ORNL/TM-2024/3633

Assessment and Usage of In-Situ Monitoring Data for American Society of Mechanical Engineers Part Qualification

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September 2024

M4CT-24OR1307021

OAK RIDGE National Laboratory

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ORNL/TM-2024/3633

Advanced Materials and Manufacturing Technologies Program

ASSESSMENT AND USAGE OF IN-SITU MONITORING DATA FOR AMERICAN SOCIETY OF MECHANICAL ENGINEERS PART QUALIFICATION

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September 2024

M4CT-24OR1307021

Prepared by
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managed by
UT-BATTELLE LLC
for the
US DEPARTMENT OF ENERGY
under contract DE-AC05-00OR22725

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ABBREVIATIONS

AM	additive manufacturing
AMMTO	Advanced Materials and Manufacturing Technologies Office
ASME	American Society of Mechanical Engineers
ASTM	ASTM International (formerly American Society for Testing and Materials)
BPVC	Boiler and Pressure Vessel Code
CCD	charge-coupled device
CMOS	complementary metal-oxide-semiconductor
DED	direct energy deposition
DIC	digital image correlation
GMAW	gas metal arc welding
HIP	hot isostatic pressing
PQR	procedure qualification record
WPS	wielding procedure specification

ABSTRACT

In-situ monitoring and anomaly detection are important components for qualification of directed energy deposition (DED) additive manufacturing (AM) processes and components. The use of in-situ monitoring requires an understanding of anomalies that can be identified during the process and how those anomalies correlate to mechanical properties of the component post-production. There is also a need to qualify the algorithms and software used to interpret the process signals for DED AM. There is no single process signal that can be used with a single algorithm that will identify all anomalies that will translate to a defect in a process. The process signals are affected by changes in material, location, resolution, acquisition rate, component geometry, and the machine itself. It is observed that multiple process signals are required to identify relevant features that can be correlated to mechanical properties.

1. Introduction

The purpose of this report is to help the US Department of Energy Advanced Materials and Manufacturing Technologies Office (AMMTO) define a path towards qualification of DED processes, in which in-situ monitoring is an important component of that path. This report will help guide the Advanced Materials and Manufacturing Technologies program and American Society of Mechanical Engineers (ASME) to develop a framework of standards using in-situ monitoring as a process and part qualification method. In this report, we use a case study to demonstrate the in-situ monitoring sensors and algorithms that could be part of a standard in qualifying DED technologies and processes. In the next section, we provide an overview of DED technologies, as well as highlight relevant literature showcasing the process and mechanical property challenges associated with DED technologies. Next, we present an overview of current literature for in-situ monitoring in DED, followed by a case study involving a hot isostatic pressing (HIP) can manufactured at Oak Ridge National Laboratory's Manufacturing Demonstration Facility. Throughout this case study, we present an analysis of melt pool data that was acquired during the process and use it to understand the formation of a leak in the HIP can that was detected during post-build inspection. We conclude with a discussion on the results of the case study and present a set of criteria for sensors and algorithms for identifying anomalies during DED processes.

The focus of this report is on wire-feed DED processes, but some findings are expected to generalize to other DED processes. We acknowledge the challenges that each DED technology and material would face in the qualification process qualification using only one type of sensor, so in this work we discuss some of the other sensor modalities and the associated anomalies discussed in the literature.
Because wire-feed DED is similar to manual welding processes, we reference ASME BPVC Section IX, which mandates that welded joints be pre-formed according to a welding procedure specification (WPS). The WPS must reference a procedure qualification record (PQR), which was performed by the organization completing the welding connection. PQRs include three categories of variables as outlined in ASME Section IX. These categories include essential, supplementary essential, and non-essential variables. These variables are related to the welding process: gas tungsten arc welding, gas metal arc welding, electron beam welding, laser beam welding, and others. Essential variables must be recorded in the PQR, and supplementary essential only need to be recorded if toughness testing is mandated according to other ASME Section(s) of the Code. An example of ASME essential and supplementary variables for weld qualification of gas metal arc welding (GMAW) is shown in **Table 1**.

