

Advanced Laser-Based Manufacturing

Multiphysics Modelling and Interoperability with VMAP Standards

Aerobase Innovations AB

ALABAMA
RESTORE
GEAR-UP

 Funded by
the European Union

Company Profile



Highlights

Spin-off from Luleå University of Technology

Gestamp, RISE, Swerim, GKN, Vicura/AVL, NIBE, FEV

We have >70y combined experience

- Computational Material Science
- Simulation of Manufacturing Processes

 Kronan H4, Luleå
 Innovatum, Trollhättan



Bijish Babu, Ph.D. 

Metals: Welding, AM, Forming, Rolling



Daniel Berglund, Ph.D. 

Metals & Composites: Forming, Crash, Welding



Henrik Tersing, Ph.D. 

Metals: Forming, Crash, Welding, HT, AM, Transmission



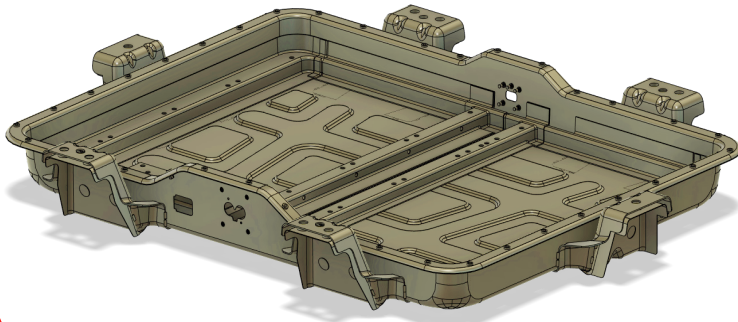
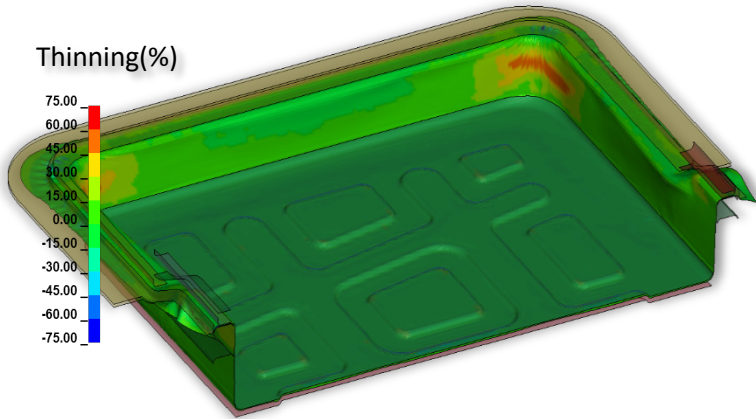
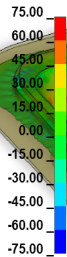
Lakshmi Narasimhan, MSc. 

Material modeling (composites)

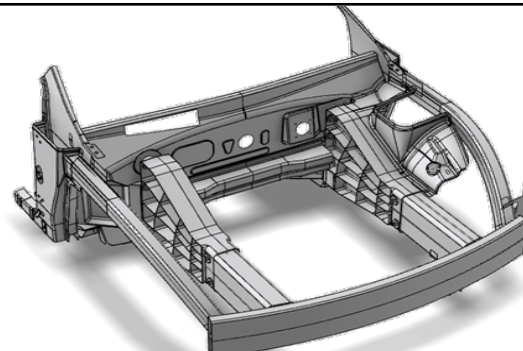


Hot forming

Thinning(%)



Crash simulations



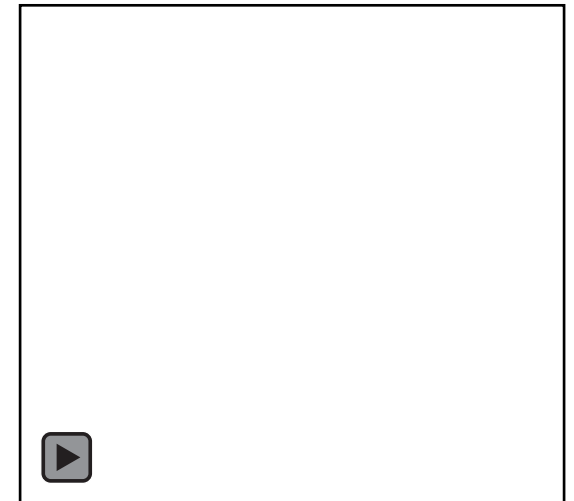
STELLANTIS



FEA SaaS



keep.



aerobase

What we offer

We make material models accessible to simulation engineers



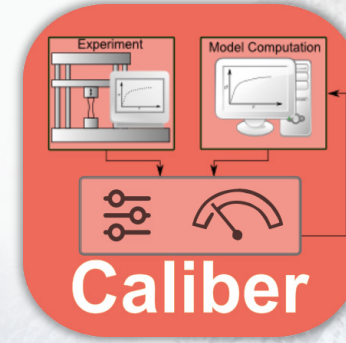
Software for prediction of Failure & Post-buckling



