3195. <https://doi.org/10.1007/s00170-017-1354-2>
- [40] N. Kobayashi, S. Yamamoto, A. Sugawara, M. Nakane, D. Tsuji, T. Hino, T. Terada, M. Ochiai, Fundamental experiments of eddy current testing for additive manufacturing metallic material toward in-

[41] D.-G. Park, C.S. Angani, B.P.C. Rao, G. Vértessy, D.-H. Lee, K.-H. Kim, Detection of the Subsurface Cracks in a Stainless Steel Plate Using Pulsed Eddy Current, *Journal of Nondestructive Evaluation* 32(4) (2013) 350-353.<https://doi.org/10.1007/s10921-013-0188-6>

[42] L. Caprio, A.G. Demir, B. Previtali, Observing molten pool surface oscillations during keyhole processing in laser powder bed fusion as a novel method to estimate the penetration depth, *Additive Manufacturing* 36 (2020) 101470.<https://doi.org/10.1016/j.addma.2020.101470>

[43] D.E. Lee, I. Hwang, C.M.O. Valente, J.F.G. Oliveira, D.A. Dornfeld, Precision Manufacturing Process Monitoring with Acoustic Emission, in: L. Wang, R.X. Gao (Eds.), *Condition Monitoring and Control for Intelligent Manufacturing*, Springer London, London, 2006, pp. 33-54.https://doi.org/10.1007/1-84628-269-1_2

[44] P. Rao, S. Bukkapatnam, O. Beyca, Z. Kong, R. Komanduri, Real-Time Identification of Incipient Surface Morphology Variations in Ultraprecision Machining Process, *Journal of Manufacturing Science and Engineering* 136(2) (2014).<https://doi.org/10.1115/1.4026210>

[45] S.T.S. Bukkapatnam, S.R.T. Kumara, A. Lakhtakia, Analysis of Acoustic Emission Signals in Machining, *Journal of Manufacturing Science and Engineering* 121(4) (1999) 568-576.<https://doi.org/10.1115/1.2833058>

[46] Z. Li, X. Zou, F. Bao, F. Gu, A.D. Ball, A Review of Acoustic Emission Monitoring on Additive Manufacturing, in: H. Zhang, G. Feng, H. Wang, F. Gu, J.K. Sinha (Eds.) *Proceedings of IncoME-VI and TEPEN 2021*, Springer International Publishing, Cham, 2023, pp. 867-878.https://doi.org/10.1007/978-3-030-99075-6_70

[47] H.N.G. Wadley, R. Mehrabian, Acoustic emission for materials processing: a review, *Materials Science and Engineering* 65(2) (1984) 245-263.[https://doi.org/10.1016/0025-5416\(84\)90086-7](https://doi.org/10.1016/0025-5416(84)90086-7)

[48] G.C. McLaskey, S.D. Glaser, Acoustic Emission Sensor Calibration for Absolute Source Measurements, *Journal of Nondestructive Evaluation* 31(2) (2012) 157-168.<https://doi.org/10.1007/s10921-012-0131-2>

[49] J. Williams, P. Dryburgh, A. Clare, P. Rao, A. Samal, Defect detection and monitoring in metal additive manufactured parts through deep learning of spatially resolved acoustic spectroscopy signals, *Smart and Sustainable Manufacturing Systems* 2(1) (2018)

[50] K. Gutknecht, M. Cloots, R. Sommerhuber, K. Wegener, Mutual comparison of acoustic, pyrometric and thermographic laser powder bed fusion monitoring, *Materials & Design* 210 (2021) 110036.<https://doi.org/10.1016/j.matdes.2021.110036>

[51] K. Moore, D. Kouprianoff, D. Louw, I. Yadroitsava, I. Yadroitsev, Monitoring for cracks in metal l-pbf using gas-borne acoustic emission, *South African Journal of Industrial Engineering* 34(4) (2023) 147-154.<http://dx.doi.org/10.7166/34-4-2981>

[52] V. Pandiyan, R. Wróbel, R.A. Richter, M. Leparoux, C. Leinenbach, S. Shevchik, Monitoring of Laser Powder Bed Fusion process by bridging dissimilar process maps using deep learning-based domain adaptation on acoustic emissions, *Additive Manufacturing* 80 (2024) 103974.<https://doi.org/10.1016/j.addma.2024.103974>

