Session 4: AM Scalability, Implementation, Readiness and Transition

Additive Manufacturing: Capabilities, Challenges and Future

Yung C. Shin, Ph.D.

Donald A. & Nancy G. Roach Professor of Advanced Manufacturing

Director of Center for Laser-based Manufacturing

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Questions and Issues

(1) What is the path for utilizing fundamental results for AM and scaling them for use in productions?

(2) What are the roadblocks that hinder the scaling of AM technologies into production and use in systems?

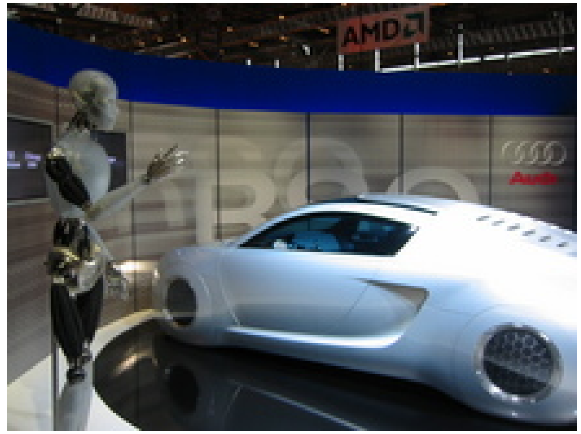
(3) Do any of these roadblocks represent problems/issues that can be best addressed through additional fundamental research?

(4) What are future applications, markets and industry partners that may leverage the fundamental research and scale it into production?

Additive Processes

(3D Printing, Rapid Prototyping, Freeform Fabrication)

- Powder Bed Fusion: SLS, EBM, DMLS
- Directed Energy Deposition: Laser
- Material Extrusion: FDM
- Vat Photopolymerization : SLA, 2PP
- Binder Jetting
- Material Jetting: MJM
- Sheet Lamination: laminated object manufacturing, ultrasonic



AMD

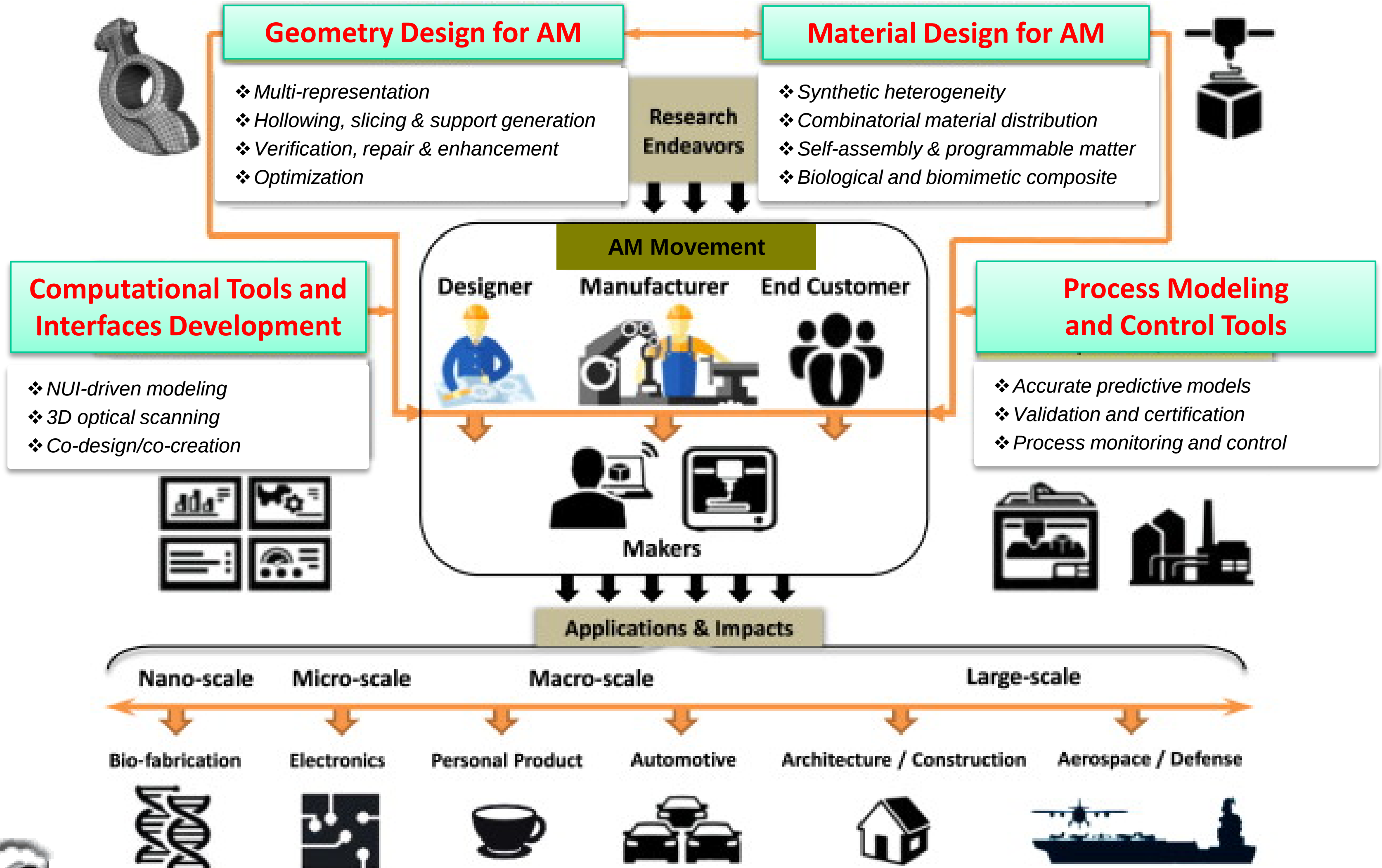




Opportunities

- Additive processes provide the capabilities of building 3D functional parts from CAD drawings in one step.
- They offer the opportunities of synthesizing novel materials and gradient structures that cannot be made by conventional processes.
- Additive processes can impart local properties as needed, thus offering new concepts of design.
- Additive processes allow digital manufacturing on demands with no inventory.
- Additive processes can provide individual customized products with no or little added cost and lead time
- New frontiers in manufacturing!!!

Additive Manufacturing Roadmap



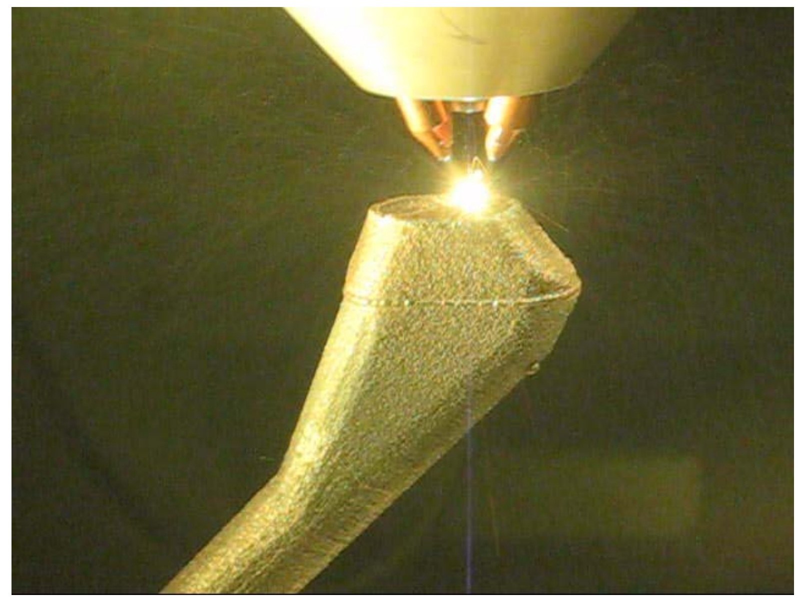
Adapted from Gao, W. et al. “The Status, Challenges, and Future of Additive Manufacturing in Engineering”, *Computer-Aided Design*, Volume 69, Dec. 2015, Pages 65–89.

Fabrication of Implants with Desired Properties

AM Process

Hip Implant

Bone Screw

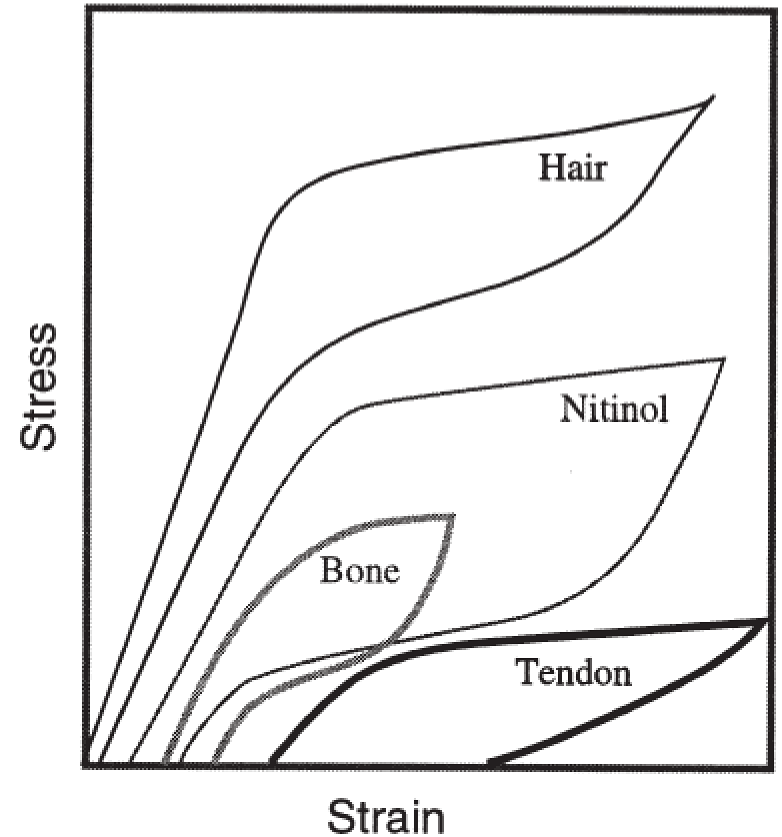


Nitinol (Shape Memory Alloy)
Current or Potential Applications

Bio-medical field applications:
- Orthopedic implants
- Medical stents
- Orthodontic wires
- Bone plates and screws
- Surgical devices