Software for prediction of Phase Evolution



Cloud-based FEM package

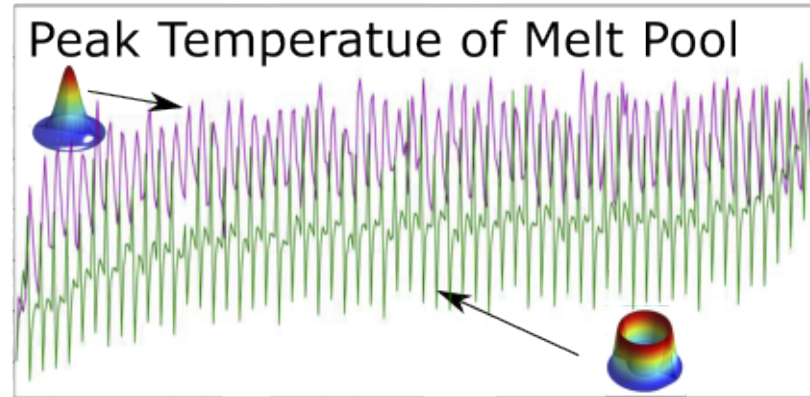
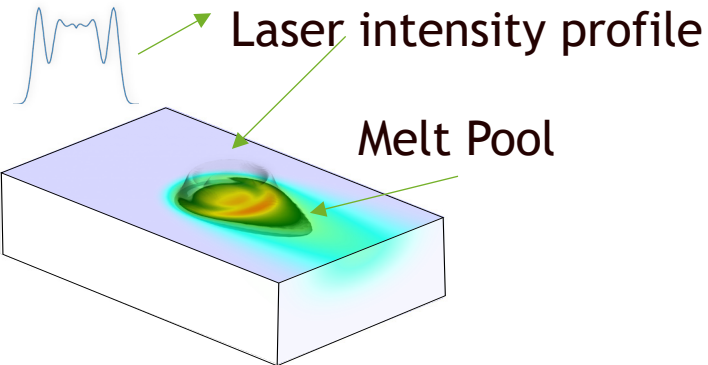


Testing & Calibration of Models



Modeling & Implementation Support

Laser-DED (AM): Fluid (Melt pool)

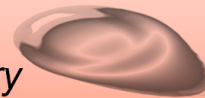


1. Which melt pool geometry is desirable?

Objective: Minimize defects & tailor microstructure

Depends on: Material, Process parameters, & Geometry

Informed by: DOE based coupon testing, Analysis & Simulations



2. Which intensity profile → desired melt pool?

Objective: Define the inverse problem

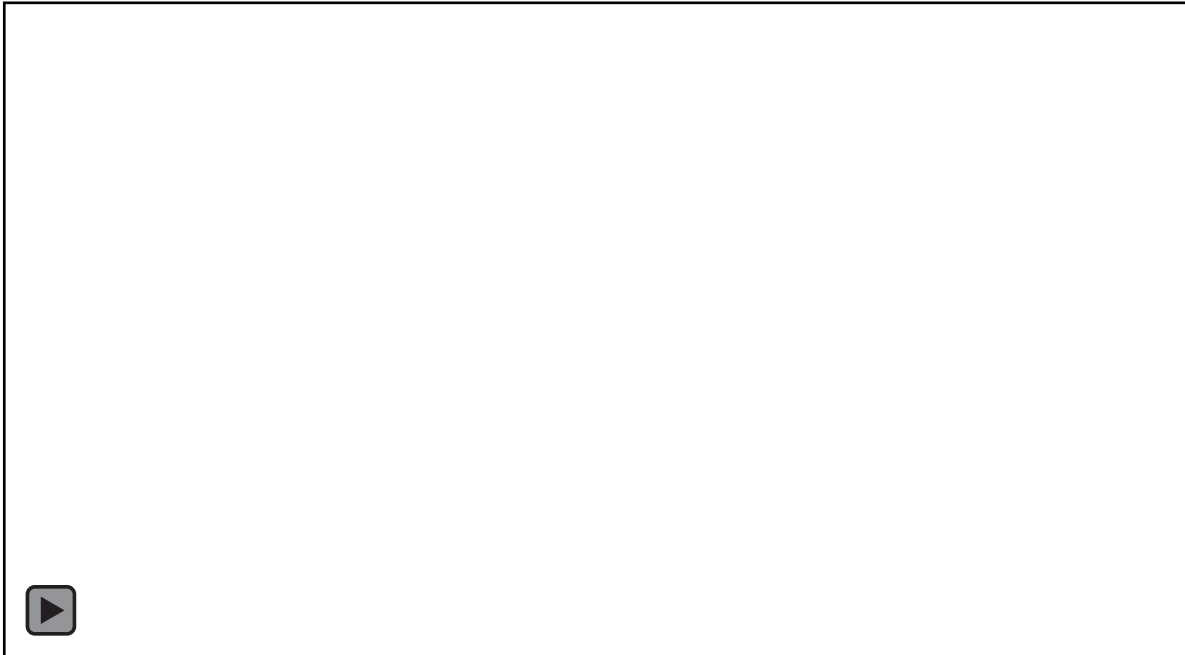
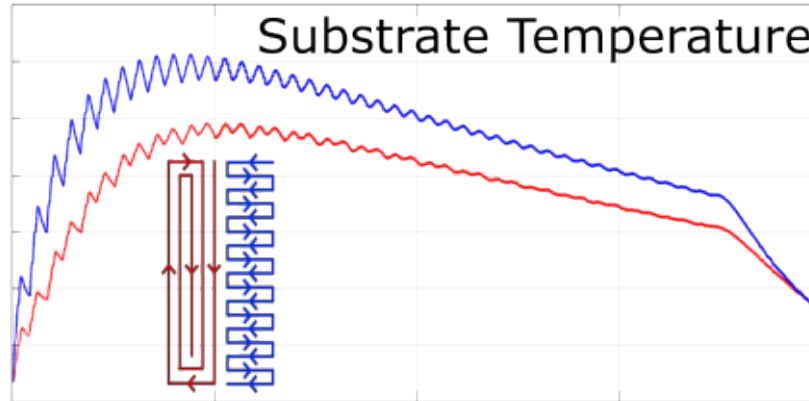
Depends on: Tailored heating & cooling, material, geometry & BC