Table 1. ASME Essential and Supplementary variables for GMAW qualification

Section IX GMAW WPS Essential and Supplementary Variables			
Paragraph	**Variable**	**Essential**	**Supplementary**
Base Metals	Group Number		X
	Thickness limits		X
	Thickness qualified	X	
	Deposit thickness qualified		X
	P-Number qualified	X	
Filler Metals	F-Number qualified	X	
	A-Number qualified	X	
	diameter		X
	Filler metal product form	X	
	Classification		X
	Change in supplemental filler by 10% volume	X	
	Alloy elements	X	
	Deposit thickness	X	
Preheat	Increase > 100ºF (55ºC)		X
Post Weld Heat Treatment (PWHT)	PWHT	X	
	PWHT (time and temperature range)		X
Gas	Torch shielding gas composition	X	
	Backing gas or change in composition	X	
	trailing or change in composition	X	
Electrical Characteristics	Heat Input		X
	Transfer mode	X	
	Current or polarity		X
Technique	Multiple to single per side		X
	single to multiple electrodes		X
	use of thermal processes	X	

To reduce the number of PQRs required by an organization to perform a welding procedure, materials of similar characteristics are grouped using P-Numbers and Group Numbers, and welding filler metals are grouped using F-Numbers in ASME Section IX Table QW-432. The P-Number, Group Number, and F-Number groups are based on the chemical composition, mechanical properties, and the weldability characteristics of the materials. For example, Type 316 SS is grouped with other austenitic stainless steels with the P-Number 8, Group Number 1. Other materials in this same group are other austenitic stainless steels such as 304, 304L, 304H, 310, 316L, 316H, 316LN, 316N, 321, 347, and others. Welded deposits may include dilutions from the substrate material. Therefore, A-Numbers are used to define weld metal composition, but only for ferrous-based alloys. When applicable to the material, the A-Number is a mandatory composition analysis for procedure qualification.

The ASME Section IX performance tests are strictly to assess the combination of welding process and material(s) to produce sound weld deposits according to the PQR test variables and the deviation permitted in WPS are defined in ASME Section IX documented by the organization performing the welding procedure. The weld performance qualification does not account for any monitoring that takes place during the process or predictions from algorithms based on in-situ monitoring. Based on the ASME Section IX qualification tests and PQR requirements, if the in-situ monitoring and associated prediction algorithms could be proven to be accurate withing the WPS deviations defined in ASME Section IX, then the process and components produced by a DED process should meet the qualification standards of wielding. These standards should be able to be included in the DED organizations PQR for applications associated with a material classification and geometry.

2. DIRECT ENERGY DEPOSITION (DED) PROCESSES

Metal additive manufacturing (AM) has been acknowledged as a method to produce metal components with complex geometries and unique material characteristics (Kladovasilakis et al. 2021). In this section, we define the DED technologies and describe some of the process and material properties from literature. In 2009, the American Society for Testing and Materials (ASTM) established standards for AM technology, which led to the definition of eight AM methods according to the ASTM F2792-12A (Kladovasilakis et al. 2021). DED is mainly comprised of the GMAW, laser welding, and wire-feed welding with the aid of robotic arms to manufacture desired components. In this technology, the feedstock is primarily in a metal powder or metal wire form, where the material is fed through the nozzle and completely melted using plasma arc, laser, electron beam, or gas metal arc on the desired path defined by the model of the component (Dass and Moridi 2019). DED is non-equilibrium processing technique, where very fast cooling rates affect microstructure and mechanical properties, like other metal AM processes (Svetlizky et al. 2021). . The major process parameters associated with DED include laser power, laser spot size, powder or wire feed rate, carrier gas flow rate, clad angle, feedstock properties, and layer thickness. As shown in **Figure 1**, the deposition rate and cooling rates lead to a complex thermal history during multi-layer DED processes. Observations of increasing peak temperature with increasing layer number can be attributed to accumulated heat of the system. Changes in the thermal signature over the build time of a component have shown changes in the post build geometric measurement DED components where mitigation requires an understanding of the thermal build up in the component (Vyatskikh et al. 2023). Thermal changes that occur during the DED processes have also been shown to influence geometric dimensions of the as built component which have been observed using digital image correlation (DIC) and the full thermomechanical history of the printed part (Haley et al. 2021). This would suggest that thermal monitoring of the system as a whole and a layer-by-layer thermal monitoring correlated geometric dimensions and mechanical properties could be part of the qualification process.