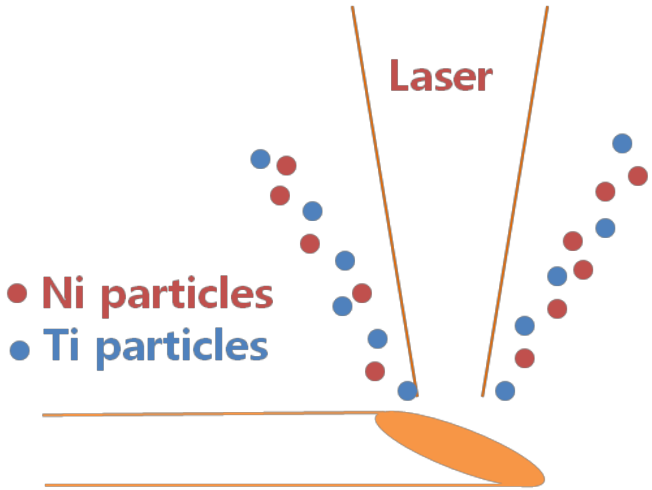
Aerospace field applications:
- Sensors / Actuators

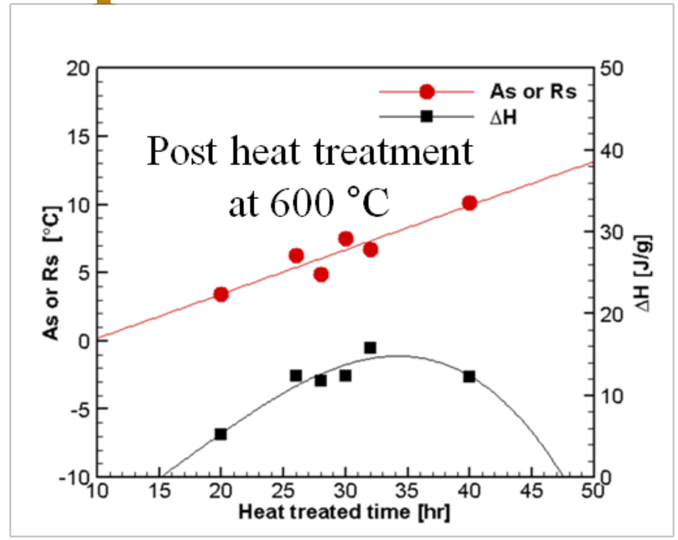
Miscellaneous:
- Vibration damper and isolator
- Commercial products



Stress–strain curves of several natural biological materials and for Nitinol*
*T. Duerig et al. (1999)