Informed by: Error minimization

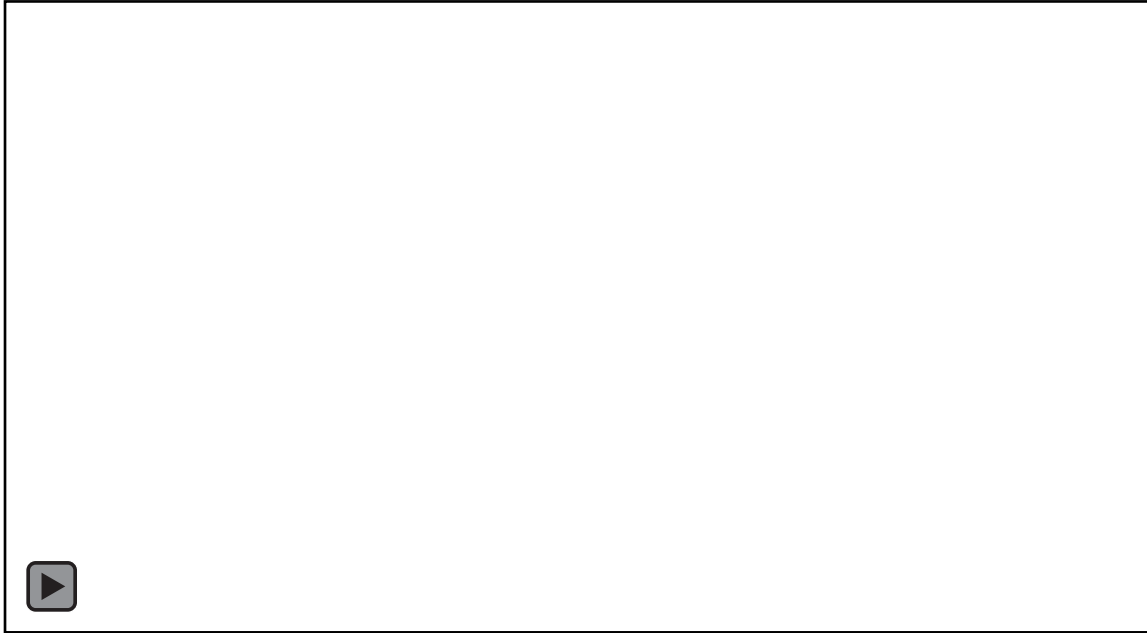


- ✓ Tailored microstructure
- ✓ Fewer defects
- ✓ High Productivity

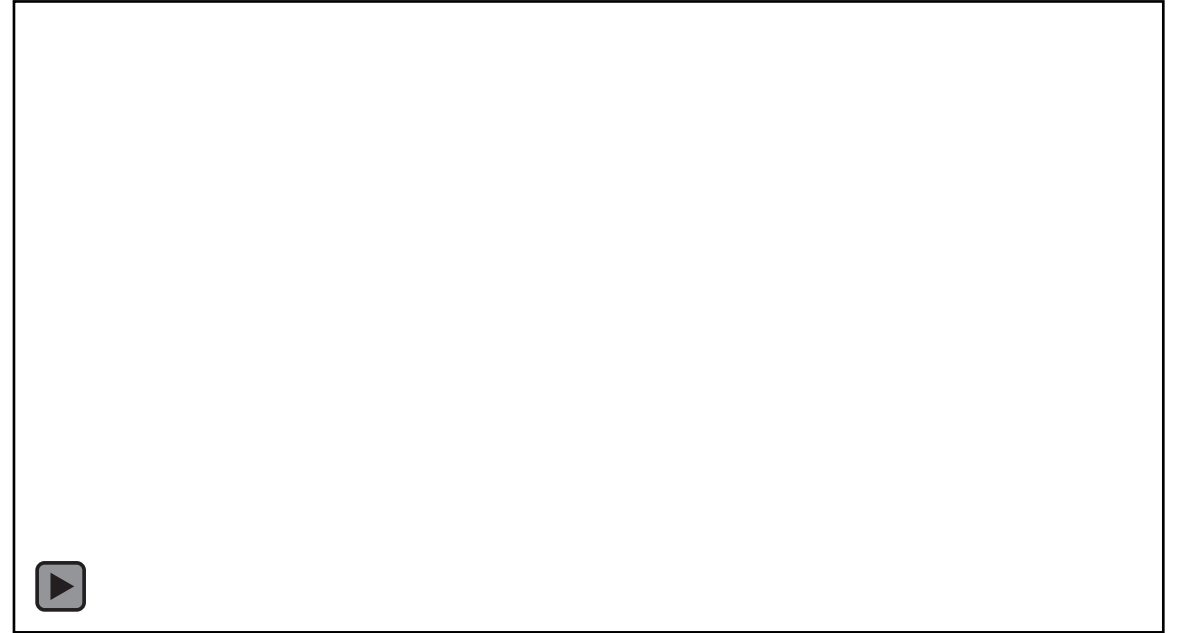
AM Simulations: Scanning Strategy



AM Simulations: Thermal



