Systems Integration for Additive Manufacturing

.. supporting infrastructure for process characterization

June 21, 2018

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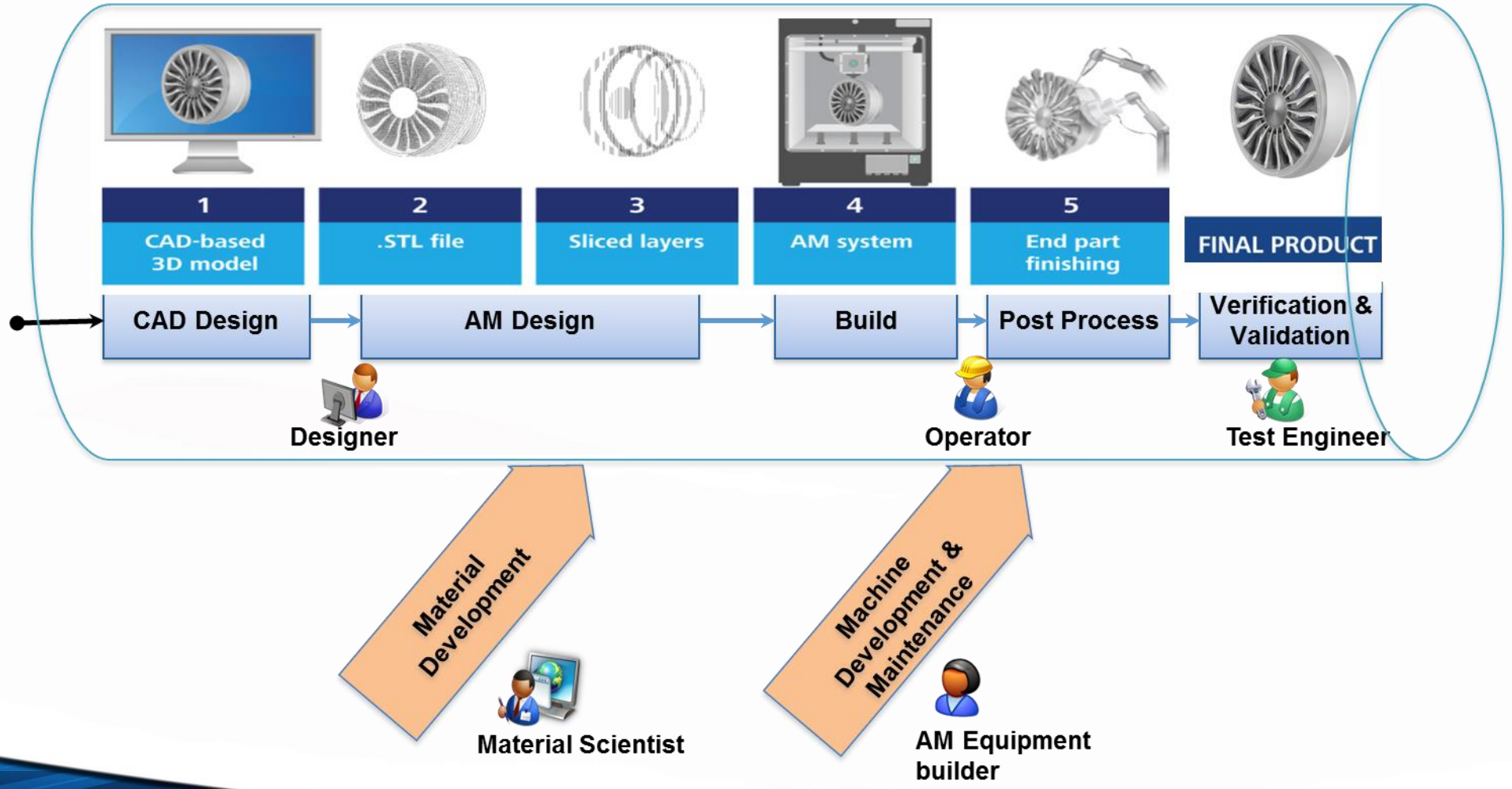
Additive Manufacturing – Activities