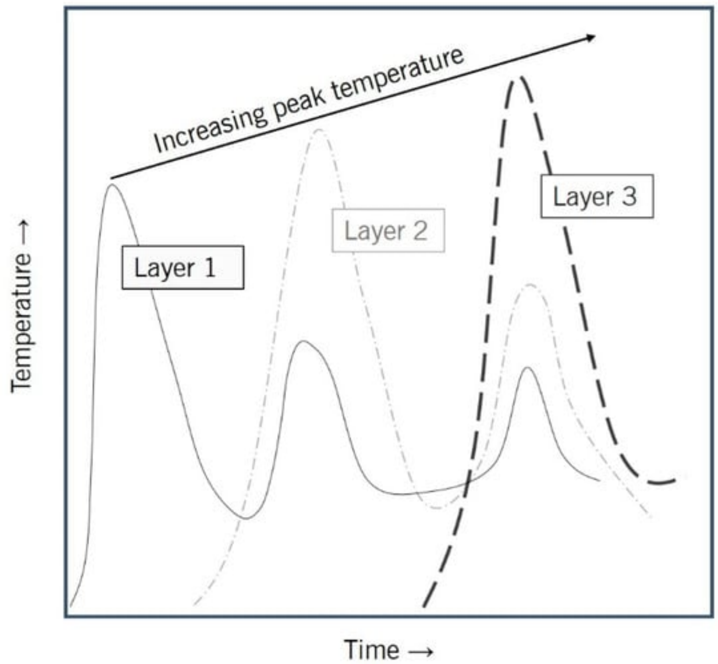


Figure 1 Generalized thermal cycle of three consecutive layers during DED process, and corresponding peak temperature trend.

Thermal signatures can also be used to identify residual stress within a component, as well as overall health of the DED process. Vyatskikh et al. demonstrated residual stress mitigation while monitoring the DED process using a thermal imager (Vyatskikh et al. 2023). Although thermal process signatures are an important in-situ method and would provide necessary data to meet the PQR essential variable for use of thermal processes, it is not the only in-situ process signal of concern. To meet the requirements of the PQR, one of the essential variables is deposit thickness, and to get a qualified measurement of layer deposit thickness, visible light imagers would provide a more informed process signal.

While not a part of the PQR, identifying cracking and porosity within the DED process would also provide important process signals that can be used with mechanical property measurements of components to provide an informed metric for qualification. The process signals are the method by which to acquire data about the layer-to-layer deposition but require local and global correlation of the process signals. Mechanical defects in the process can occur as the component cools which may require additional process signals to detect.

3. SENSING EQUIPMENT

The sensor equipment used as part of in-situ monitoring for DED processes is varied, and no single sensor will provide all the information needed to capture all anomalies that will become a defect. Some anomaly classes are easier to identify in certain sensor signatures. While each sensor type is capable of being used to identify multiple anomaly classes each sensor type will have limitation dependent on the application. The limitations are but not limited to sample rate, signal-to-noise, and resolution. Each sensor type has a specific dynamic range and has been shown to identify certain types of anomalies during controlled experiments. Where anomaly can be defined as any process signal signature that is not normal melt for DED, such as incomplete melted feedstock or changes in the melt pool geometry. A flaw is identified as an anomaly that could lead to a defect and a defect is lack-of-fusion, porosity, or other artifact in the process signal that is known to correlate to changes in the mechanical properties. The most used sensor in the literature are cameras since these are the most versatile sensors and have a wide range of uses and dynamic ranges. Most of the research in the use of imaging sensors, (photodiodes, high-speed video, high-resolution layerwise images) for AM processes has been focused on the melt pool and understanding the melt pool dynamics (Snow et al. 2021). Other sensor types have been used to acquire process signatures that occur during the cooling of the component, where defects such as cracking would more likely occur. In this section, we describe various sensors and the process signature anomalies they are used to identify.