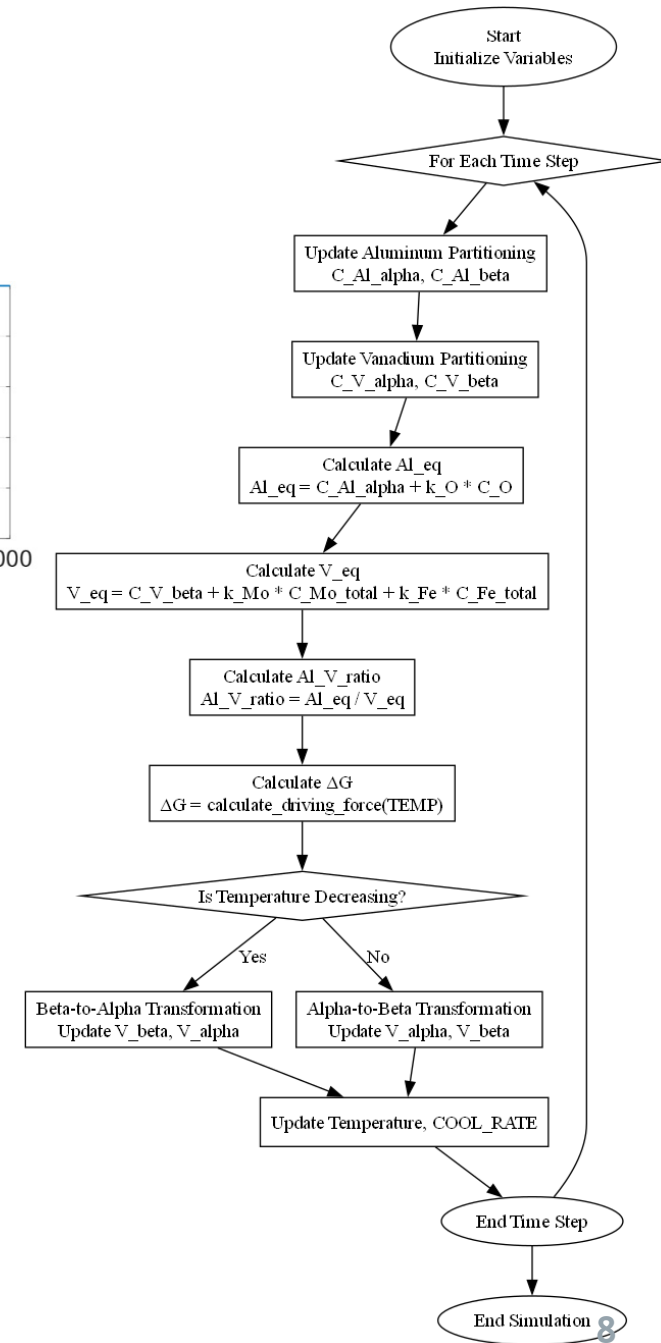
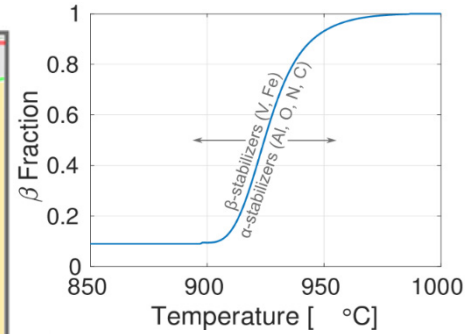
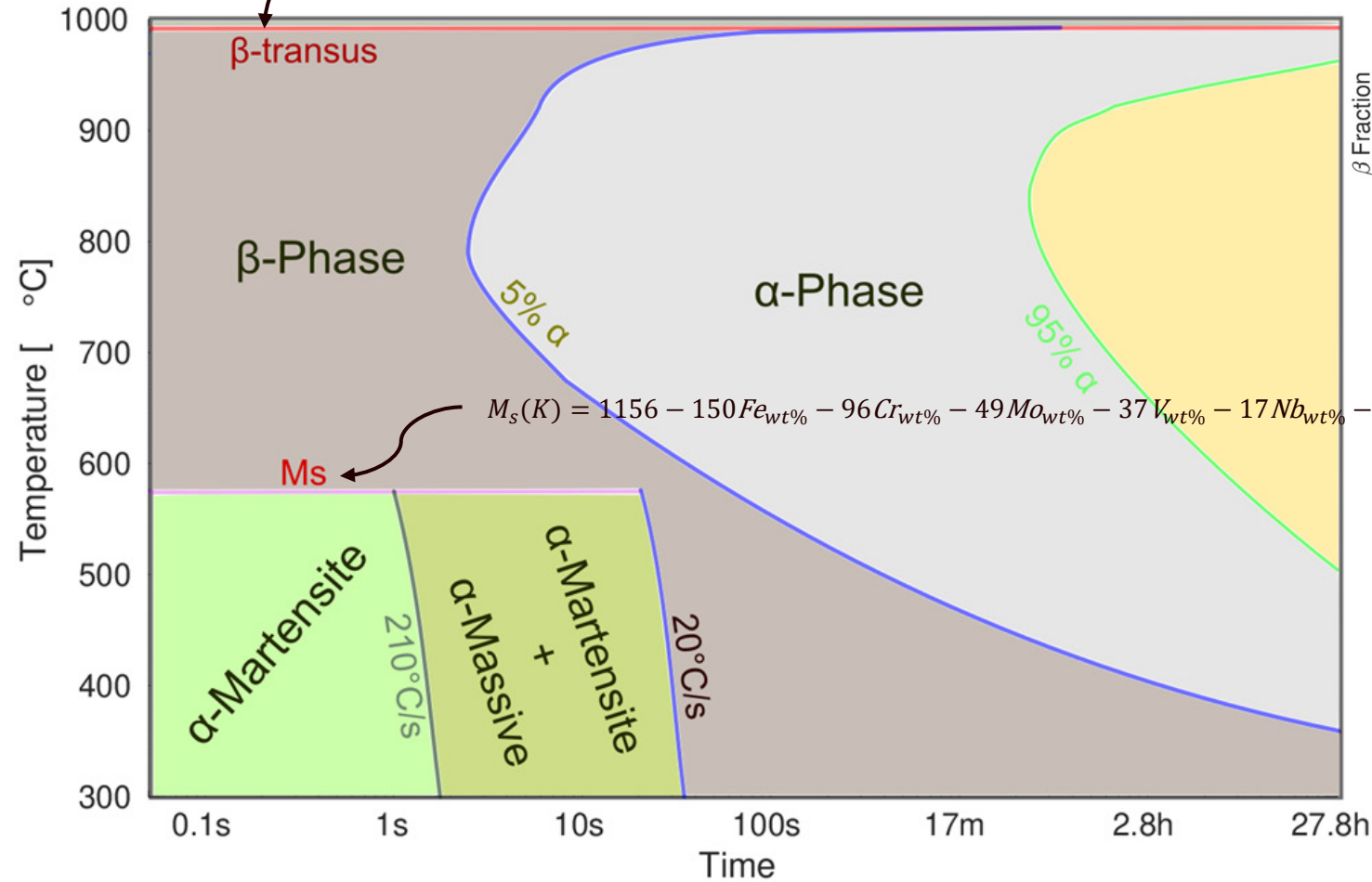
Total Layers	4
Total Beads	48
Total Elements	896
Total Dwell Moves	94
Active Distance (mm)	1120.00
Travel Distance (mm)	713.41
Total Time (s)	1883.41