[53] V. Pandiyan, R. Wróbel, C. Leinenbach, S. Shevchik, Optimizing in-situ monitoring for laser powder bed fusion process: Deciphering acoustic emission and sensor sensitivity with explainable machine learning, *Journal of Materials Processing Technology* 321 (2023) 118144.<https://doi.org/10.1016/j.jmatprotec.2023.118144>

- [54] D. Dornfeld, Application of acoustic emission techniques in manufacturing, *NDT & E International* 25(6) (1992) 259-269. [https://doi.org/10.1016/0963-8695\(92\)90636-U](https://doi.org/10.1016/0963-8695(92)90636-U)
- [55] C.B. Scruby, An introduction to acoustic emission, *Journal of Physics E: Scientific Instruments* 20(8) (1987) 946. <https://dx.doi.org/10.1088/0022-3735/20/8/001>
- [56] X. Chen, J. Tang, D. Dornfeld, Monitoring and Analysis of Ultraprecision Metal Cutting With Acoustic Emission, 1996, pp. 387-393. <https://doi.org/10.1115/IMECE1996-0361>
- [57] Y. Lee, A.K. Chang, D.A. Dornfeld, Acoustic emission monitoring for the diamond machining of oxygen-free high-conductivity copper, *Journal of Materials Processing Technology* 127(2) (2002) 199-205. [https://doi.org/10.1016/S0924-0136\(02\)00126-7](https://doi.org/10.1016/S0924-0136(02)00126-7)
- [58] L.W. Koester, L.J. Bond, H. Taheri, P.C. Collins, 18 - Nondestructive evaluation of additively manufactured metallic parts: In situ and post deposition, in: F. Froes, R. Boyer (Eds.), *Additive Manufacturing for the Aerospace Industry*, Elsevier 2019, pp. 401-417. <https://doi.org/10.1016/B978-0-12-814062-8.00020-0>
- [59] H. Taheri, M.R.B.M. Shoaib, L.W. Koester, T.A. Bigelow, P.C. Collins, L.J. Bond, Powder-based additive manufacturing - a review of types of defects, generation mechanisms, detection, property evaluation and metrology, *International Journal of Additive and Subtractive Materials Manufacturing* 1(2) (2017) 172-209. <https://www.inderscienceonline.com/doi/abs/10.1504/IJASMM.2017.088204>
- [60] H. Liu, C. Gobert, K. Ferguson, B. Abranovic, H. Chen, J.L. Beuth, A.D. Rollett, L.B. Kara, Inference of highly time-resolved melt pool visual characteristics and spatially-dependent lack-of-fusion defects in laser powder bed fusion using acoustic and thermal emission data, *Additive Manufacturing* 83 (2024) 104057. <https://doi.org/10.1016/j.addma.2024.104057>
- [61] P.R. Prem, A.P. Sanker, S. Sebastian, S.K. Kaliyavaradhan, A Review on Application of Acoustic Emission Testing During Additive Manufacturing, *Journal of Nondestructive Evaluation* 42(4) (2023) 96. <https://doi.org/10.1007/s10921-023-01005-0>
- [62] M.G. Mohammadi, M. Elbestawi, Real Time Monitoring in L-PBF Using a Machine Learning Approach, *Procedia Manufacturing* 51 (2020) 725-731. <https://doi.org/10.1016/j.promfg.2020.10.102>
- [63] M. Ghayoomi Mohammadi, D. Mahmoud, M. Elbestawi, On the application of machine learning for defect detection in L-PBF additive manufacturing, *Optics & Laser Technology* 143 (2021) 107338. <https://doi.org/10.1016/j.optlastec.2021.107338>
- [64] N. Eschner, L. Weiser, B. Häfner, G. Lanza, Classification of specimen density in Laser Powder Bed Fusion (L-PBF) using in-process structure-borne acoustic process emissions, *Additive Manufacturing* 34 (2020) 101324. <https://doi.org/10.1016/j.addma.2020.101324>
- [65] Y. Plotnikov, D. Henkel, J. Burdick, A. French, J. Sions, K. Bourne, Infrared-assisted acoustic emission process monitoring for additive manufacturing, *AIP Conference Proceedings* 2102(1) (2019) 020006. <https://doi.org/10.1063/1.5099710>
- [66] D.Y. Kononenko, V. Nikonova, M. Seleznev, J. van den Brink, D. Chernyavsky, An in situ crack detection approach in additive manufacturing based on acoustic emission and machine learning, *Additive Manufacturing Letters* 5 (2023) 100130. <https://doi.org/10.1016/j.addlet.2023.100130>
- [67] S. Dalela, P.S. Balaji, D.P. Jena, A review on application of mechanical metamaterials for vibration control, *Mechanics of advanced materials and structures* 29(22) (2022) 3237-3262. <https://doi.org/10.1080/15376494.2021.1892244>
- [68] M.A. Muktadir, M.N. Hasan, M. Alam, Additive manufacturing and acoustic Emission: a brief review, *Journal of Additive Manufacturing Technologies* 2(1) (2022) 632-632. <https://doi.org/10.18416/JAMTECH.2212632>