3.1 IMAGING SENSORS

Monitoring of the melt pool in DED is widely considered to be an important process monitoring signal signature as the complex physics taking place with the melt pool also drive many of the flaw formation mechanisms (Liu et al. 2024). Here some of the complex physics demonstrating how some of the flaw formation mechanics may manifest due to the melt pool dynamics. Here are some examples of some of the research and monitoring of the melt pool and the interesting detections are presented.

The Marangoni effect is a convective heat transfer phenomenon, which affects the melt pool dynamics and indirectly contributes towards the porosity in some of the process parameter schemes. The movement in the melt pool is mainly from regions of high surface tension to low surface tension, finally leading to variable melt pool penetration. A small melt pool length is due to a negative surface tension gradient and signifies bulk turbulence flow in the melt pool. Conversely, the melt pool depth is increased with positive gradient of surface tension, and surface turbulence occurs in the melt pool, which can trap undesired oxides in the melt pool (Dass and Moridi 2019). This process indicates that melt pool shape would be important in characterizing the quality of a component. Shen et al. developed a prognostics and health management (PHM) approach using a charged-couple device (CCD) camera and pyrometer for in-situ monitoring and used support vector machines (SVMs) for classification various defects (Shin et al. 2023). During their work they found effective quantification of balling, low pores, and high pores, but they did not correlate those findings in the in-situ data with overall mechanical properties. In a survey of in-situ monitoring for DED, it was found that for melt pool, feedstock, and deposition layers sensors that employ visible light spectrums were capable of monitoring these characteristics, but challenges were identified with monitoring heat source spectrum, spatter inference, and tracing the small dynamic melt pool (Tang et al. 2020). The detection of these classifications of anomalies and flaws along with correlation to mechanical properties is an important step towards using in-situ as a qualification method.

Temperature process signals are significantly relevant to the quality of a DED component because of the high-energy heat sources required to fuse metal powder and wire. In contrast with the visible light signals, the optical signals with an infrared spectrum are more capable of calculating temperature data in DED processes (Ogoke and Farimani 2021). The image signals from infrared sensors are not as sensitive to other process phenomena or experiments, such as different colors of deposited layers. CMOS/CCD cameras capable of gathering the infrared signals of short wavelength and thermal imagers with different infrared wavelength ranges are the preferred sensing equipment used to obtain image signals with an infrared spectrum. Both types of sensors can be calibrated using a blackbody furnace calibration method. **Table 2** shows a comparison of different imaging sensors and their advantages and disadvantages. Along with identifying changes in a process to indicate out of process conditions, thermal in-situ monitoring could be used as a feedback control process signal to mitigate conditions that could create flaws and defects.

Table 2. Comparison of different images sensors

Sensing Equipment	Spectral Range (µm)	Advantages	Disadvantages
CDD/CMOS sensors	0.3-1.0	Low cost, high resolution, high frame rate	Requires optical filters to eliminate visible spectrum, poor ability at temperature motoring
Infrared sensors short wavelength	0.9-1.7	Strong ability at high temperature motoring, medium cost range	Requires optical filters to avoid laser source interference
Infrared sensors medium wavelength	3.0 - 5.0	Strong ability at high and medium temperature motoring	high cost
Infrared sensors long wavelength	8.0 - 14.	Medium cost	Low frame rate, poor high temperature motoring

Along with the above comparisons of the different image sensing equipment, there may be a requirement to incorporate auxiliary illumination devices when utilizing visible light imaging sensors, such as LED, laser diodes, UV arrays, and vertical-cavity surface-emitting lasers [11, 12]. When monitoring melt pools, laser light sources are the preferred illumination devices due to the illumination being directed at the melt pool instead of globally at the build area. Illuminations devices can be installed coaxially or paraxially. Passive light sources, paraxial devices, are used primarily to light the process area, while coaxial illuminates are more attractive to practical applications of lighting the melt region. Although the illumination device can improve the contrast of the imaging sensor, it may also disturb some of the spectrum signals. Therefore, optical filters may be required to attenuate undesired spectrums and structured light may be preferred over other illumination devices. Structured light uses projected light patterns to capture the 3D shape of an object that would not be visible with broad spectrum lighting of the monitored region [4, 5]