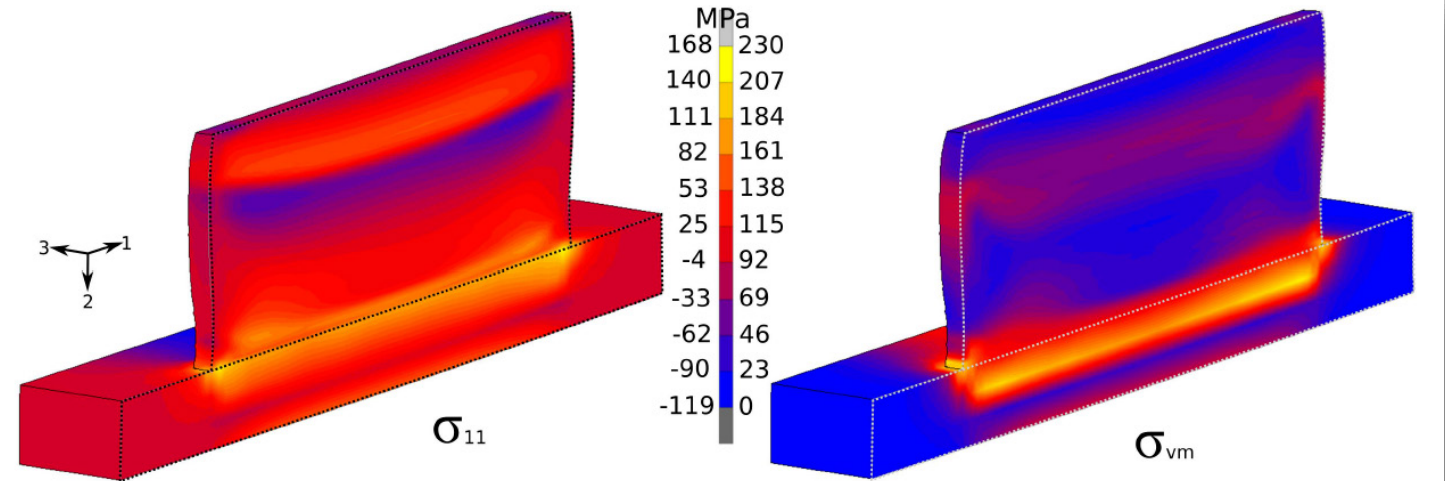
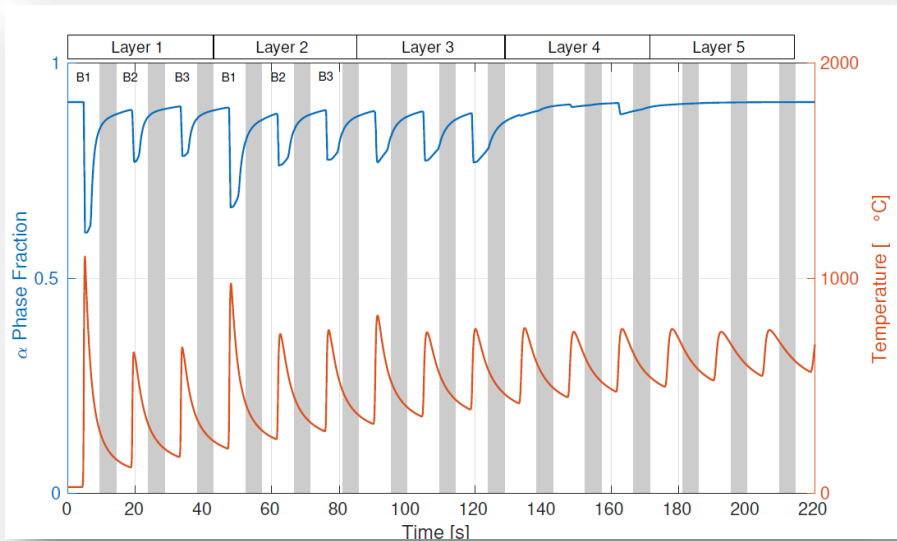
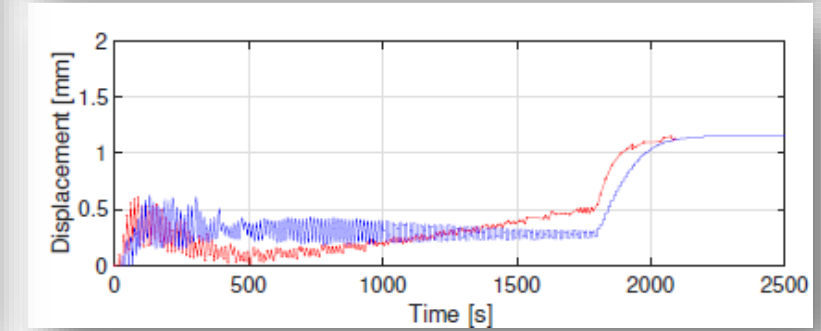
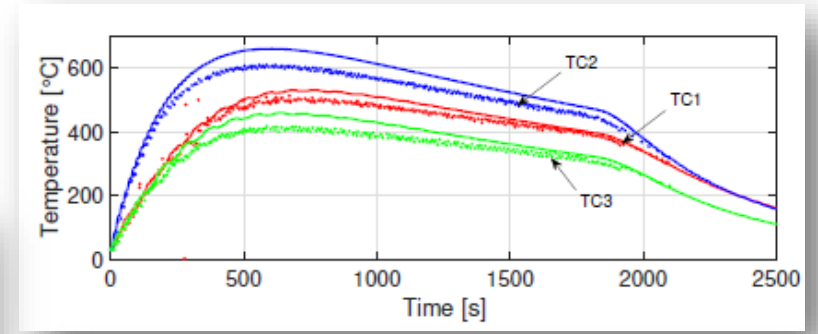
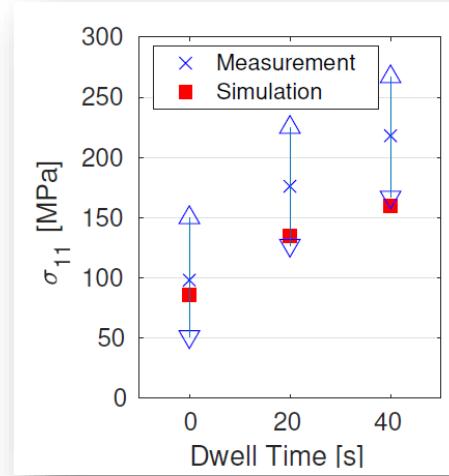