- [69] M. Sifuzzaman, M.R. Islam, M.Z. Ali, Application of wavelet transform and its advantages compared to Fourier transform, (2009)
- [70] S.A. Shevchik, C. Kenel, C. Leinenbach, K. Wasmer, Acoustic emission for in situ quality monitoring in additive manufacturing using spectral convolutional neural networks, *Additive Manufacturing* 21 (2018) 598-604. <https://doi.org/10.1016/j.addma.2017.11.012>
- [71] S.A. Shevchik, G. Masinelli, C. Kenel, C. Leinenbach, K. Wasmer, Deep Learning for In Situ and Real-Time Quality Monitoring in Additive Manufacturing Using Acoustic Emission, *IEEE Transactions on Industrial Informatics* 15(9) (2019) 5194-5203. <https://doi.org/10.1109/TII.2019.2910524>
- [72] K. Wasmer, T. Le-Quang, B. Meylan, S.A. Shevchik, In Situ Quality Monitoring in AM Using Acoustic Emission: A Reinforcement Learning Approach, *Journal of Materials Engineering and Performance* 28(2) (2019) 666-672. <https://doi.org/10.1007/s11665-018-3690-2>
- [73] R.J. Smith, M. Hirsch, R. Patel, W. Li, A.T. Clare, S.D. Sharples, Spatially resolved acoustic spectroscopy for selective laser melting, *Journal of Materials Processing Technology* 236 (2016) 93-102. <https://doi.org/10.1016/j.jmatprotec.2016.05.005>
- [74] M. Clark, A. Clare, P. Dryburgh, W. Li, R. Patel, D. Pieris, S. Sharples, R. Smith, Spatially resolved acoustic spectroscopy (SRAS) microstructural imaging, *AIP Conference Proceedings* 2102(1) (2019) 020001. <https://doi.org/10.1063/1.5099705>
- [75] P. Dryburgh, R. Patel, D.M. Pieris, M. Hirsch, W. Li, S.D. Sharples, R.J. Smith, A.T. Clare, M. Clark, Spatially resolved acoustic spectroscopy for texture imaging in powder bed fusion nickel superalloys, *AIP Conference Proceedings* 2102(1) (2019) 020004. <https://doi.org/10.1063/1.5099708>
- [76] A. Riensche, B.D. Bevans, Z. Smoqi, R. Yavari, A. Krishnan, J. Gilligan, N. Piercy, K. Cole, P. Rao, Feedforward control of thermal history in laser powder bed fusion: Toward physics-based optimization of processing parameters, *Materials & Design* 224 (2022) 111351. <https://doi.org/10.1016/j.matdes.2022.111351>
- [77] R. Yavari, Z. Smoqi, A. Riensche, B. Bevans, H. Kobir, H. Mendoza, H. Song, K. Cole, P. Rao, Part-scale thermal simulation of laser powder bed fusion using graph theory: Effect of thermal history on porosity, microstructure evolution, and recoater crash, *Materials & Design* 204 (2021) 109685. <https://doi.org/10.1016/j.matdes.2021.109685>
- [78] Y. Plotnikov, D. Henkel, J. Burdick, K. Bourne, Synchronous multi-sensor monitoring for additive manufacturing, *Mater. Eval* 78(2) (2020) 193-202
- [79] V. Cruz, Y. Qiu, N. Birbilis, S. Thomas, Stress corrosion cracking of 316L manufactured by laser powder bed fusion in 6% ferric chloride solution, *Corrosion Science* 207 (2022) 110535. <https://doi.org/10.1016/j.corsci.2022.110535>
- [80] N. Ahmed, I. Barsoum, G. Haidemenopoulos, R.K.A. Al-Rub, Process parameter selection and optimization of laser powder bed fusion for 316L stainless steel: A review, *Journal of Manufacturing Processes* 75 (2022) 415-434. <https://doi.org/10.1016/j.jmapro.2021.12.064>
- [81] T. Yang, T. Liu, W. Liao, H. Wei, C. Zhang, X. Chen, K. Zhang, Effect of processing parameters on overhanging surface roughness during laser powder bed fusion of AlSi10Mg, *Journal of Manufacturing Processes* 61 (2021) 440-453. <https://doi.org/10.1016/j.jmapro.2020.11.030>
- [82] K. Benarji, Y. Ravi Kumar, A.N. Jinoop, C.P. Paul, K.S. Bindra, Effect of Heat-Treatment on the Microstructure, Mechanical Properties and Corrosion Behaviour of SS 316 Structures Built by Laser Directed Energy Deposition Based Additive Manufacturing, *Metals and Materials International* 27(3) (2021) 488-499. <https://doi.org/10.1007/s12540-020-00838-y>