3.2 ACOUSTIC SENSORS

Signals generated by stress waves can be monitored using acoustic sensors and can provide an abundant information about powder transmission, pores, and cracks (Prem et al. 2023; AbouelNour and Gupta 2022). These signals have been studied in powder bed fusion (PBF) and fused deposition modeling (FDM), which can be a reference for DED technologies. Some challenges, such as the analysis of high-frequency acoustic signals, overheating substrates, and the noise from the powder strikes on the previous deposited layer and substrate, impede the application of acoustic emission signals. In addition, when the stress wave source and sensor are positioned relatively differently to propagation path of the detector, the same acoustic emission mechanism may lead to different detected signals skewing any classification of defects.

3.3 OTHER SIGNAL SENSING EQUIPMENT

In recent years, X-ray signals have been gradually applied in high-energy heat processes, including DED. In this method of in-situ monitoring, the sensing equipment is comprised of X-ray sources, an undulator, a slit, and high-speed camera (Wang et al. 2021). In this type of setup, the melt pools and feedstock for powder DED are the primary subjects under investigation. Additionally, the use of thermocouples and current signals are used for monitor DED processes to identify anomalies in the process signal signature, but the signals may lack the spatial-temporal resolution needed to identify and classify defects.

4. SIGNAL SIGNATURES OBTAINED DURING IN-SITU MONITORING

Signal signatures are obtained or calculated from acquiring sensor data in-situ or from other algorithms. Multiple sensors may contribute to the same signal process signature. Temperature signatures from in-situ data can be obtained by an infrared camera, two color pyrometer, hyperspectral imager, thermocouple, and in some cases visible light camera. This section will review some of the process signals that have been acquired and reported on the literature for DED processes.

4.1 MELT POOL AND DEPOSITED LAYER GEOMETRIC CHARACTERISTICS

Melt pool and deposited layer geometric characteristics are acquired through the sensors of visible light or infrared imagers. Process signal signatures acquired using visible light or infrared can indicate geometric characteristics such as height, width, length, and area of melt pool and deposited layer. Other characteristics, such as balling and lack-of-fusion, may also be characterized using these two types of sensors (Wu et al. 2024). In the case of laser DED, coaxial monitoring and characterization of the 2D melt pool geometries can provide important process quality information. Characteristics such as width and length can provide information to simulation models that will greatly enhance the accuracy of the models and provide information about the mechanisms for defect formation. The requirement for getting geometric information requires the calibration of imaging sensor. This is a fixed property, so any new positioning of the imager or change of the plane of view would require a recalibration and is not easily accomplished during the DED process.