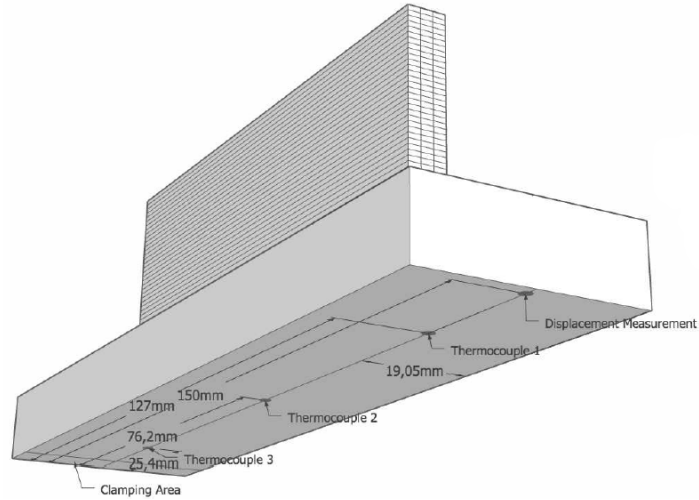
Total Layers	4
Total Beads	12
Total Elements	896
Total Dwell Moves	22
Active Distance (mm)	2201.45
Travel Distance (mm)	390.64
Total Time (s)	2606.10