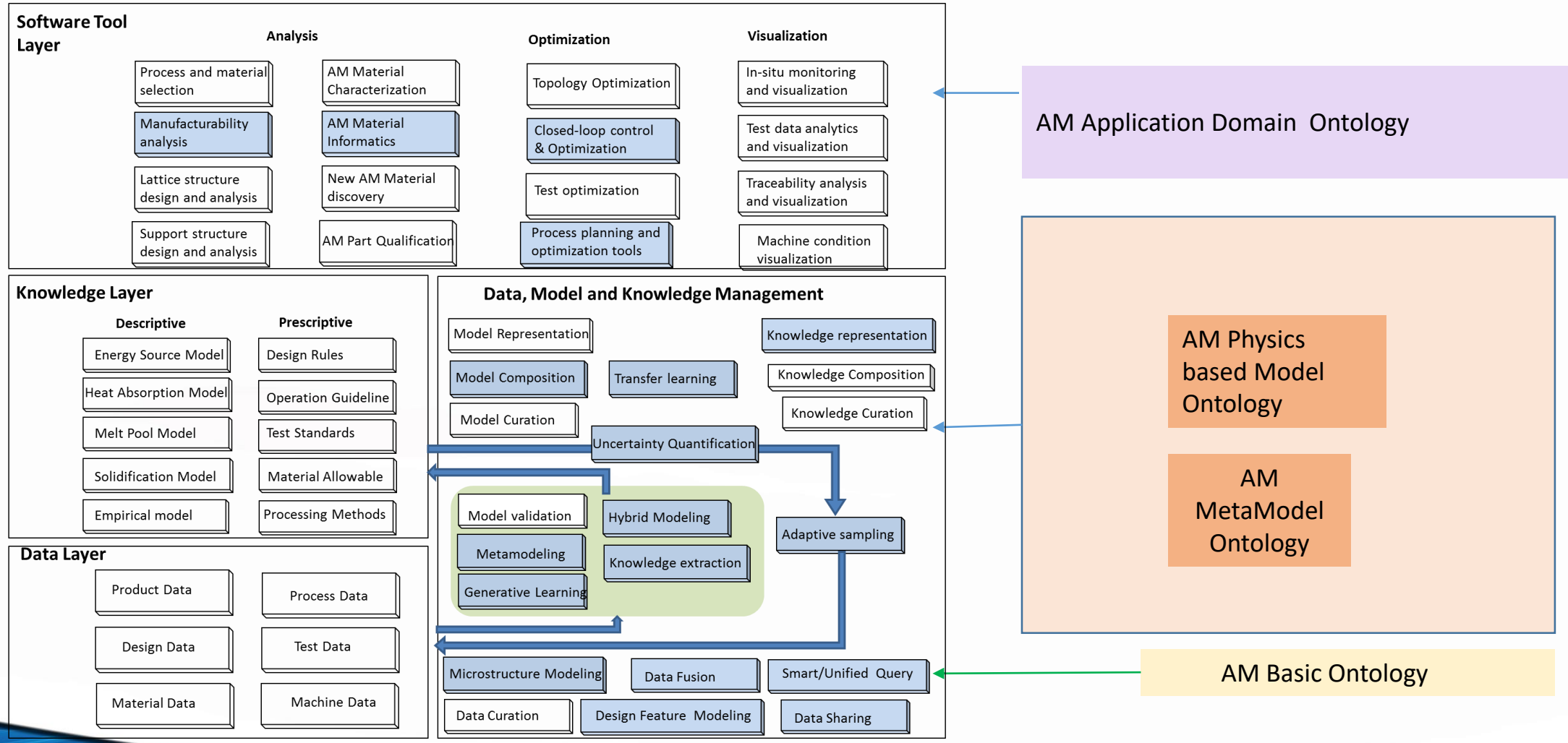
Research topics

- Industry drivers
  - Limited connectivity exists between AM lifecycle activities and supply chain activities.
  - AM software tools are disconnected from each other.
  - Limited process understanding and knowledge exists for design decision support.
  - Heterogenous models and knowledge for AM are acquired, represented and managed isolated
  - Data is generated individually and costly through AM lifecycle activities without coordination.
- Research challenges
- Scientific and engineering approaches

Research topics

- Industry drivers
- Research challenges
  - Collection and curation of data
  - **Data → information → knowledge**
  - Integration across models – fidelity, underlying assumptions and constraints, scales, time, …
  - Availability of knowledge, information, and data for decision making at all levels
  - **Qualification, verification and validation**
- Scientific and engineering approaches

Research Challenges: Data -> Information -> Knowledge



Research Challenges: Qualification, verification, and validation

What is AM-Bench?

