Modeling and Simulation for Qualification of Additive Manufacturing

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Ansys Additive Manufacturing Research Lab (AMRL)

- Optomec LENS 450
- EOS M290 DMLS
- ExOne Innovent
- Mitsubishi EDM MV2400-S Wire EDM

- Established in 2015
- 2,000 sq ft lab space
Build Failures - Laser Powder Bed Fusion
Modified Inherent Strain Method

Detailed model
- meso-scale (~0.1mm)
- sequentially coupled thermomechanical analysis

Inherent strain model
- macro-scale (~100mm)
- Quasi-static mechanical analysis

Extract inherent strains (element by element)
\[ \varepsilon^{In} = \varepsilon^{Plastic}_{ti} + (\varepsilon^{Elastic}_{ti} - \varepsilon^{Elastic}_{ts}) \]

Apply inherent strains (layer-by-layer)

�� Reduce error in deformation from 40% to 10% compared to original inherent strain model

Modified Inherent Strain Method

Bearing Bracket Support (Re)-Design

- Combine global-local analysis, J-integral, and modified inherent strain method to predict interfacial cracking between solid component and support structure

Build Orientation Optimization

- Combine particle swarm optimization and modified inherent strain method to efficiently optimize build orientation for residual stress

Optimal Orientation

- Reduce maximum residual stress by 40-50%
- No cracking!

Support Structure Optimization

- Combine modified inherent strain method and topology optimization to design support structure

Un-optimized support

Optimized support


- Reduce maximum residual stress by 30-40%
Fast Grain Growth Model

- Assumes epitaxial columnar dendrite is the dominant growth mechanism
- Each epitaxial columnar dendrite is modeled by a line segment
- Each dendrite is grown according to the local thermal gradient

Melt Pool Variation and Defect Formation

5 cm height

1 cm height

Pre-deposition temperature profile along building height
Melt Pool and Defect Prediction

- Mesoscale computational fluid dynamics to model the heat transfer and fluid flow
- Predict the melt pool morphology and anticipated defects

Melt pool geometry

Keyhole pore generation
Effect of Preheating Temperature

Keyhole regime ($P = 250$ W and $V = 0.5$ m/s)

Keyhole Pore Generation

For melt pool in keyhole regime ($P = 250$ W, $V = 0.5$ m/s):
- Increasing the preheating temperature leads to deep melt pool
- Probability of porosity occurrence is increased at higher preheating temperature

Process Window (P-V Map)

Cunningham et al. (2016, 2017) JOM
GPU-based AM Process Simulator

Key Features:
- Based on *voxel mesh* and *matrix-free finite element formulation*
- Runs on a $10-30k$ workstation but with supercomputer performance
- Handles highly complex geometry
- **300 times faster** running on 1 GPU than running on 1 CPU core

Layer-by-layer simulation of the “UTEP QTA block” on multi-GPUs

<table>
<thead>
<tr>
<th></th>
<th>Simulation time</th>
<th>Speedup</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 GPU</td>
<td>17h</td>
<td>-</td>
</tr>
<tr>
<td>2 GPU</td>
<td>10h 51 min</td>
<td>1.57</td>
</tr>
<tr>
<td>3 GPU</td>
<td>8h 50 min</td>
<td>1.92</td>
</tr>
<tr>
<td>4 GPU</td>
<td>7h 40 min</td>
<td>2.22</td>
</tr>
<tr>
<td>Actual build time</td>
<td>14 hours</td>
<td>-</td>
</tr>
</tbody>
</table>

Physical domain: 41x41x41 mm³  
Number of nodes: 206x206x206  
Element resolution in x and y direction: 200 microns  
Layer thickness: 30 microns  
Material properties: Ti64 (temperature dependent)

Multiscale Process Simulation

- Layerwise simulation is fast and can be used to detect “hot spots”
- Scanwise simulation is time-consuming and should be restricted to small millimeter-scale region
- Developing a global-local process simulation to simulate thermal history, melt pool geometry, and microstructure including porous defects
Challenges and Opportunities

• Predicting detailed temperature history and microstructure/property everywhere in a part
  • Phase field and cellular automaton limited to 1-mm region
  • Property prediction beyond static strength is challenging, and experimental data is limited

• Capturing melt pool variability
  • Laser diameter dependency on location
  • Spatter shadowing in laser path
  • Laser power/focus varies over time and differ between machines

• Predicting porosity in the “allowable process window” within a part
  • Porosity caused by spattering difficult to predict

• Data curation, storage, and mining
  • In-situ monitoring, ex-situ characterization, simulations
  • Many terabytes of data
Thank you