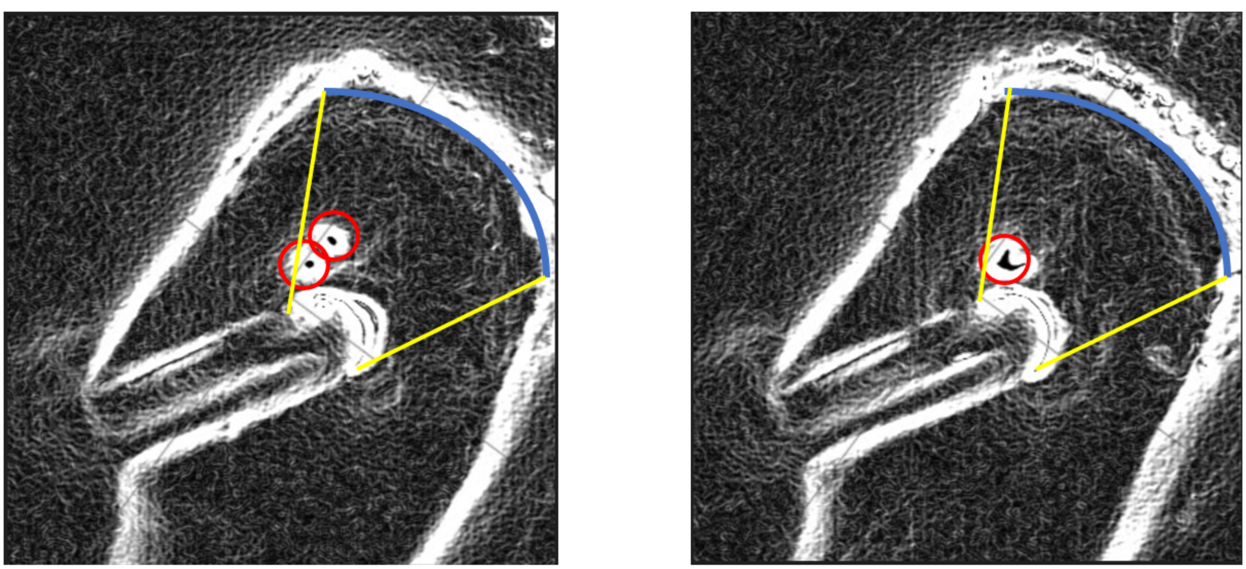
Feedstock information, especially with blown powder through a nozzle or wire-feed systems, may benefit from the use of visible light imagers. They allow for the calculation of pixel color variation that can be observed through camera sensors, but to correctly differentiate variation may require more bit depth of the imager. This information can be used to enhance the understanding of feedstock characteristics as a function of the DED process. In the case of powder feed DED systems, the camera can be setup paraxially by focusing on powder feed concentration distributions, although these types of measurements require a camera with a high frame rate. The interaction between the feedstock-through-nozzle rate and the geometric characteristics of the deposition layer are interconnected, and improved information can be used to inform predictive algorithms and simulation modeling.

Thermal characteristics of the deposited layer and melt pool are especially important for predictive algorithms on microstructure, which influence the mechanical properties of the material. Process signals at the time of melt pool formation and over time will greatly influence the formation of mechanistic defects. Not only the thermal signature of the melt pool alone important but also the influence from variations in feedstock material as part of the process signature. This indicates that a single process signal signature is not enough to characterize or qualify a process or component developed by DED. The requirement for qualification will require a multi-process signal signature and a suite of qualified algorithms to perform the analysis and correlate those classification with that of mechanical testing to provide a quality assessment from in-situ monitoring process signals.

5. CASE STUDY HOT ISOSTATIC PRESSING CAN

The literature research has primarily focused on two main characteristics for in-situ monitoring of DED processes: melt pool dimension and porosity. We used a paraxial thermal imager to collect data during the manufacturing process. We were interested in melt pool characteristics and porosity that remained visible during the melt pool scan direction transition. From the images collected during DED process, there are three characteristics that are quantifiable: scan direction, melt pool width, and aspect ratio of "porosity". The melt pool variation over the build did not lead to any significant statistical difference, so we focused on the morphology of cooler blob formations within the melt pool.

The region of focus in the melt pool where the formation was most prevalent and with the melt direction could be tracked for the maximum frame count were those formations that occurred between the melt pool crest and center of the melt pool. We further focus on the region defined by the cone that connects the center of the melt pool with that of the forward crest as shown in **Figure 2**. The processing of the in-situ melt pool data was done post-build with the knowledge that the HIP can had a pressure leak that had to be corrected after initial fabrication. In the region of interest for each frame of the melt pool data, aspect ratio of the surface porosity formation and number of blob formations are quantified and tracked for the duration of their existence using computer vision techniques. Due to the paraxial view of the thermal imager, the melt pool crest appears closer to the melt pool center depending on direction of travel of the melt tail as shown in **Figure 3**. From the views of the melt pool based on travel direction and field-of-view of the imager, we assumed that porosities exist after passing the center of the melt pool. The surface porosity formations seen after the melt pool could also be anomalies brought to the surface due to turbulence in the melt pool dynamics. We also have no observation from the forward crest images that have porosity, that show porosity in the visible trail within 6 frames after passing the melt center, so we assumed that the observed porosity in the tail of the reverse direction is a percentage of the porosity that existed between the crest and melt center and resurfaces due to melt pool dynamics. When we compare porosity aspect ratio and frame duration with forward and reverse melt pool we observe a smaller distribution of small porosity in the reverse scan direction. From this observation we assume that small porosity seen in the forward scan direction does not continue to exist post melt pool center.



