Evaluation of Quality Signatures™ using In-Situ Process Control during Additive Manufacturing with Aluminum Alloy AlSi10Mg

To
Sigma Labs Inc.

by
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Evaluation of Quality Signatures™ using In-Situ Process Control during Additive Manufacturing with Aluminum Alloy AlSi10Mg

Introduction
This build was designed to establish a correlation between in-process dependent data mined from in-situ sensor raw trace signals, independent process input variables for example laser power, and post-process dependent data measured during destructive metallographic testing for porosity of as-built specimens.

Materials
The powder metal used for these experiments was Aluminum Alloy AlSi10Mg. It had a particle size distribution (PSD) of 15-50µm. The material was supplied by Valimet.

Machine
All builds were performed using a standard EOS M290 additive manufacturing machine.

Sensors
Four (4) in-situ sensors were used during all three (3) experiments. The sensor types comprised non-contact, non-imaging optical sensors as well as non-contact thermal sensors. One (1) sensor was a photodetector placed in a fixed, or Eulerian frame of reference and positioned above the build plate. Its field of view (FOV) was of the entire build plate. A second photodetector was placed in moving, or Lagrangian frame of reference within the optics train. Its FOV was restricted to a narrow region immediately surrounding the melt pool. The third sensor was a high-speed, single wave length pyrometer, placed in a fixed frame of reference above the build plate and focused onto a 10mm, right circular cylinder, aka, a Process Control Specimen (PCS). Its FOV was 1mm. The fourth sensor collects X and Y command signals from the scan head controller and is used to visualize in-process dependent data or In-Process Quality Metric™ (IPQM®) data in a 3D point cloud. All sensor data was collected by a high-speed data acquisition system running at 50 kHz per channel, aka PrintRite3D SENSORPAK® and was subsequently analyzed by Sigma’s proprietary, multivariate classifier PrintRite3D INSPECT® software.
Experimental Approach

Variations in Laser Power using Stacked Columns
For this experiment, right circular cylinders 10mm in diameter, and 10mm tall were built using the configuration shown in Figure 1. A total of nine (9) cylinders were built with one directly beneath the fixed pyrometer. The configuration was intentionally designed to space the specimens across the build plate and allow for determination of spatial and temporal variation that may exist due to machine or sensor variability.

Figure 1: CAD Image of the Build Configuration used. The PCS cylinder is positioned in the front, right corner of the build plate. Individual parametric build segments are numbered starting at 1 directly against the build plate.

Processing Conditions
The starting or control parameters were provided by EOS and are suitable for lasing Al metal powder. Table 1 lists the control parameters and the ten (10) different sets of processing parameters used. Layer thickness was held constant at 30μm. Each build segment contained 333 layers. Chamber atmosphere was Argon (Ar). Build plate preheat temperature was 170°C.

Table 1: Independent Process Input Variables.

<table>
<thead>
<tr>
<th>Segment ID</th>
<th>Power Variation (%)</th>
<th>Laser Power (W)</th>
<th>Scan Speed (mm/s)</th>
<th>Hatch Spacing (mm)</th>
<th>GED (J/mm²)</th>
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<tr>
<td>1</td>
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<td>370</td>
<td>1300</td>
<td>0.19</td>
<td>1.49</td>
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<td>2</td>
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<td>1300</td>
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<td>1.42</td>
</tr>
<tr>
<td>3</td>
<td>-10</td>
<td>333</td>
<td>1300</td>
<td>0.19</td>
<td>1.35</td>
</tr>
<tr>
<td>4</td>
<td>-15</td>
<td>314.5</td>
<td>1300</td>
<td>0.19</td>
<td>1.27</td>
</tr>
</tbody>
</table>

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Data Analysis – Process Control Specimen

Univariate Trend Plots – Melt Pool Level

The trend plots in Figures 7 and 8 were generated using Sigma’s standard PrintRite3D INSPECT® software and algorithms using dependent in-process data mined from the high-speed pyrometer raw trace signal. The control data set (blue markers) used for this analysis was taken from Build Segment 1, Layers 50 to 325. Recall that there were 11 vertical build segments each contained 333 layers and identified in Figure 7 by blue arrows. Each trend plot was reported on a layer by layer basis and included a calculated +/- 3σ upper and lower control limit (UCL, LCL) represented as dashed lines.

Figure 7 comprises three (3) trend plots of dependent in-process data that individually allowed the melt pool to be tracked according to its peak temperature, heating rate, and cooling rate for a given layer. The melt pool dependent in-process data were mined at a fast time scale, e.g., microseconds (μs). By doing so, it was possible to infer changes in the melt pool geometry/volume associated with changes to independent process input variables, e.g., changes in laser power level. Each data point represents a single laser scan for a given layer. By doing so it is possible to track subtle changes to the melt pool which ultimately would be induced by other process disturbances such as presence of large powder particles or melt pool spatter not necessarily changes to independent process input variables. Therefore, Sigma’s algorithms would allow for process disturbances to be distinguishable from natural process variation.