AM Simulations: Metallurgy

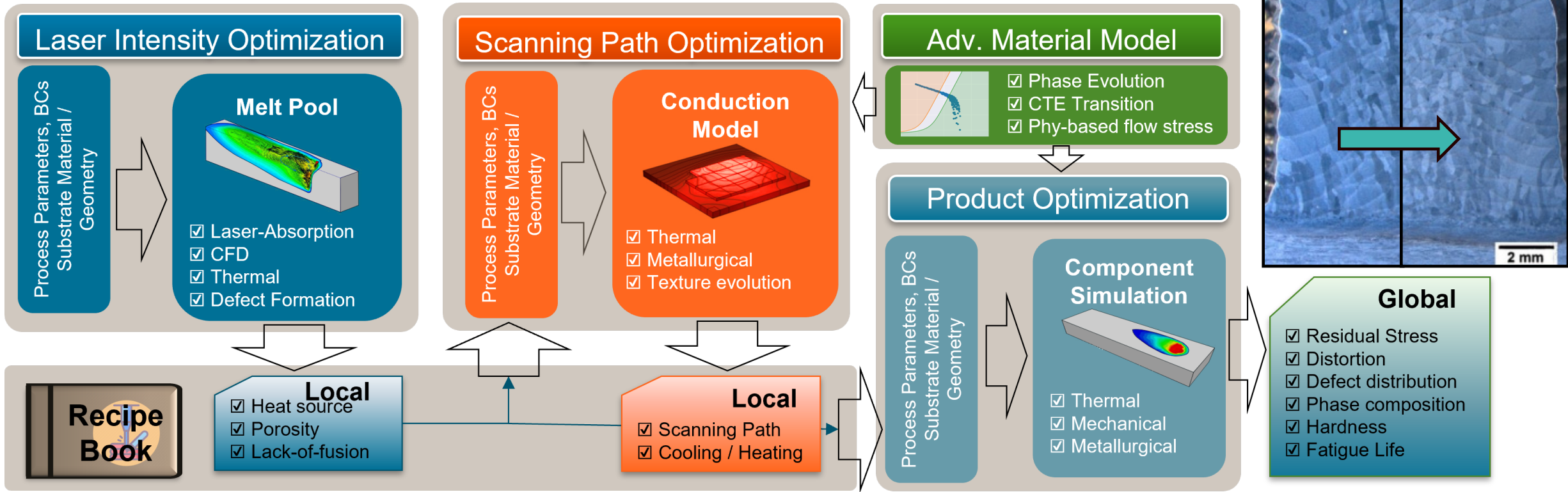
$$X_{\beta}^{eq} = 1 - 0.89e^{-\left(\frac{T^*+1.83}{1.73}\right)^2} - 0.28e^{-\left(\frac{T^*+0.59}{0.67}\right)^2}, \text{ where } T^* = (T - T_{chem})/24$$



AM Simulations: Mechanical



AM simulations: Why do we do it?



- ✓ Tailored microstructure
- ✓ Fewer defects
- ✓ High Productivity

AM simulations: Who is it for?

In collaboration with




**On the brink of a revolution?
Engineering simulation in
the age of AI**

Feb 12, 2025

by Jan Paul Stein
with Alessandro Faure Ragani, Joe Walsh, and Roger Keene

Harvard Data Science Review • Special Issue 5: Grappling With the Generative AI Revolution

How Can Large Language Models Help Humans in Design and Manufacturing? Part 1: Elements of the LLM-Enabled Computational Design and Manufacturing Pipeline **May 28, 2024**

Liane Makatura¹ Michael Foshey¹ Bohan Wang¹ Felix Hähnlein² Pingchuan Ma¹ Bolei Deng¹ Megan Tjandrasuwita¹ Andrew Spielberg¹ Crystal Owens² Peter Yichen Chen¹ Allan Zhao¹ Amy Zhu² Wil Norton¹ Edward Gu¹ Joshua Jacob¹ Yifei Li¹ Adriana Schulz² Wojciech Matusik¹

¹Massachusetts Institute of Technology, Cambridge, Massachusetts, United States of America.
²University of Washington, Seattle, Washington, United States of America.