(a) Circular small area porosity (b) Elongated large area porosity

Figure 2 Computer vision augmented view of the melt pool and porosity formations. (Blue lines) Crest and (yellow lines) region of interest shows porosities in the melt pool, as well as (red) detected porosity.

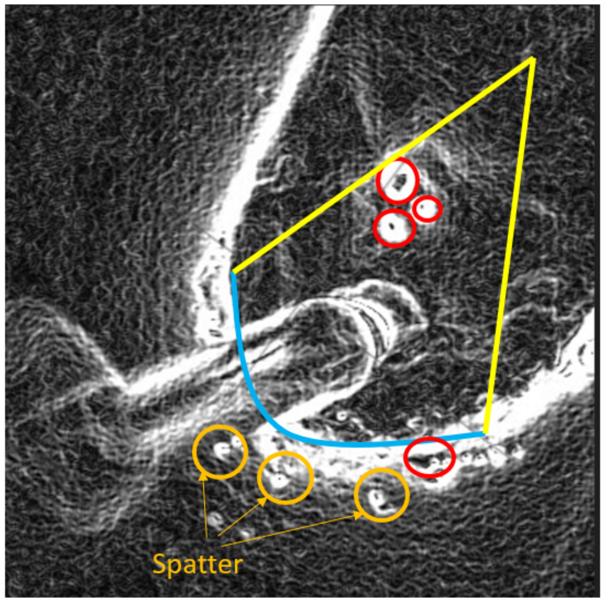


Figure 3 Opposite scan direction, paraxial thermal imager view. Spatter particles are shown ahead of the melt pool crest.

We assume that larger porosity is more likely to exist when the aspect ratio is circular it does not return to the surface of the melt region during turbulent melt pool dynamics becoming a trapped gas porosity (Dass and Moridi 2019). The surface porosity formations that remain are then treated as porosity that will exist during the next deposition layer. We see that the larger area and larger aspect ratio surface porosity formations continue to exist even after observable imager capability **Figure 4**. The data shows that most of the large porosity is more often observed during the changing of scan direction. The region of the leak during post pressure inspection and where there was a concentration of direction changes correlated, but did not match up exactly. Due to the turbulent nature of the melt pool is assumed that surface porosity from one deposition layer can migrate through the melt pool to transition to other regions. This migration is not expected to be more than the melt pool width. This could explain the reason for a pressure leak in this region when there was not a statistically higher formation of surface porosity, but there was a higher change of scan direction in this region.