In all three trend plots the dependent in-process data appeared to be normally distributed. Of interest is the drop in Peak Temperature as the build increased in the Z direction. This corresponded with a decrease in power levels as expected since the melt pool would be expected to reduce in size and maximum temperature as reductions in laser power all other independent process input variables. Of further note were the apparent natural data breaks (red circles) present because of standard upskin/downskin parametric changes visible around layers 3,300 and 3,700. These upskin/downskin parameter changes were pre-programmed into the EOS M290 and occurred between build segments since each segment was programmed as a separate part. Lastly, it is interesting to note, that there was a shift in cooling rate which was also expected as power levels decreased.

A final note about the Melt Pool trend plots in Figure 7. The Y-axes were labeled “Corrected” because the proprietary algorithms used by Sigma incorporated emissivity correction factors for the given material.
Figure 2: Scan Level Trend Plots for Dependent In-process Data Mined from the Pyrometer. Pyrometer was focused on the Process Control Specimen.

Univariate Trend Plots – Layer Level

It was also possible to mine the in-process pyrometer raw trace at a slower time scale for additional dependent in-process data and infer information about the bulk materials response to the energy input such as defects associated with lack of fusion (LOF) or spherical porosity associated with keyholing.

In Figure 8, here again there were similar trend plots generated but this time displayed using thermal history information rolled up for the entire layer from scan level information. It is important to note that the layer level trend plots exhibit similar trends to those generated at a scan level. For example, there was
a decrease in peak temperature and heating rate accompanied by an increase in cooling rate as the power levels were intentionally decreased.

![Peak Temperature](image1.png)

![Heating Rate](image2.png)

![Cooling Rate](image3.png)

**Figure 3:** Layer Level Trend Plots for Dependent In-process Data from the Pyrometer. The Pyrometer was focused on the Process Control Specimen.

**Multivariate Trend Plot – Melt Pool Level**

It is convenient to represent multiple univariate trend plots in one (1) trend plot while maintaining data continuity without the loss of process sensitivity or data integrity. Therefore, Sigma uses a proprietary multivariate analytics software engine to represent such trend plots. In Figure 9, a Multi-Variate Statistical Process Control (MVSPC) trend plot combined the results for all univariate trend plots for melt
pool information from Figure 7, i.e., peak temperature, heating rate and cooling rate. This combined dependent in-process data was termed In-Process Quality Metric™ or IPQM®. The Y-axis for the MVSPC trend plot in Figure 9 is on a log scale because when a data point is flagged as an outlier it may in fact be a significant outlier and far from the normal distribution, hence it is convenient to display such data on a semi-log trend plot. For MVSPC trend plots there is only one control limit (blue dashed line) because the multivariate classifier control data set is defined by a single sided distribution, and it was established using a 95% confidence limit. This means that 95% of the data population lies within the boundary and 5% lies outside the boundary. The control limit is user definable and can be set between 90 and 99 percent.

For the melt pool MVSPC trend plot in Figure 9 there was an increasing trend in the IPQM® values, which correlated with the parametric changes by segment observed in the univariate trend plots in Figure 7. The MVSPC trend plot in Figure 9 is a convenient way for a process engineer to quickly determine if the process is under control. If this were an actual build without intentional changes in laser power the operator would be alerted that the process has trended out of control. Lastly, as a confirmation of data continuity, Figure 9 upskin/downskin parametric changes were still visible around layers 3,300 and 3,700 (blue arrows).

![Figure 4: Multivariate Trend Plot of Melt Pool Level IPQM® Pyrometer Data Collected from the Process Control Specimen.](image)

**Multivariate Trend Plot – Layer Level**

Figure 10 is also a MVSPC trend plot which combined the results for all univariate trend plots for layer level information from Figure 8, i.e., peak temperature, heating rate and cooling rate. For the layer level MVSPC trend plot in Figure 10 it was observed that here was a slight increasing trend in the IPQM® values starting around layer 2,300 which correlated with the parametric changes by segment observed in the univariate trend plots in Figure 8.
Figure 5. Multivariate Trend Plot of Layer Level IPQM® Pyrometer Data Collected from the Process Control Specimen.

Data Analysis – All Specimens
Multivariate Trend Plots – Part Level

Figure 11 contains a trend plot of in-process independent data collected from both on-axis and off-axis photodetectors for an entire layer; it clearly captured the independent process input parameter changes by layer. All scans, for all parts for a layer are rolled up and plotted as a single data point for that layer. Then each test layer is compared to the control data set (displayed as the control limit/blue dashed line) and the resultant IPQM® value is displayed on a log scale for ease of viewing. The results indicate that as the independent input variable (power level) was changed, there was a corresponding change in the in-process dependent variable (IPQM® value).

The intermittent points between each build section were the upskin and downskin scans (blue box) that were preprogrammed into the M290 between the completion of one build segment and the start of the next.