- [83] N. Igata, K. Miyahara, T. Uda, S. Asada, Effects of specimen thickness and grain size on the mechanical properties of types 304 and 316 austenitic stainless steel, *The Use of Small-Scale Specimens for Testing Irradiated Material*, ASTM International 1986,
- [84] K. Basu, M. Das, D. Bhattacharjee, P.C. Chakraborti, Effect of grain size on austenite stability and room temperature low cycle fatigue behaviour of solution annealed AISI 316LN austenitic stainless steel, *Materials Science and Technology* 23(11) (2007) 1278-1284. <https://doi.org/10.1179/174328407X179575>
- [85] H. Zhang, C. Li, Q. Guo, Z. Ma, H. Li, Y. Liu, Improving creep resistance of nickel-based superalloy Inconel 718 by tailoring gamma double prime variants, *Scripta Materialia* 164 (2019) 66-70. <https://doi.org/10.1016/j.scriptamat.2019.01.041>
- [86] C. Elangeswaran, A. Cutolo, S. Gallas, T.D. Dinh, N. Lammens, H. Erdelyi, M. Schulz, G.K. Muralidharan, L. Thijs, T. Craeghs, E. De Bruycker, K.V. Boer, S. Clijsters, J. Peirs, W. Desmet, W. Van Paepeghem, B. Van Hooreweder, Predicting fatigue life of metal LPBF components by combining a large fatigue database for different sample conditions with novel simulation strategies, *Additive Manufacturing* 50 (2022) 102570. <https://doi.org/10.1016/j.addma.2021.102570>
- [87] M. Rhif, A. Ben Abbes, I.R. Farah, B. Martínez, Y. Sang, Wavelet Transform Application for/in Non-Stationary Time-Series Analysis: A Review, *Applied Sciences*, 2019. <https://doi.org/10.3390/app9071345>
- [88] M.J. Shensa, The discrete wavelet transform: wedding the a trous and Mallat algorithms, *IEEE Transactions on signal processing* 40(10) (1992) 2464-2482
- [89] B. Bevans, A. Ramalho, Z. Smoqi, A. Gaikwad, T.G. Santos, P. Rao, J.P. Oliveira, Monitoring and flaw detection during wire-based directed energy deposition using in-situ acoustic sensing and wavelet graph signal analysis, *Materials & Design* 225 (2023) 111480. <https://doi.org/10.1016/j.matdes.2022.111480>
- [90] S. Chowdhury, N. Yadaiah, C. Prakash, S. Ramakrishna, S. Dixit, L.R. Gupta, D. Buddhi, Laser powder bed fusion: a state-of-the-art review of the technology, materials, properties & defects, and numerical modelling, *Journal of Materials Research and Technology* 20 (2022) 2109-2172. <https://doi.org/10.1016/j.jmrt.2022.07.121>
- [91] B. Bevans, C. Barrett, T. Spears, A. Gaikwad, A. Riensche, Z. Smoqi, H. Halliday, P. Rao, Heterogeneous sensor data fusion for multiscale, shape agnostic flaw detection in laser powder bed fusion additive manufacturing, *Virtual and Physical Prototyping* 18(1) (2023) e2196266. <https://doi.org/10.1080/17452759.2023.2196266>
- [92] M.H. Kobir, R. Yavari, A.R. Riensche, B.D. Bevans, L. Castro, K.D. Cole, P. Rao, Prediction of recoater crash in laser powder bed fusion additive manufacturing using graph theory thermomechanical modeling, *Progress in Additive Manufacturing* 8(3) (2023) 355-380. <https://doi.org/10.1007/s40964-022-00331-5>
- [93] O. Diegel, T. Wohlers, Understanding build failures in laser powder bed fusion: an overview, *Metal AM* 5(1) (2019) 155-159
- [94] Y. Liu, J. Li, K. Xu, T. Cheng, D. Zhao, W. Li, Q. Teng, Q. Wei, An optimized scanning strategy to mitigate excessive heat accumulation caused by short scanning lines in laser powder bed fusion process, *Additive Manufacturing* 60 (2022) 103256. <https://doi.org/10.1016/j.addma.2022.103256>
- [95] S. Rott, A. Ladewig, K. Friedberger, J. Casper, M. Full, J.H. Schleifenbaum, Surface roughness in laser powder bed fusion – Interdependency of surface orientation and laser incidence, *Additive Manufacturing* 36 (2020) 101437. <https://doi.org/10.1016/j.addma.2020.101437>
- [96] S.A. Khairallah, A.T. Anderson, A. Rubenchik, W.E. King, Laser powder-bed fusion additive manufacturing: Physics of complex melt flow and formation mechanisms of pores, spatter, and denudation zones, *Acta Materialia* 108 (2016) 36-45. <https://doi.org/10.1016/j.actamat.2016.02.014>