In-situ Synthesis of Implant Material





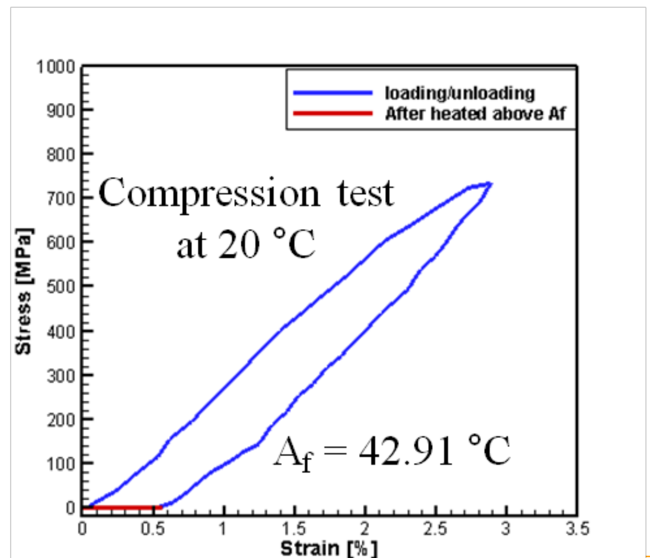
Laser direct deposition

↓

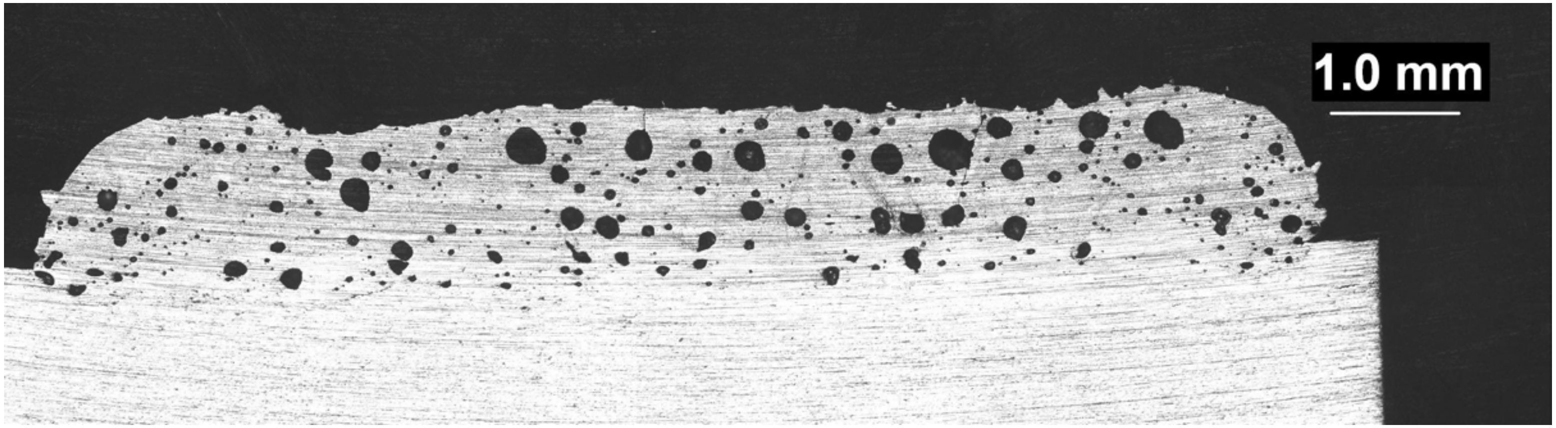
Post heat treatment

↓

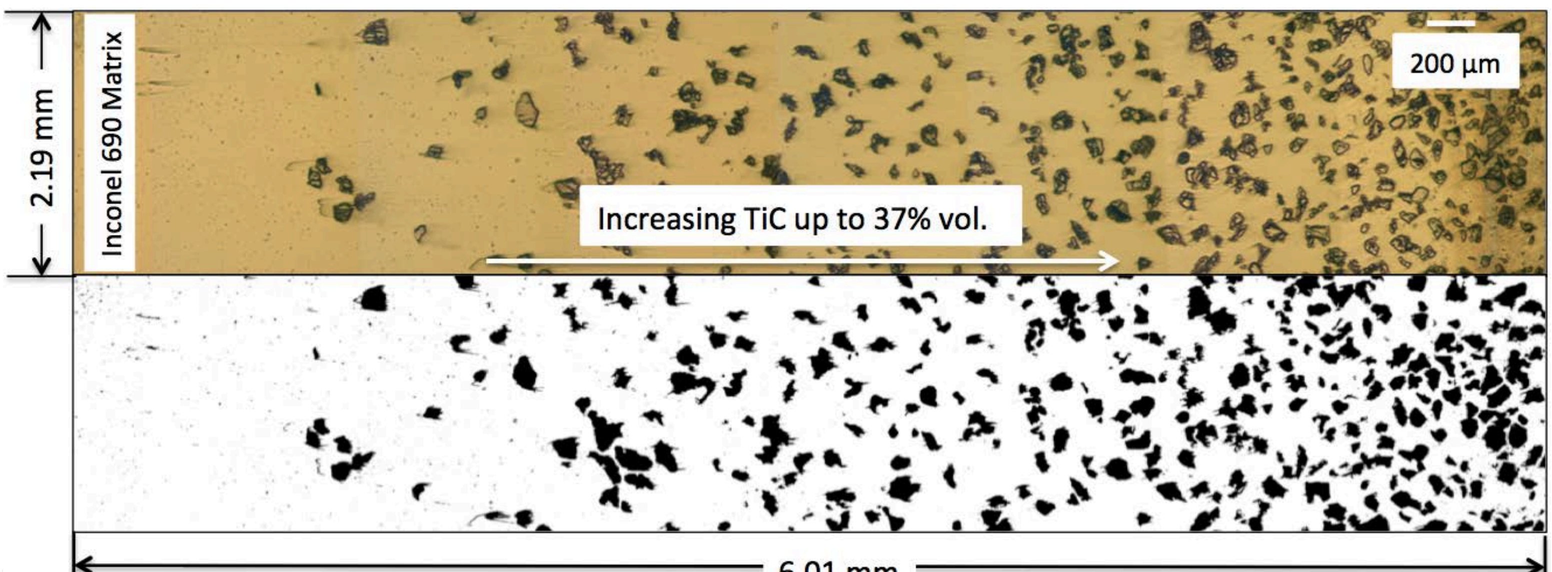
Formation of biomaterial



Synthesis of Functionally Gradient Materials

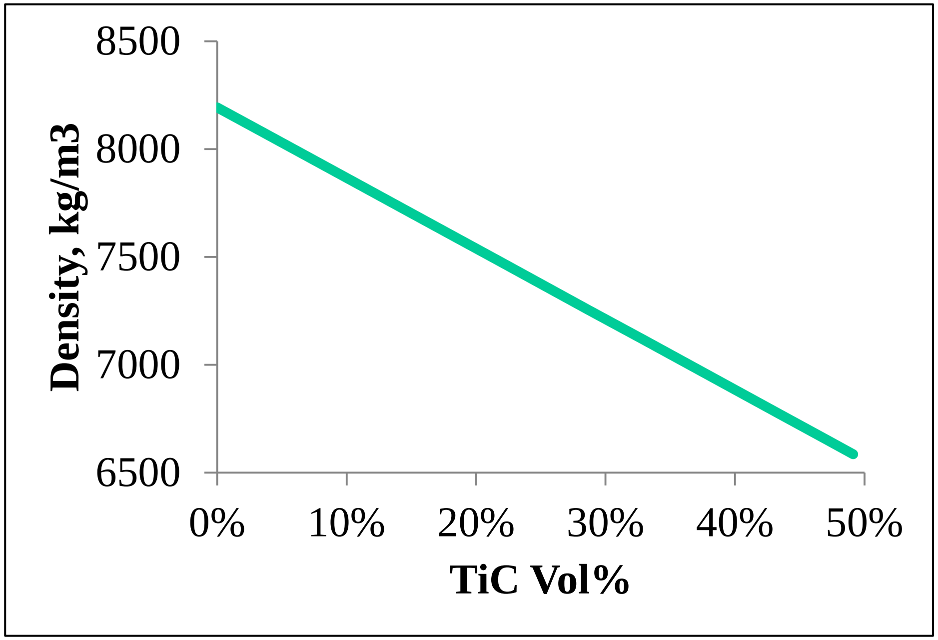


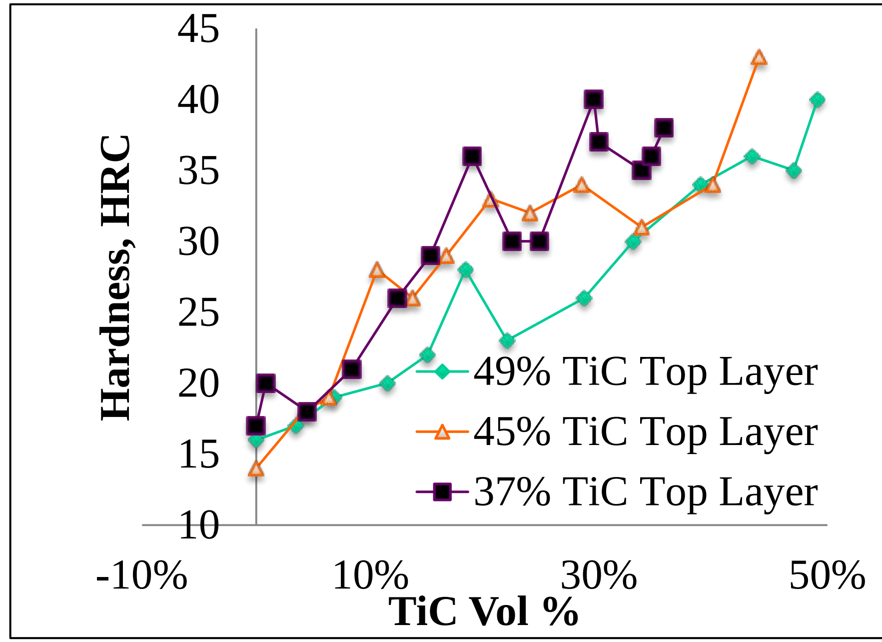
porosity/density control of titanium layer



Functionally gradient metal matrix composite

Micro hardness Results

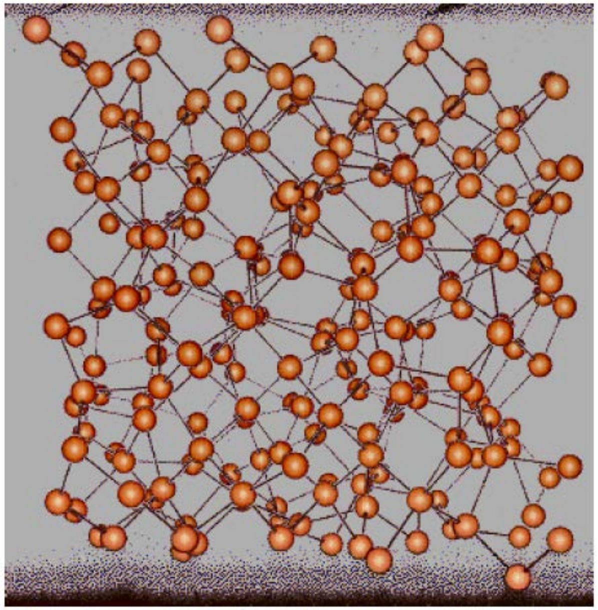


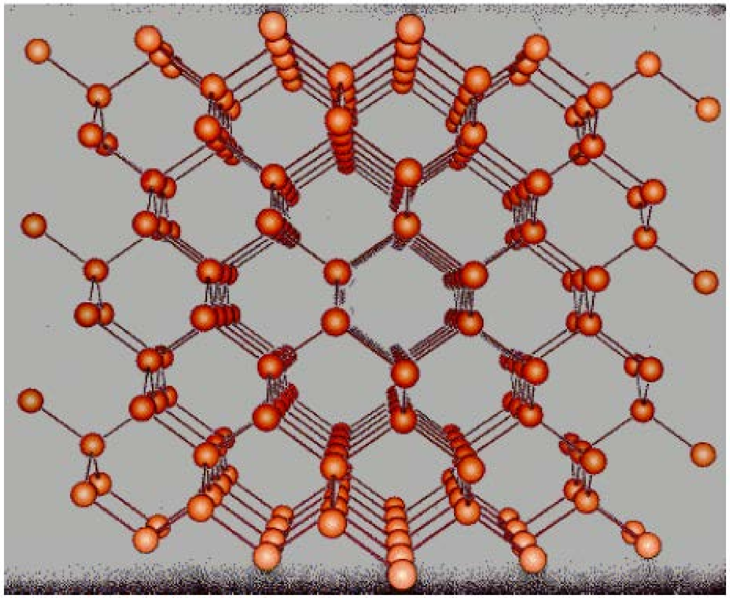


- LECO KM 247AT test machine
- Significant increase in the surface hardness and a decrease in density

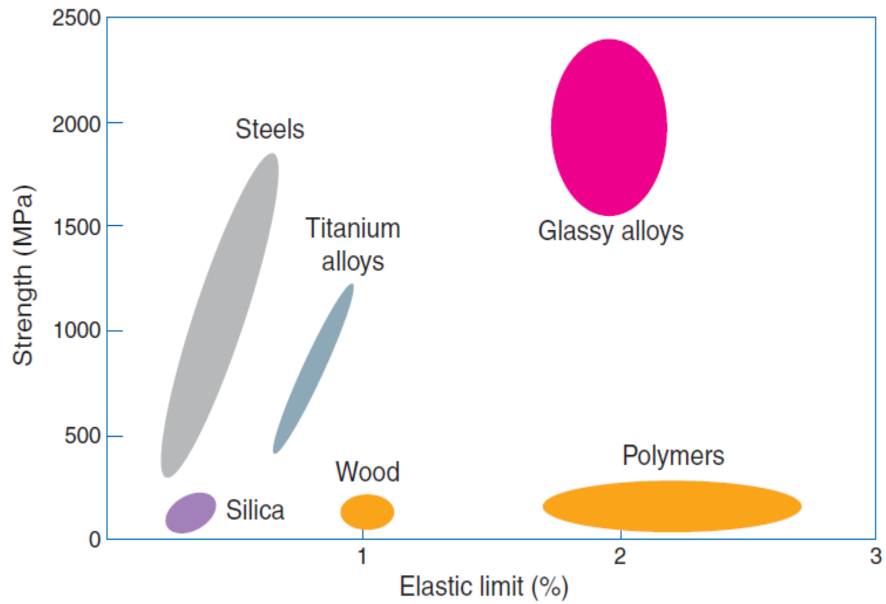
New Material Synthesis
Bulk Metallic Glasses

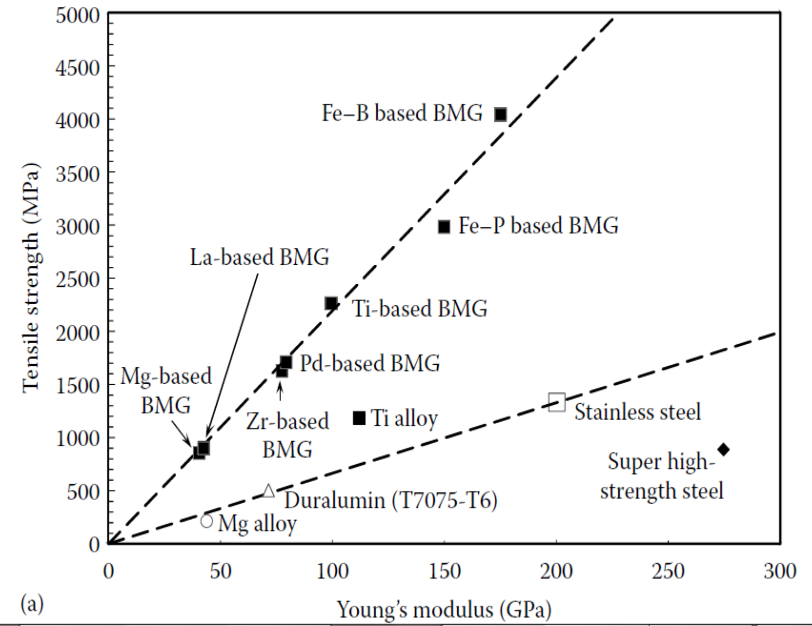
- Atomic Arrangement
  – Suppressed nucleation of crystalline phases
- Combined Superior Properties
  – Strength, hardness, wear/corrosion resistance.