Figure 6: Multivariate Trend Plot of IPQM® Parts Graph from Photodetector Data Collected from the Entire Build Layer by Layer.

Figure 12 contains a trend plot of the data collected by the photodetectors for Part 2 (aka, Process Control Specimen) which is the process control specimen. Once again there were clear changes in the dependent
in-process IPQM® in response to the intentional process parameter changes to laser power. Note the individual data points in between each build segment. These represent upskin and downskin parametric changes as compared to control parameter settings.

Figure 7: Multivariate Trend Plot of the PCS specimen, Part 2 generated using In-process Photodetector Data Collected from a Build and rolled up.

Figure 13, is a 3D point cloud visualization of Sigma’s proprietary In-Process Quality Metric™ known as TED™ or Thermal Emission Density™. TED™ is dependent in-process data mined from and calculated using photodetector raw trace signals. Each vertical build segment has a different TED™ value assigned to it and correlates with intentional changes to independent process input variables, e.g., changes in laser power level.

Figure 8: 3D Point Cloud Visualization of Sigma’s Proprietary TED™ (Thermal Emission Density™) Metric.
As a separate verification that Sigma’s proprietary TED™ metrics correlated with changes in laser power, Figure 15 is a trend plot of TED™ as a function of laser power with visualization of process control specimen. It indicated that changes in Sigma’s TED™ metrics correlated with variations in laser power. An R² value of 0.9948 for the trendline indicated that the TED™ data is represented very well by a linear model.

![TED™ vs Laser Power](image)

Figure 9: Trend Plot of TED™ as a function of Laser Power. With Visualization of only the Process Control Specimen annotated with Sigma’s proprietary TED™ IPQM® and Corresponding Changes to the Independent Process Input Variable, e.g., Laser Power.

**Metallography and Analysis**

Metallographic services provided by Metals Engineering and Testing Laboratories, laboratory number 107-553. Three samples (labeled Parts 2, 5 and 8) were sectioned into 2 pieces, mounted and polished in accordance with ASTM E3. Each part consisted of 11 sections. Once prepared the samples were examined from 20-500X magnifications in the as polished condition. Photomicrographs were taken at 50X in the center of each section of all three parts for porosity testing. Imaging analysis techniques were used to estimate the (defect density) average areal percent porosity of all 33 segments. Table 2 includes the results.
Table 2 contains metallographic results for percent porosity measured. Figures 10, 11 and 12 are photomicrographs in etched condition (using Kellers Etch) taken of Part 5 Segments 1, 7 and 11, respectively.

Table 2: Percent Porosity per segment.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Part 2 % Porosity</th>
<th>Part 5 % Porosity</th>
<th>Part 8 % Porosity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.09</td>
<td>0.02</td>
<td>0.07</td>
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<tr>
<td>11</td>
<td>5.3</td>
<td>1.58</td>
<td>4.77</td>
</tr>
</tbody>
</table>

Figure 10: Photomicrograph of examined Section 1 of Part 5, 0.02% Porosity.
Figure 11: Photomicrograph of examined Section 7 of Part 5, 0.14% Porosity.

Figure 12: Photomicrograph of examined Section 11 of Part 5, 1.58% Porosity.
Figure 13 shows the bivariate fit of percent porosity by TED™, a fourth order polynomial was fitted to the data for all 33 segments evaluated. An asymptotic relationship of percent porosity as a function of TED™ is present.

Figure 13: Percent Porosity vs TED™ for all 33 Segments Tested.
Figure 14 shows power (W) & TED™ vs. porosity (%) for both power versus porosity and TED versus porosity an asymptotic relationship of percent porosity as a function of TED™ and power is present.

Figure 14: Power (W) & TED™ vs. Porosity (%).

Figure 15 shows TED™ and GED versus percent porosity; once again an asymptotic relationship is present.

Figure 15: TED™ & GED vs. Porosity (%).
Summary

Experiment 1: This experiment evaluated the sensitivity of the PrintRite3D INSPECT® software and Sigma’s proprietary TED™ IPQM® to changes in the independent process input parameter (laser power) on layer by layer basis. Using Sigma’s PrintRite3D INSPECT® software and proprietary algorithms that indirectly measure dependent in-process data captured from a pyrometer and photodetector raw trace signals, it was possible to infer changes in melt pool and bulk material thermal responses.

It was observed that in-process thermal dynamical trend data exhibited a Gaussian behavior when analyzed using the PrintRite3D INSPECT® in-process quality metrics or IPQM®s. Trend charts also contained a user defined upper control limit which enabled statistical process control capability on a layer basis. Using Sigma’s proprietary TED™ IPQM® and the on-axis photodetector in-process data for an entire layer, upskin and downskin scan locations were clearly visible. A strong correlation between TED™ and power was observed.

By analyzing TED™, Power and percent porosity data per build segment an asymptotic relationship of percent porosity as a function of TED™ was observed.