- [97] N. Jeyapragash, M. Saravana Kumar, C.-H. Yang, Y. Cheng, N. Radhika, S. Sivasankaran, Effect of microstructural evolution during melt pool formation on nano-mechanical properties in LPBF based SS316L parts, *Journal of Alloys and Compounds* 972 (2024) 172745. <https://doi.org/10.1016/j.jallcom.2023.172745>
- [98] N. Raghavan, S. Simunovic, R. Dehoff, A. Plotkowski, J. Turner, M. Kirka, S. Babu, Localized melt-scan strategy for site specific control of grain size and primary dendrite arm spacing in electron beam additive manufacturing, *Acta Materialia* 140 (2017) 375-387. <https://doi.org/10.1016/j.actamat.2017.08.038>
- [99] B.W. Baker, T.R. McNelley, L.N. Brewer, Grain size and particle dispersion effects on the tensile behavior of friction stir welded MA956 oxide dispersion strengthened steel from low to elevated temperatures, *Materials Science and Engineering: A* 589 (2014) 217-227. <https://doi.org/10.1016/j.msea.2013.09.092>

Acknowledgments

Prahalada Rao acknowledges funding from the National Science Foundation (NSF) via Grant numbers CMMI-2309483/1752069, OIA-1929172, PFI-TT 2322322/2044710, CMMI-1920245, ECCS-2020246, CMMI-1739696, and CMMI-1719388; US Department of Navy, Naval Surface Warfare Center (NAVAIR, [N6833524C0215](#)) and Office of Naval Research (ONR, N00014-21-1-2781); and the National Institute of Standards and Technology (NIST, 70NANB23H029T) for supporting his research program.

The characterization aspects of this work was made possible by the use of Virginia Tech's Materials Characterization Facility, which is supported by the Institute for Critical Technology and Applied Science, the Macromolecules Innovation Institute, and the Office of the Vice President for Research and Innovation.

- Understanding the causal influence of process parameters and thermal history on part quality and detection of defect formation using in-situ sensing was the major aspect of CMMI-2309483/1752069. This grant partially funded the graduate work of Alex Riensche and Ben Bevans. (Program Officers: Steve Schmid, Brigid Mullany, Kershed Cooper, Kevin Chou, Andrew Wells, and Pranav Soman).
- Commercialization of the graph theory thermal approach for ultrafast simulation of metal additive manufacturing processes is being pursued under PFI-TT 2322322/2044710 (Program Officer: Samir Iqbal).
- Predicting (detecting) flaws in laser powder bed fusion by combining thermal simulations with in-situ sensor data was funded via NIST 70NANB23H029T.
- Assessment of part quality as a function of processing parameters, including microstructures was funded by N00014-21-1-2781. This grant funded Kaustubh Deshmukh Ph.D. work.