Amorphous Atomic Structure


Crystalline Atomic Structure

BMG Properties



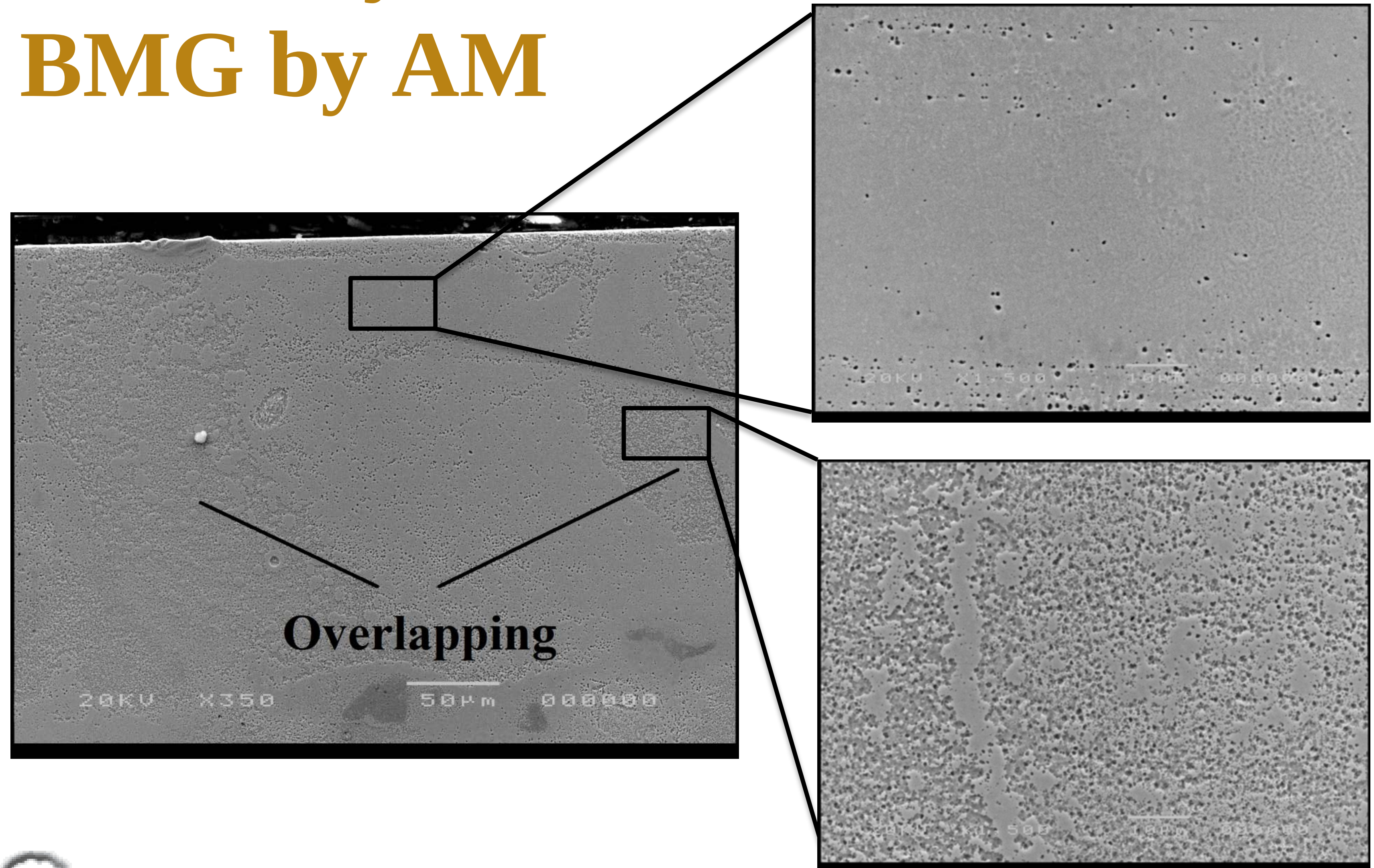


- A combination of high yield strength and elastic limit
- Excellent resistance to wear and corrosion

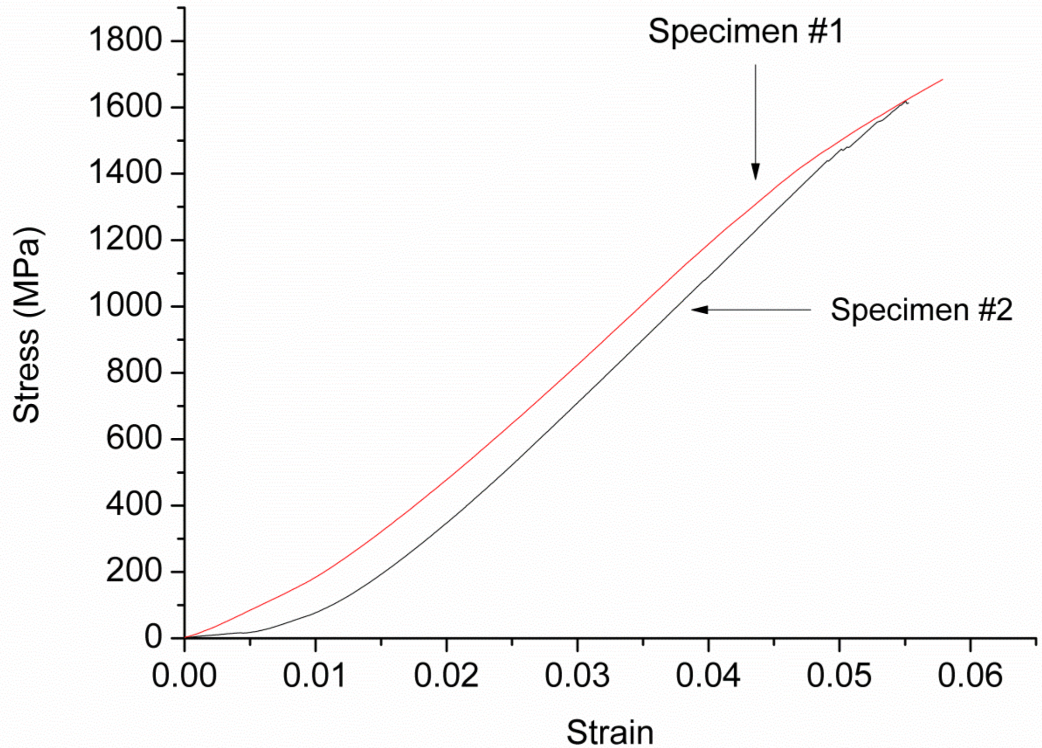
- Limited glass forming ability
- Limited fracture toughness
- Limited ductility and failure strain

Telford, M. (2004). "The case for bulk metallic glass." Materials today 7(3): 36-43.
Miller, M. and Liaw, P. (2008). Bulk metallic glasses, Springer.

In-situ Synthesis of Zr-based BMG by AM



Results – Uniaxial Compression

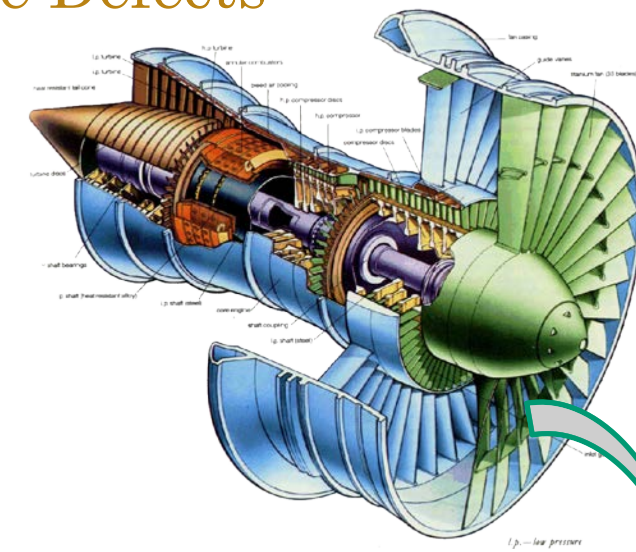


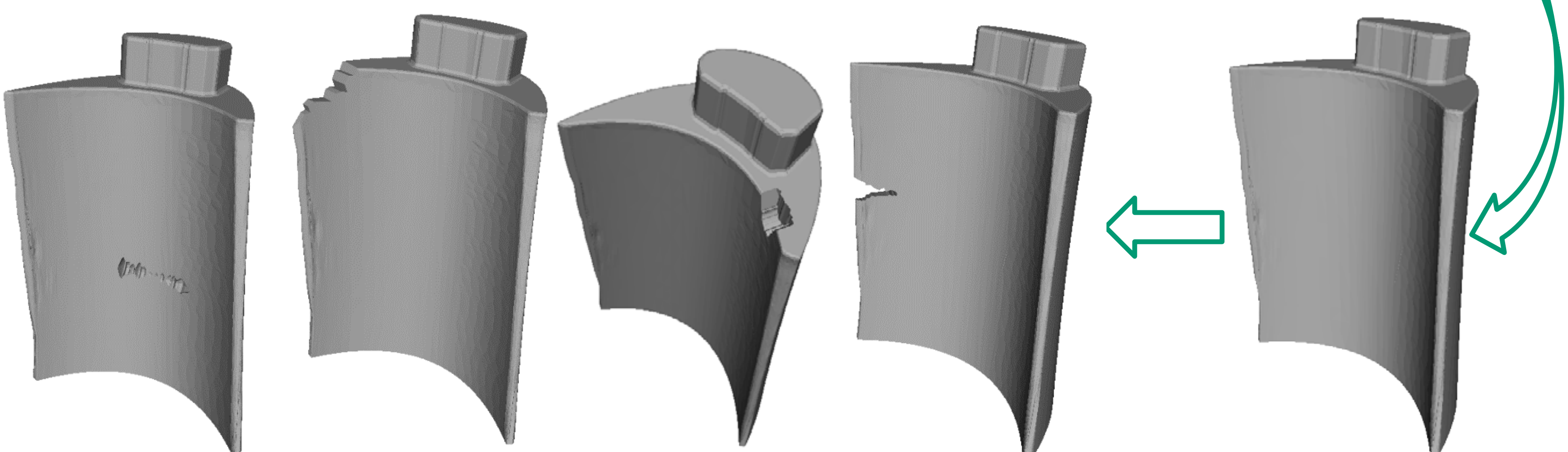
- Yield Strength: 1390 MPa
- Failure Strength: 1684 MPa
- Yield Strain: 4.1%
- Failure Strain: 5.8%

Remanufacturing:

Gas Turbine Blade Defects

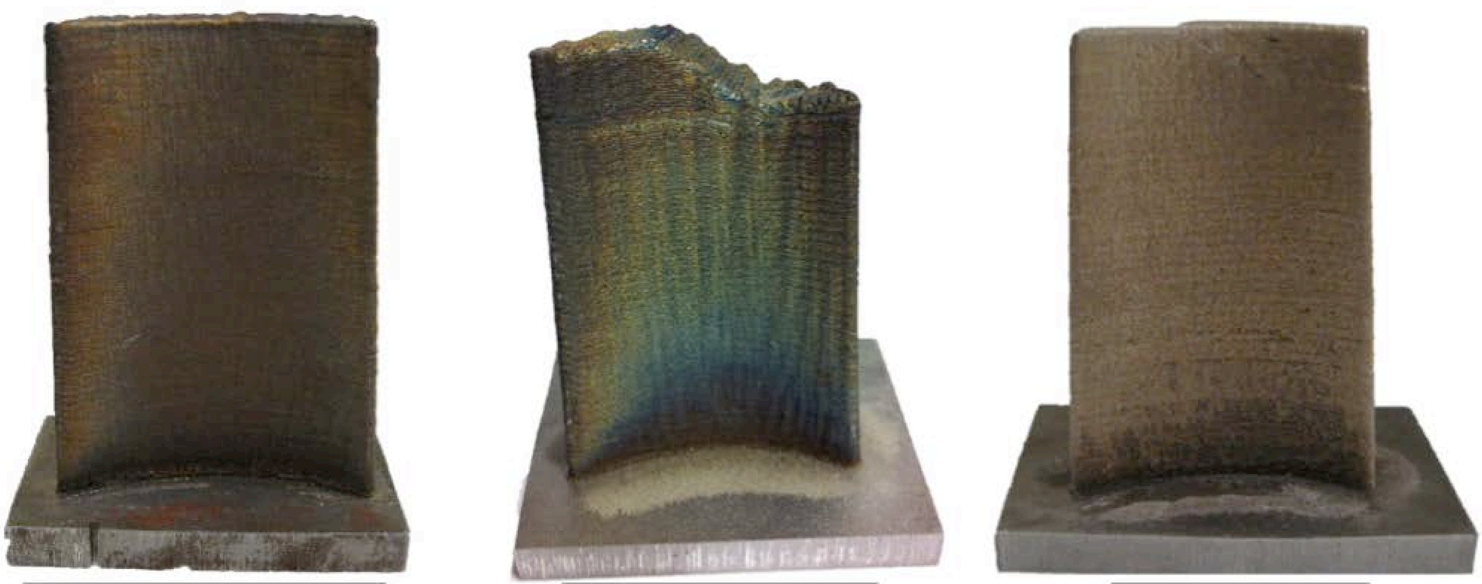
- Gas turbine blades in contemporary aeronautical designs are subjected to increasing operating conditions (temperature, velocity etc.).
- Expedited erosion of the external protective barrier on blades.
- Increased vulnerability to abrasive effects of ingested particles.





Common Blade Defects **Non-Defective Blade**

Repair of Turbine Blades



(a) Baseline Undamaged Blade

(b) Damaged Blade

(c) PCS Restored Blade

- A scaled down model of the defective blade was acquired.
- A tip defect was introduced into the blade with a CNC machine.
- The defect was repaired using LDD technology.
- The geometry of the repair volume was obtained using the PCS reconstruction method.

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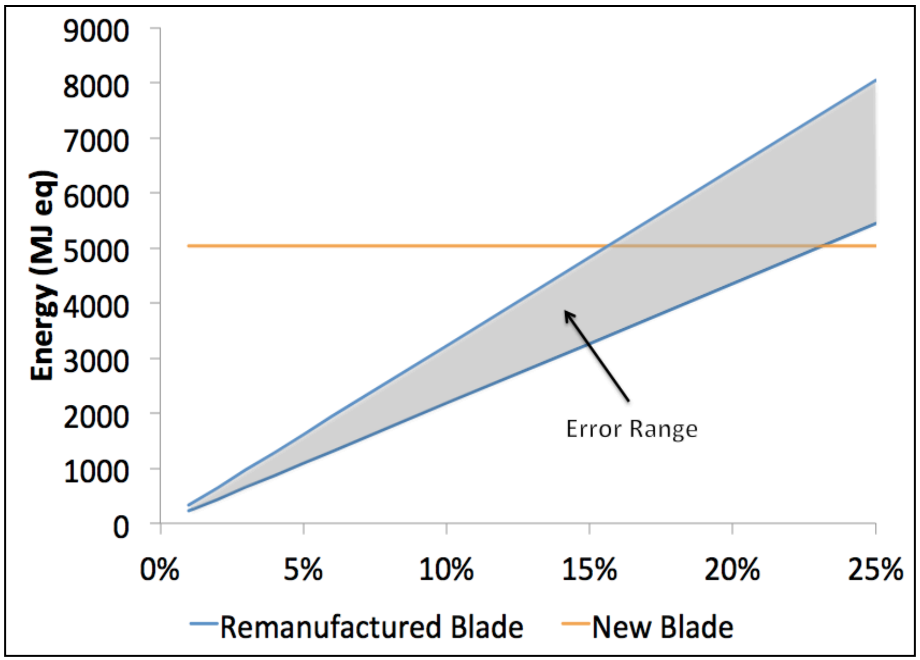
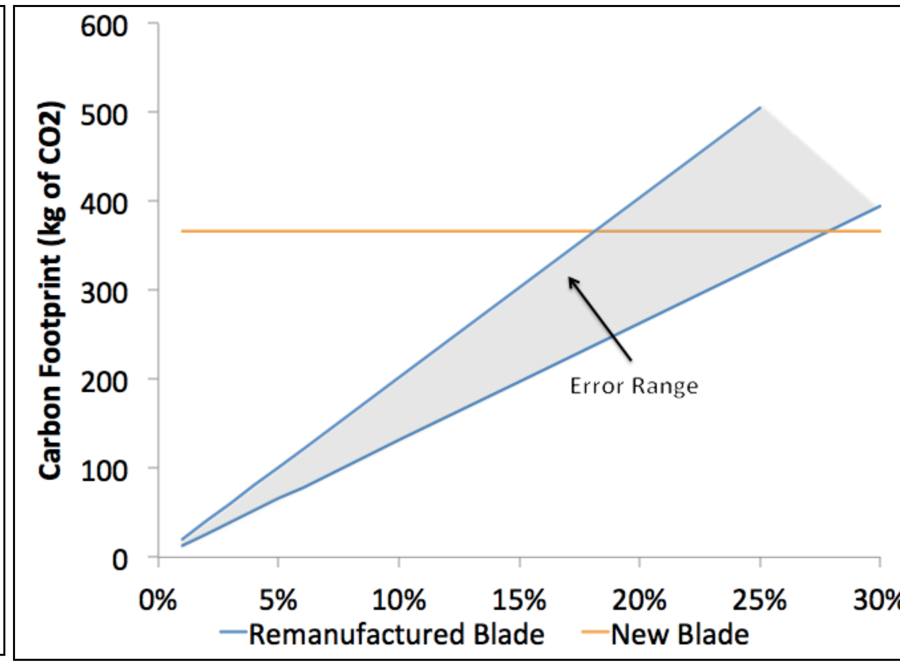
LDD Remanufacturing Benefits

Energy Savings



Environmental Impact



What are the roadblocks that hinder the scaling of AM technologies into production and use in systems?

- Current design tools are not adequate for AM
- Material design capabilities for AM are inadequate
- Different AM processes involve different materials and mechanics
- Lack of accurate and reliable predictive computational tools
  - Should be capable of predicting resultant microstructure, phase, density, foam accuracy, finish, residual stresses, and other mechanical, chemical and thermal properties.
- Lack of validation and certification standards (physical and numerical results)
- Mostly open-loop process control
- Long build time – requires the process throughput improvement

Geometry Design for AM (challenges)

- Currently most CAD systems are based on boundary representations
- Use of STL format does not fully support AM processes
- Lack of topology optimization with local material properties
- Does not allow to design with multi-materials or embedding foreign objects (e.g. hybrid processes)

Material Design for AM (challenges)

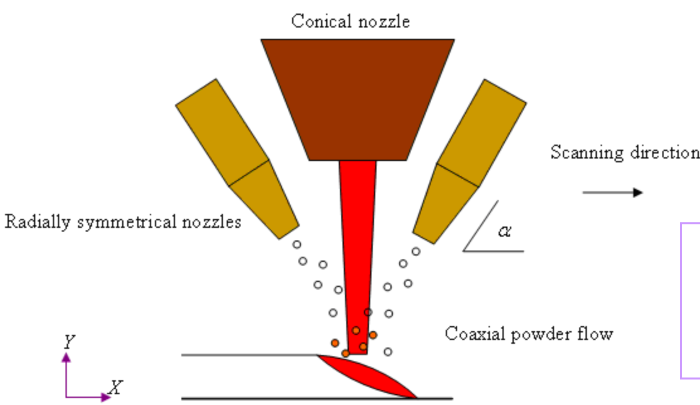
- Current design practice is limited to the shape design with given material
- Complex structural design with optimized design performance is needed
- Multi-material modeling for heterogeneous objects is needed
- Limited material choices for AM

AM Process Modeling (challenges)

- Various different AM processes involve different physical mechanisms and materials
- AM processes require more process parameters than traditional manufacturing processes
- Currently there exists no simulation system that can be directly used by AM developers and users
- Existing computational models are not suitable for iterative or real time design since they are too computational intensive
- AM research on process modeling is currently fragmented

Laser Deposition Modeling

➢ Strategy



- Laser Shape/Profile/Traverse Speed
- Powder Feedrate/Concentration Profile
- Material Properties (deposition, substrate, liquid melt)
- Incoming Powder Velocity/Thermal Energy
- Gas Velocity/Convection Boundary

Free Surface (L/G Interface) Shape Tracking Model

Conduction Model in the Solid Deposition/Substrate

coupled

Liquid Melt Pool/Mushy Zone Flow Model (Surface tension, Buoyancy, Marangoni Flow)