A continuing series of highly controlled benchmark tests for additive manufacturing, with modeling challenge problems and a corresponding conference series

Primary Goal

To allow modelers to test their simulations against rigorous, highly controlled additive manufacturing benchmark test data

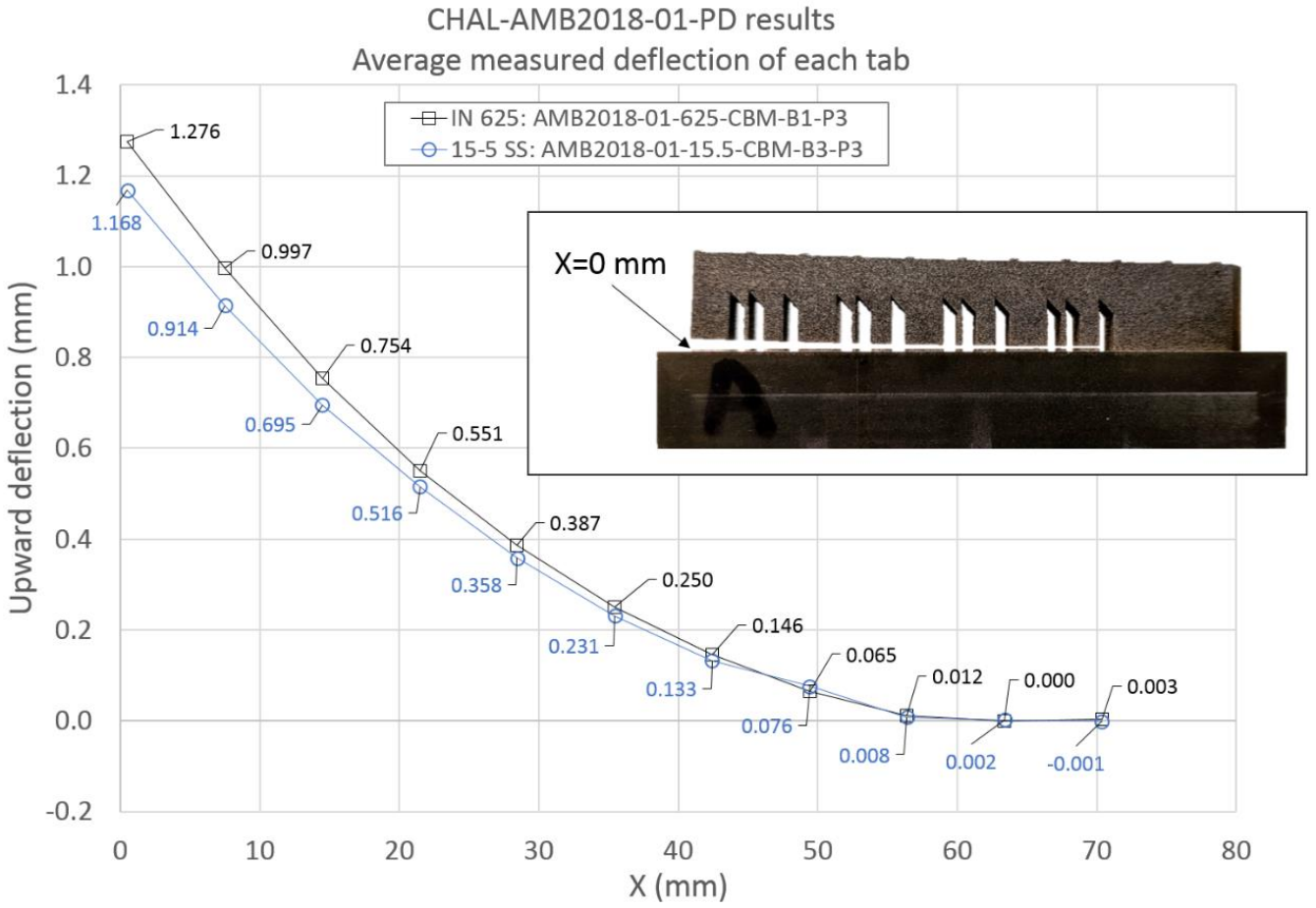
Who benefits?

- Simulation software companies
- Companies that use AM
- AM machine manufacturers
- End users of AM products
- Academia, national labs
- Everyone!