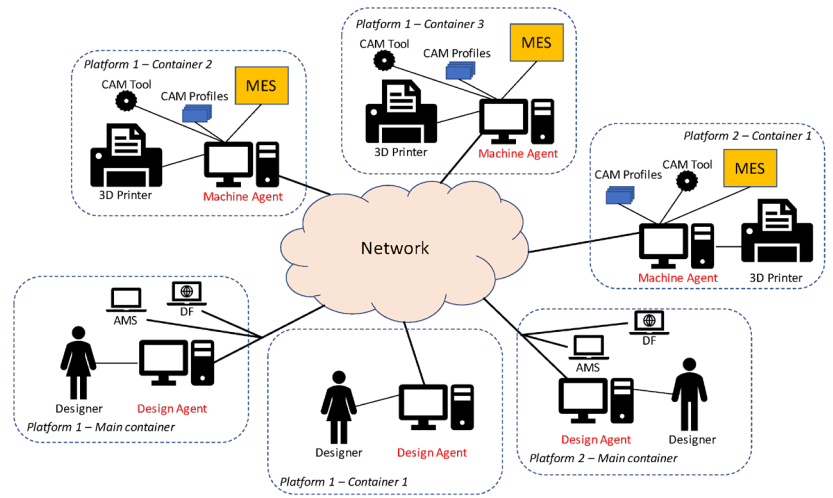
Harvard Data Science Review • Special Issue 5: Grappling With the Generative AI Revolution

How Can Large Language Models Help Humans in Design And Manufacturing? Part 2: Synthesizing an End-to-End LLM-Enabled Design and Manufacturing Workflow **Dec 23, 2024**

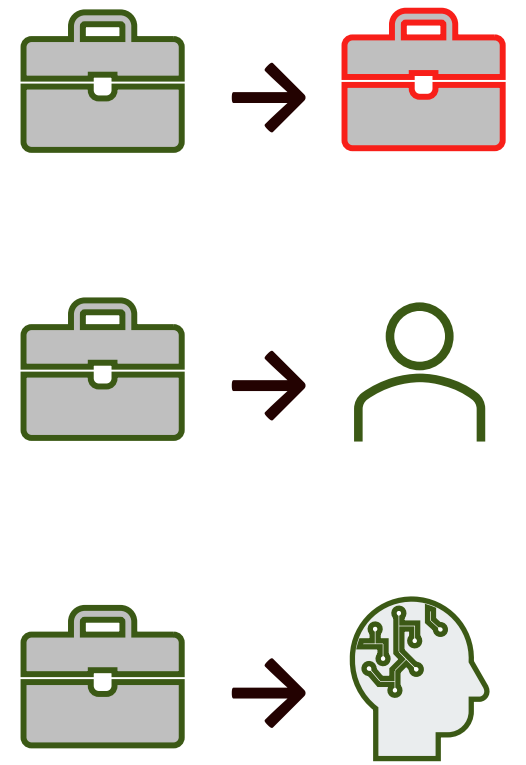
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¹Massachusetts Institute of Technology, Cambridge, Massachusetts, United States of America.
²University of Washington, Seattle, Washington, United States of America.

An Agent-Based Platform for AM



<https://doi.org/10.3390/app10144953>



AM simulations: **VMAP Standards**

- **Standardized Data Exchange**
 - Seamless data exchange between simulation software using the VMAP format, allowing consistent and compatible export/import of material properties, boundary conditions, load cases, and results.
- **Interoperability with Multiphysics Software**
 - In Multiphysics workflows (e.g., structural, thermal, fluid simulations), interoperability with other software like CFD tools is essential. Communication with simulation environments using VMAP enables streamlined multi-physics simulations.
- **Material Property Transfer**
 - Simulation workflows often require transferring complex material models with various properties. The VMAP wrapper would standardize the data structure for seamless transfer between software.
- **Efficient Data Management**
 - Facilitate data organization for easier storage, retrieval, and management in cloud or local environments. This is especially true for large-scale simulations or iterative design processes.

AM simulations: **VMAP Standards**

- **User-friendly interface for Engineers**
 - A VMAP wrapper with an intuitive interface would facilitate quick integration into their workflow, reducing the learning curve and minimizing data transfer errors.
- **Data Structuring and Labeling**
 - The VMAP wrapper should organize and label simulation data to meet ML model requirements by tagging variables (e.g., material properties, load conditions, results) and providing metadata. This structure allows ML algorithms to process data effectively without manual reformatting.
- **Bidirectional Data Flow**
 - A robust VMAP wrapper should export simulation data to ML models and allow feedback from ML predictions back into the simulation. This creates iterative learning, where ML optimizes parameters and configurations in future runs.



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