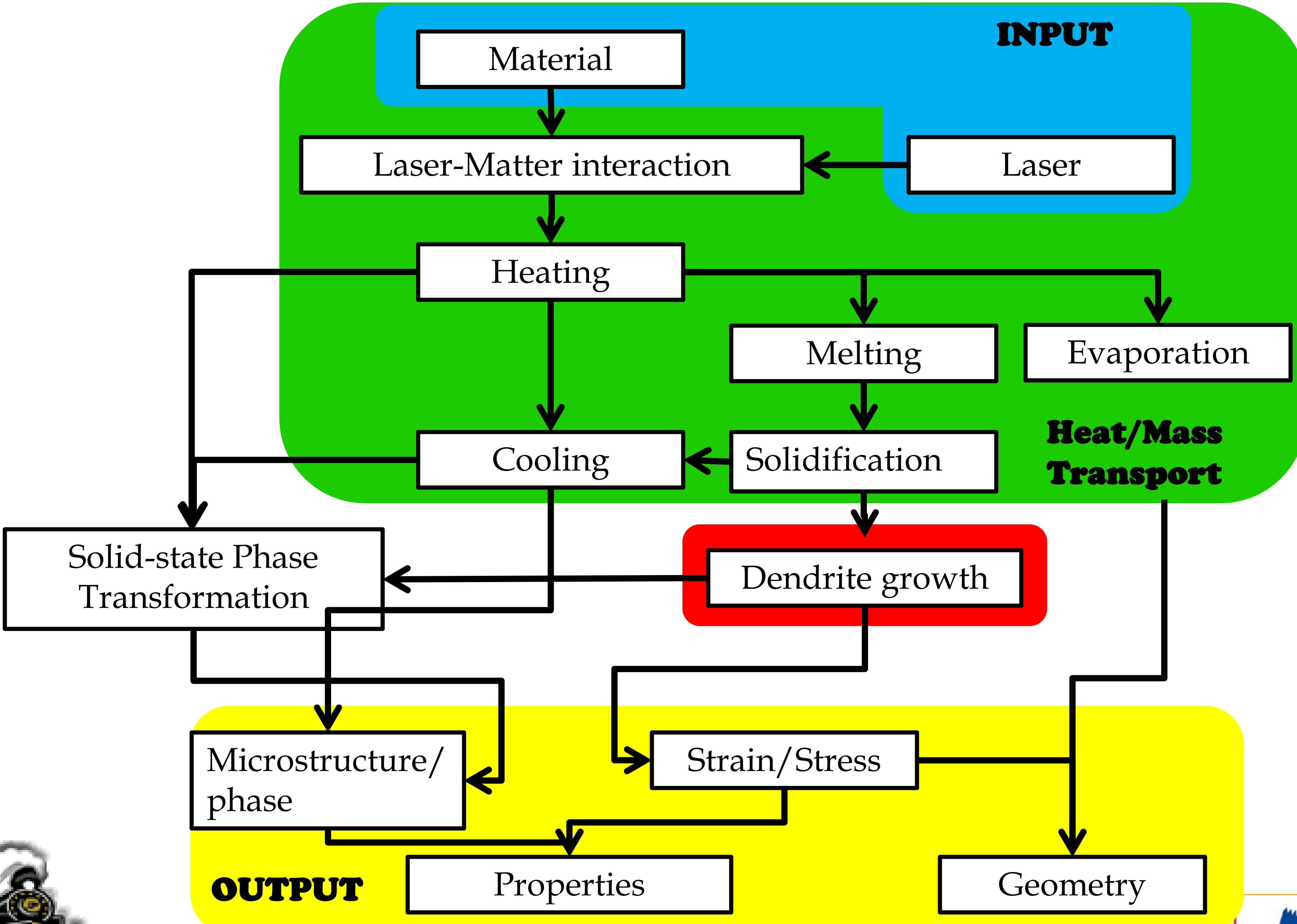
Energy Transfer in the Melt Pool/Mushy Zone

Deposition Geometry

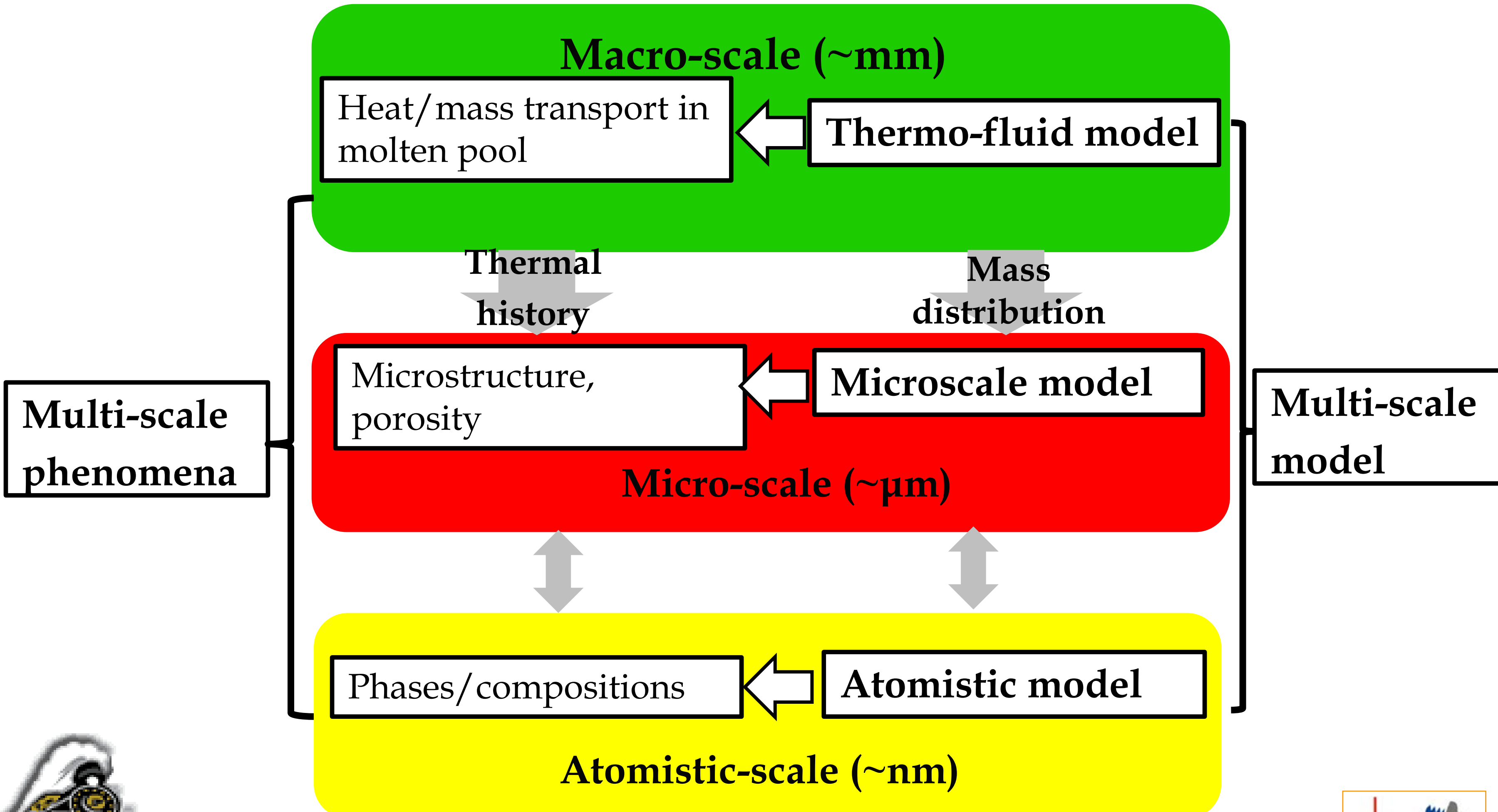
Liquid Pool Shape/Velocity Profile

Deposition Thermal History

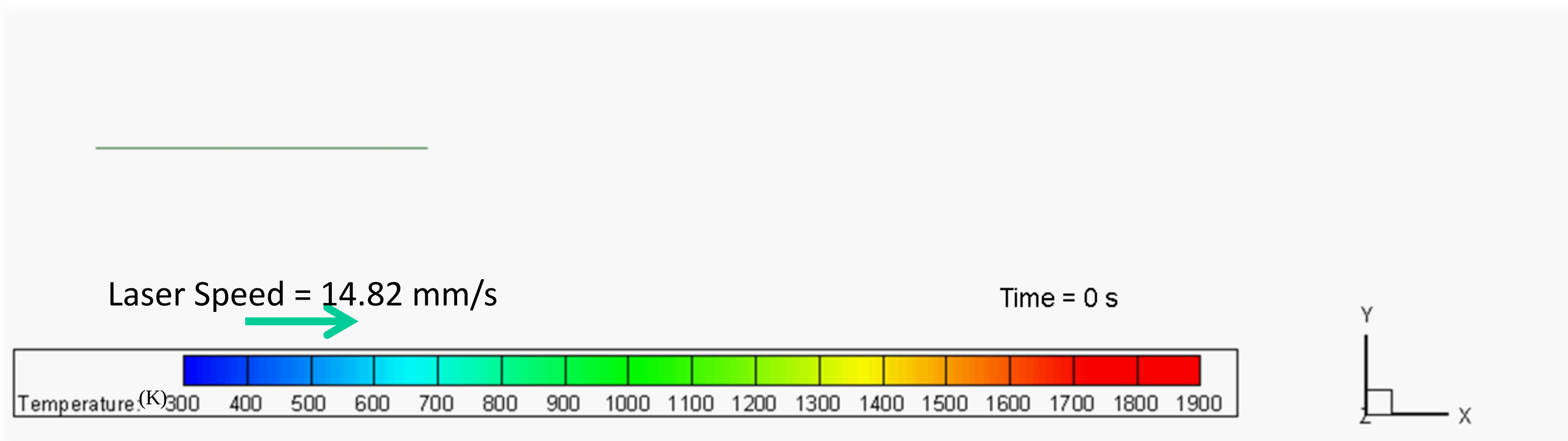
Multiscale Modeling of Laser-based Processes