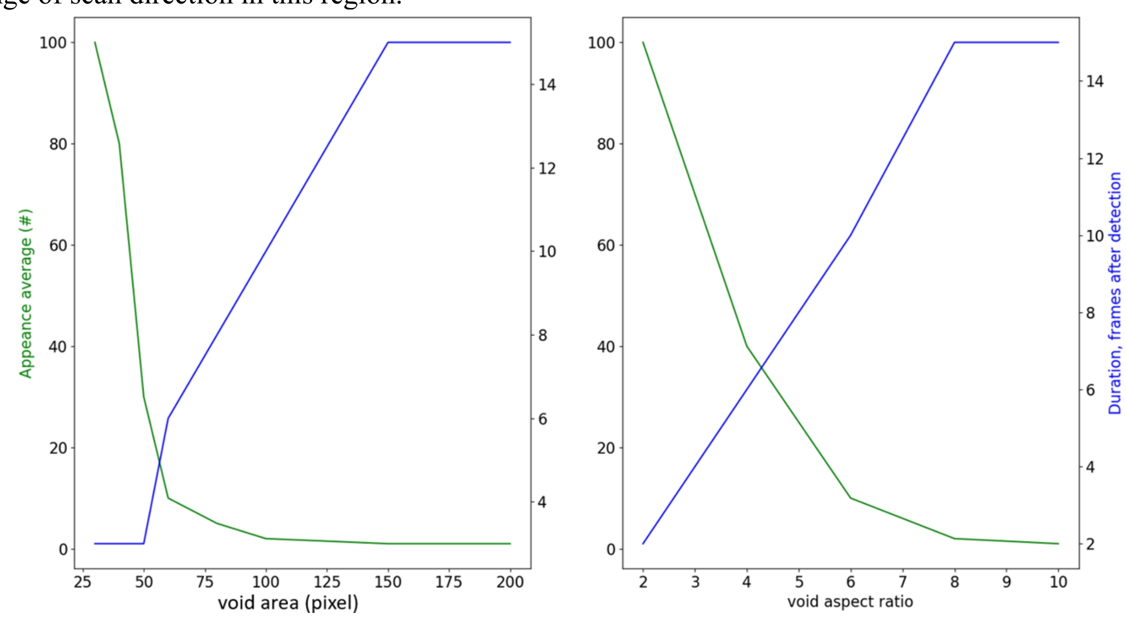


Figure 4 Area and aspect ratio of surface porosity formation and frame duration seen in thermal images.

Although there were observations of surface porosity formations near the pressure leak test location, there is not enough evidence to suggest that the quality of the DED component was good or poor. The surface porosity found in any one region or combined with adjacent regions did not offer statistically significant change from other regions. We were not able to conclude any regions that had surface porosity that remained after manufacturing due to lack of algorithms that are trained on data from this type of operation. The ability to generalize any suite of algorithms to be able to cross DED technologies and materials even when using a similar process signal source remains an area of open research. The creation of a benchmark or suite of benchmark datasets to establish the validity of a software system to predict the quality of component made using DED AM would provide a path towards reliability and acceptance of an in-situ quality assessment system.

6. DISCUSSION

The path towards qualification of DED components using in-situ monitoring requires standards for the sensors and a benchmark dataset to qualify the process signals and algorithms used to predict quality. No single process signal signature or algorithm will provide enough information to provide the information to identify every anomaly that occurs. The anomalies that do occur within a process do not all present as defects in the component, and this is partially due to changes in material, geometry, and the machine being used. The location and proximity of a sensor shows an effect on the process signal signature that is acquired and will change the identification of those signals using an algorithm that is trained a priori. Therefore, the understanding of the anomaly classes and their importance to the mechanical properties of the component are important in establishing standards of in-situ monitoring techniques.

With the promises of metal AM, especially DED there, is still a gap between in-situ monitoring of DED processes as qualified components and existing mechanical property inspection. The areas of deficiency that require further research are in process, multi-signature analysis, software and algorithm research, and advanced sensing devices.
More advanced sensing devices and technologies, such as in-situ X-ray diffraction, and electromagnetic acoustic transducer, should be applied to acquire additional process signals to augment the visual, thermal, and other methods for process signal acquisition. Processes such and electron melting DED would greatly benefit from signal sensors from photons, electrons, X-ray, and backscattered electrons and would provide a rich array of process signals. Continued improvements in coaxial monitoring for laser DED systems could only improve the process signal and lessen the noise that is currently seen in the data. The need to integrate as many sensing signals as possible to adapt to the flexibility and adaptability of DED processes cannot be understated.

Lastly, the understanding of mechanistic formation of flaws and defects and correlating this to sensor signals is a must, but also the algorithms and software used to analyze and make predictions from those signals requires qualification. The current trend of applying more deep learning (DL) models that provide a non-linear approximation function are necessary for multi-signal analysis and quality predictions. However, physics-informed DL models will provide a higher confidence on the predictions and would provide a mechanistic model for process improvement. This would require a more software quality assurance processes than is currently provided with OEM in-situ monitoring software systems of which are mainly developed for powder bed fusion processes.

The path towards qualification using in-situ monitoring process signals is a viable solution to qualify components manufactured using DED processes, but there is still research required in developing appropriate datasets, algorithms, geometry, machine influence, and understanding of which anomalies during specific stages in a process are needed to determine the quality of component for a given application.

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