Multi-scale Modeling of Laser-based AM Manufacturing

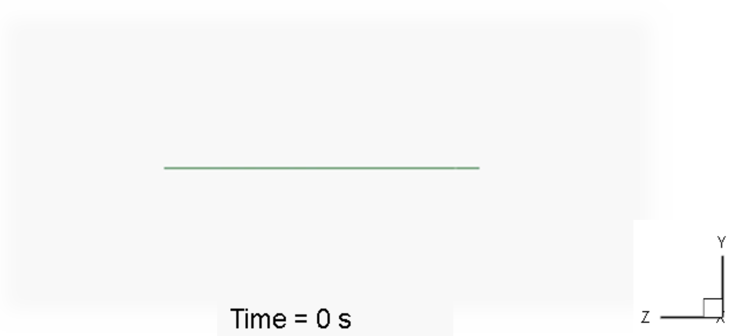


LAM Simulation Results

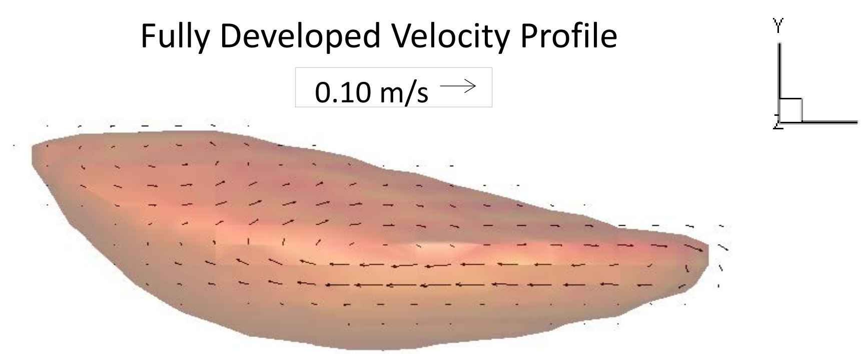


Side View of Molten Pool/Track

Front View of Molten Pool



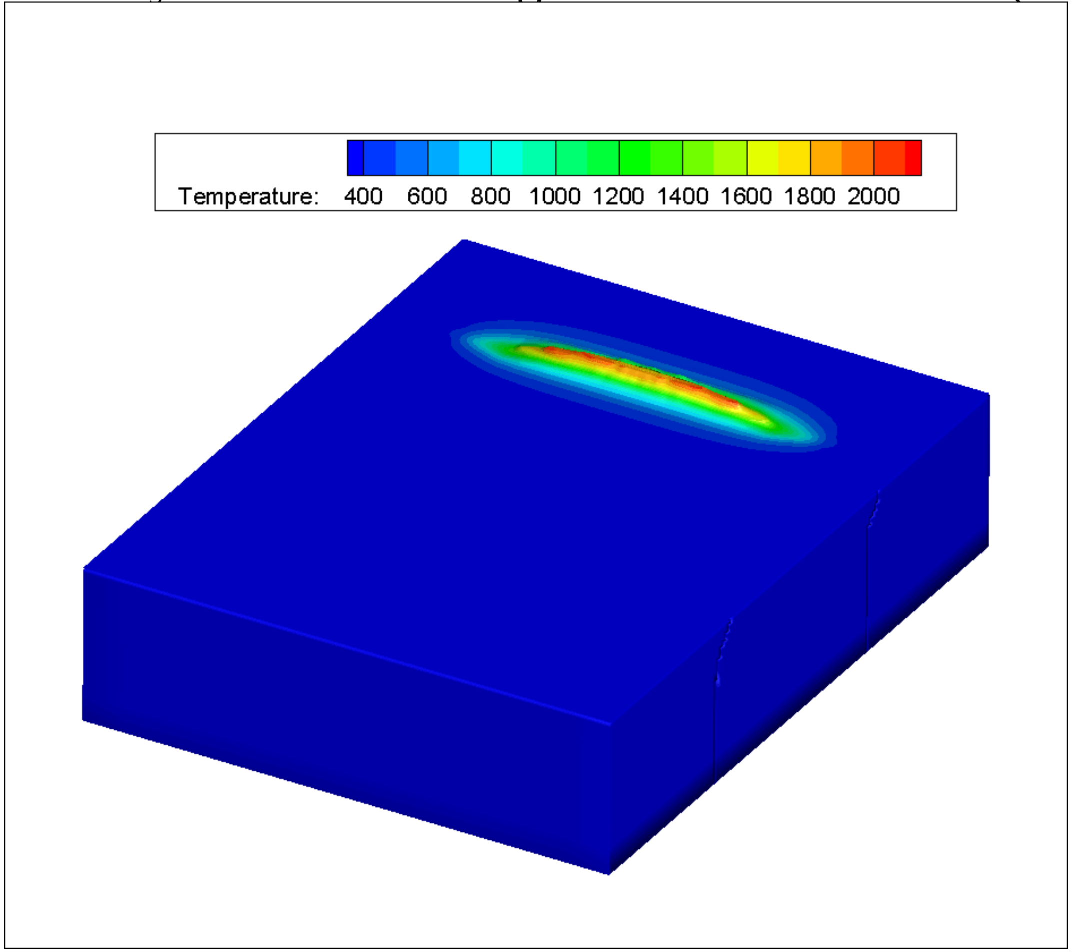
Fully Developed Velocity Profile



- 374,976 computational cells on 48 processing cores (2.3 GHz cores)
- Requires 54hrs of computation time to simulate 2mm deposition

Modeling of Laser Cladding

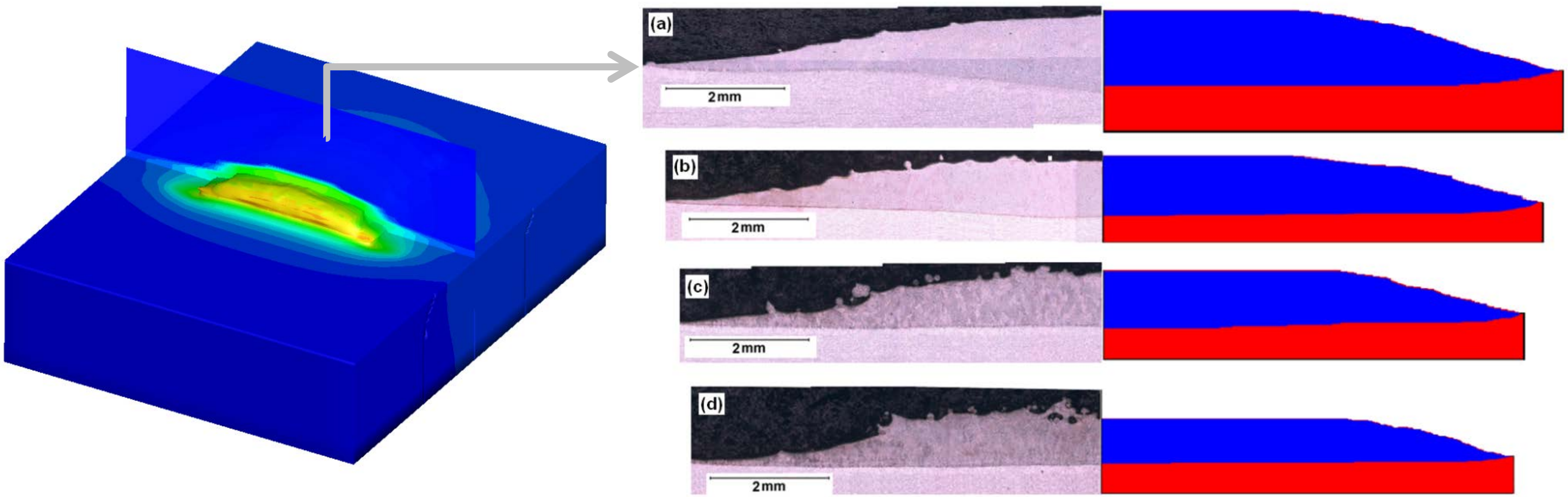
- Substrate: 316L SS & Powder: 316L SS (53-180μm)
- 4kW Nuvonyx ISL-4000L High Power Diode Laser (λ=808nm)



Modeling of Laser Cladding

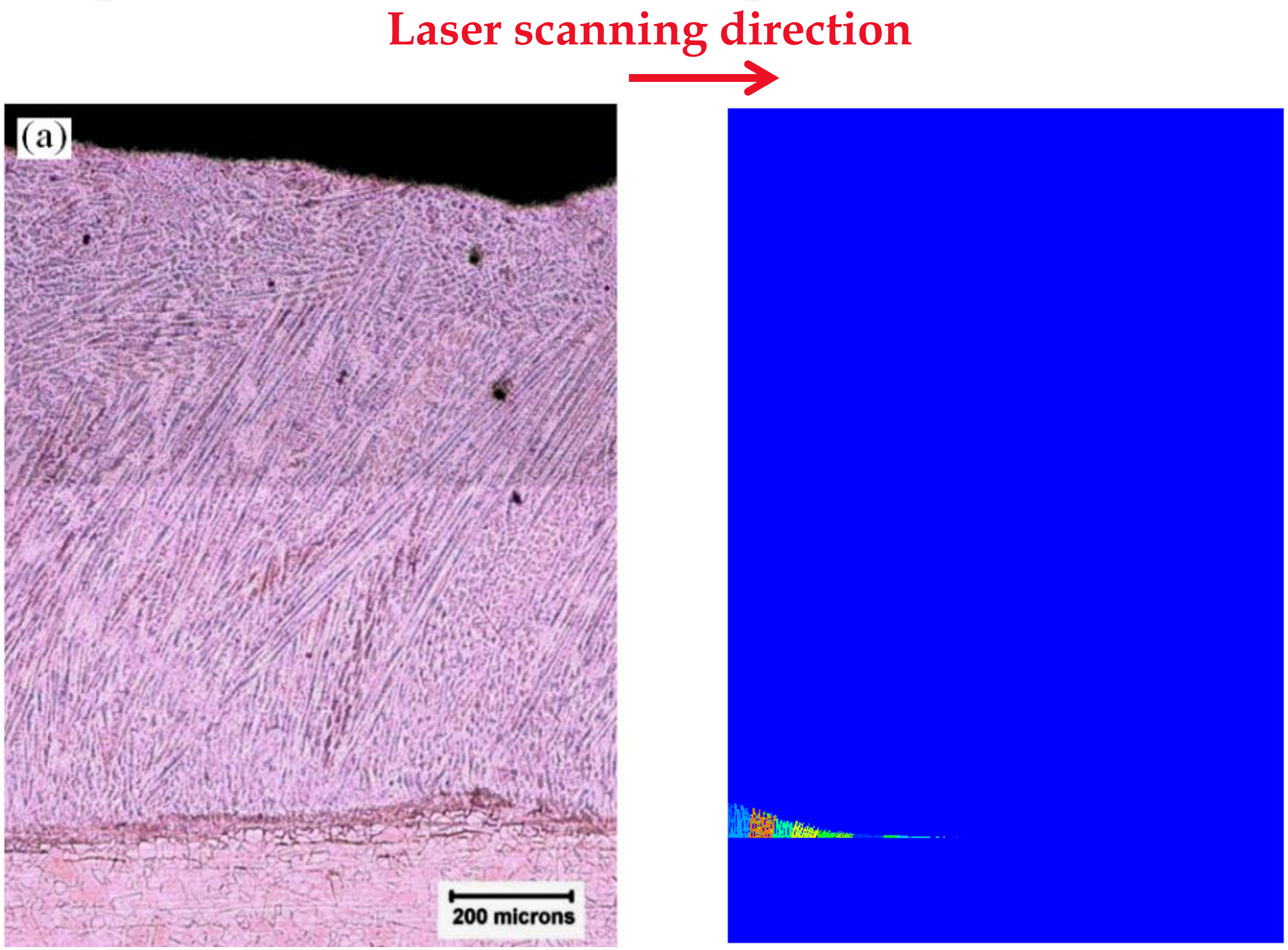
- Simulation Result
  - Geometry of clad tracks

	Laser power (W)	Scanning speed (mm/s)	Powder feed rate (g/min)
1	2400	2	20
2	2400	3	30
3	2800	5	50
4	3600	7	70



Experimental (left) and predicted (right) track geometry: (a) case 1; (b) case 2; (c) case 3; (d) case 4.

Microstructure Evolution Modeling During Laser Cladding



Experimental microstructure and predicted microstructure evolution.

Challenges and Possible Solutions of AM Simulation

The trade-off between model predictive capability and computational effort must be well-understood and balanced effectively.

Challenges

- High computational expense
  - Typically 8 coupled equations per computational cell
  - Laser deposition of H13 steel would require 16 equations per cell, including 8 species

Solutions

- Increase parallelization of code (CPU/GPU)
- Simplify the problem by reducing complexity of physics
  - Assume homogenous alloy properties
  - Possible to simplify too much!

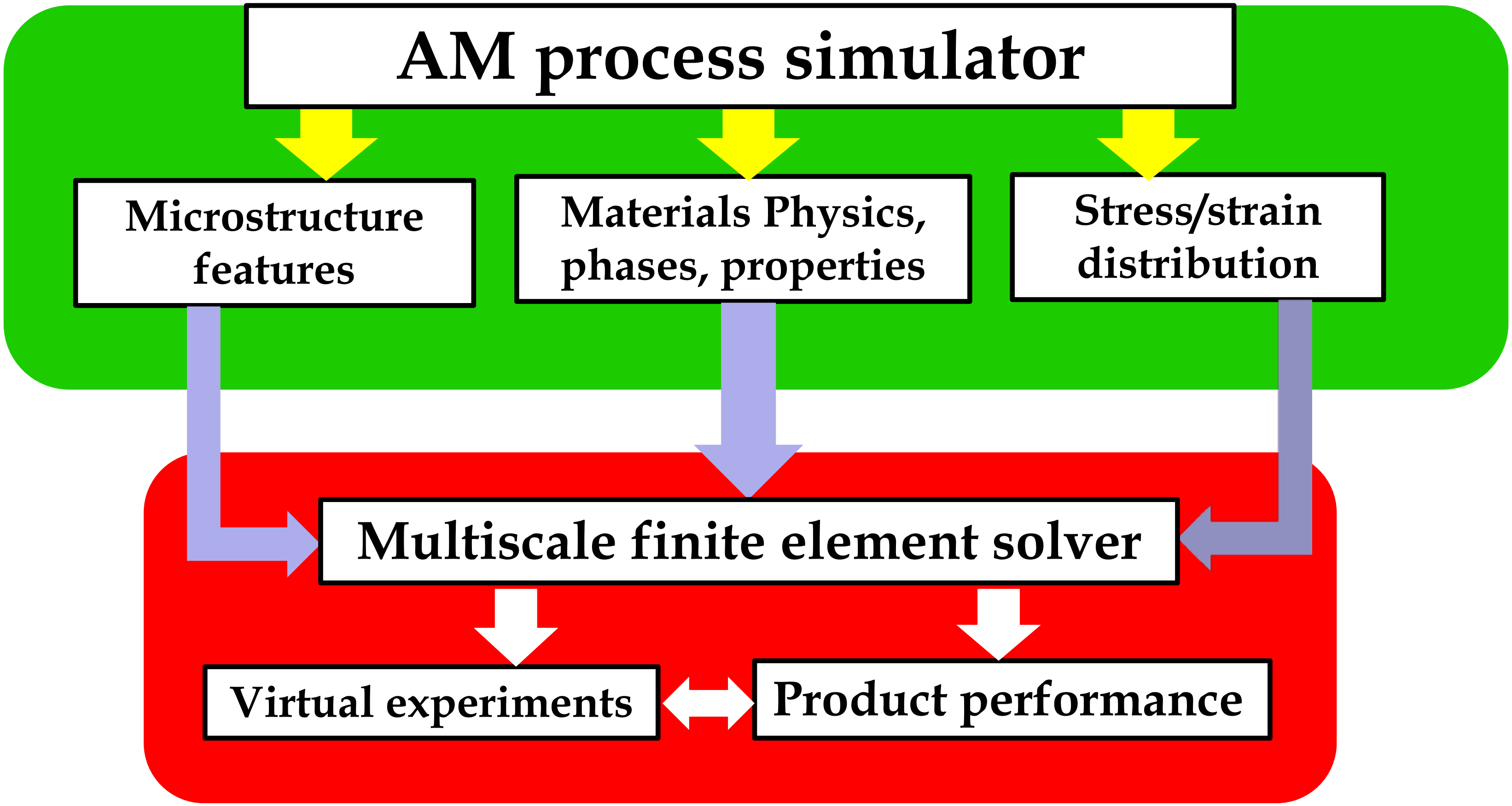
- Material design/prediction capability requires numerous simulations for optimization
  - Steady state solution of utmost importance
  - ~10 tracks to reach steady state

- Multiscale modeling
  - Use atomistic modeling
  - to archive critical material properties at various conditions
- Reduce model dimensionality
  - Reduces model accuracy

What is the path for utilizing fundamental results for AM and scaling them for use in productions?

- New design tools for additive manufacturing
  - Multi-scale design (nano-meso-macro)
  - High dimensional volume or voxel-based approaches to represent complex geometries and multiple materials with process parameters embedded
  - Model validation and printability checking

Schematic of the Concept for Process Validation Models



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- New design tools for additive manufacturing
  - Multi-scale design (nano-meso-macro)
  - High dimensional volume or voxel-based approaches to represent complex geometries and multiple materials with process parameters embedded
  - Model validation and printability checking
  - Creation of neural file format that is fully compatible with AM processes
    - Geometry, material, process parameters, support structure, hybrid processes
    - Can this be open-source?
  - Topology optimization

What is the path for utilizing fundamental results for AM and scaling them for use in productions?

- Material design for additive manufacturing
  - Engineering material properties via combinatorial material distribution or microstructure control
    - Multi-material modeling
    - Heterogeneous multi-functional design
  - Functionally gradient material
  - New material synthesis
  - Self assembly and programmable matter
  - Biological and biomimetic composites design

What is the path for utilizing fundamental results for AM and scaling them for use in productions?

- Process modeling, validation models and monitoring and control for additive manufacturing
  - Develop a better understanding of the basic physics for various AM processes: multiscale modeling needed
  - Establishment of mechanisms for longer-term collaborative efforts among researchers or between academia and industry to develop robust, accurate and efficient process models for various AM processes
    - National level consortia for AM process modeling (can be divided into process specific ones)
    - Repository or database for material selection, properties or response surfaces
  - Shared high power (parallel processing) computational resources
  - Develop robust in-process monitoring and feedback control methods for AM processes

What is the path for utilizing fundamental results for AM and scaling them for use in productions?

- Process modeling, validation models and monitoring and control for additive manufacturing
  - Develop a better understanding of the basic physics for various AM processes: needs more fundamental research
  - Establishment of mechanisms for longer-term collaborative efforts among researchers in academia, government and industry to develop robust, accurate and efficient process models for various AM processes
    - National level consortia (or ERC or other large scale joint efforts) for AM process modeling (can be divided into process specific ones)
    - Repository or database for process simulation models, material selection, properties or response surfaces
  - Shared high power (parallel processing) computational resources
  - Develop robust in-process monitoring and feedback control methods for AM processes

What is the path for utilizing fundamental results for AM and scaling them for use in productions?

- New design tools for additive manufacturing
  - Process-structure-multimaterial information embedded in CAD/CAE/CAM tools with optimization
- Establishment of mechanisms for longer-term collaborative efforts among researchers in academia, government and industry to develop robust, accurate and efficient process models for various AM processes
  - Consortia for AM process modeling
  - Repository or database for simulation models, material selection and properties
- Need standards for certification and validation of additive manufacturing processes
- Need robust and reliable in-process monitoring and closed-loop feedback control methods

What are future applications, markets and industry partners that may leverage the fundamental research and scale it into production?

- **Future applications**
  - High performance products with localized properties, geometric complexity and/or embedded sensors, electronics and actuators
  - Remanufacturing
  - Multiscale products
  - Customized products: ex) implants, prostheses
  - Tooling and fixtures
  - Rapid prototyping, education, etc.