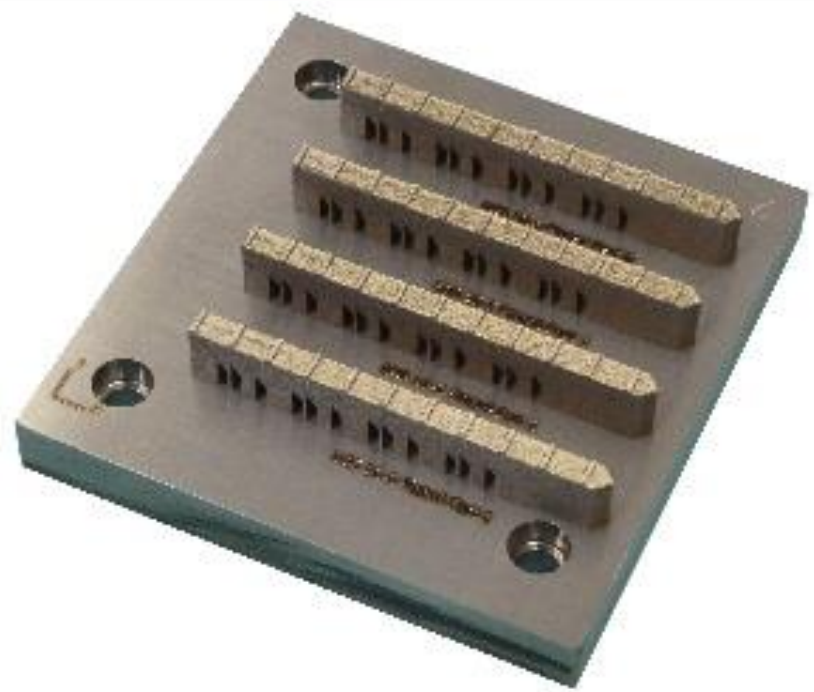
AM-Bench was born on October 7, 2015

Planned two-year cycle

Research Challenges: Qualification, verification, and validation (AM Bench)



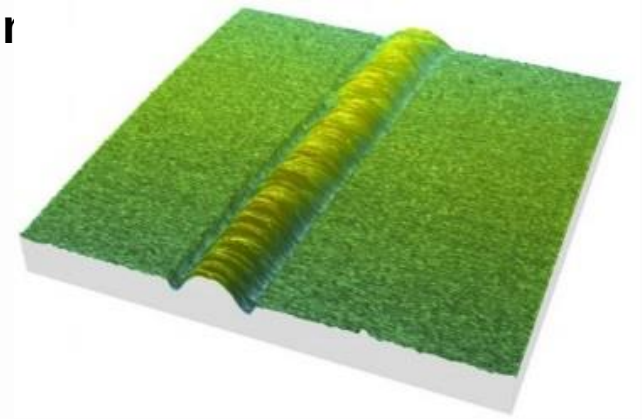
Measurement results from the 3D part build



Part deflection (after partial removal from the build plate)

Research Challenges: Qualification, verification, and validation (AM Bench)

AMB2018-02: Individual laser traces on bare metal plates of IN625, using the three cases: A) 150 W, 400 mm/s, B) 195 W, 800 mm/s, C) 195 W, 1200 r



- **Melt pool geometry** CHAL-AMB2018-02-MP
- **Cooling rate** CHAL-AMB2018-02-CR
- **Topography** CHAL-AMB2018-02-TP
- **Grain structure** CHAL-AMB2018-02-GS
- **Dendritic microstructure** CHAL-AMB2018-02-DM
- **Three-dimensional structure** CHAL-AMB2018-02-3D

NIST: Carolyn Campbell, Sandra Claggett, Jarred Heigel, Brandon Lane, Lyle Levine, Thien Phan, Richard Ricker, Mark Stoudt, Maureen Williams

NRL: Richard Fonda, David Rowenhorst

Benchmark Challenges

Research Challenges: Qualification, verification, and validation (AM Bench)

Breadth of benchmarks

1. Tremendous range of additive processes and materials
   - ❑ Metals (steels, Ni-based super alloys, Ti alloys, Al alloys…)
     - Powder bed fusion (laser & e-beam)
     - Binder jet (infiltration & consolidation)
     - Direct energy Deposition (laser, e-beam; powder, wire fed)
     - Sheet lamination (ultrasonics)
   - ❑ Polymers (Thermoplastics, UV curable…)
     - Material extrusion
     - Powder bed fusion
     - Material jetting
     - Vat photo polymerization
   - ❑ Ceramics…
   - ❑ Composites…
2. Unexplained build variability between machines, processes, etc.
   - ❑ Round robin testing
   - ❑ Metrological-level measurements (AMMT, state of the art measurements)

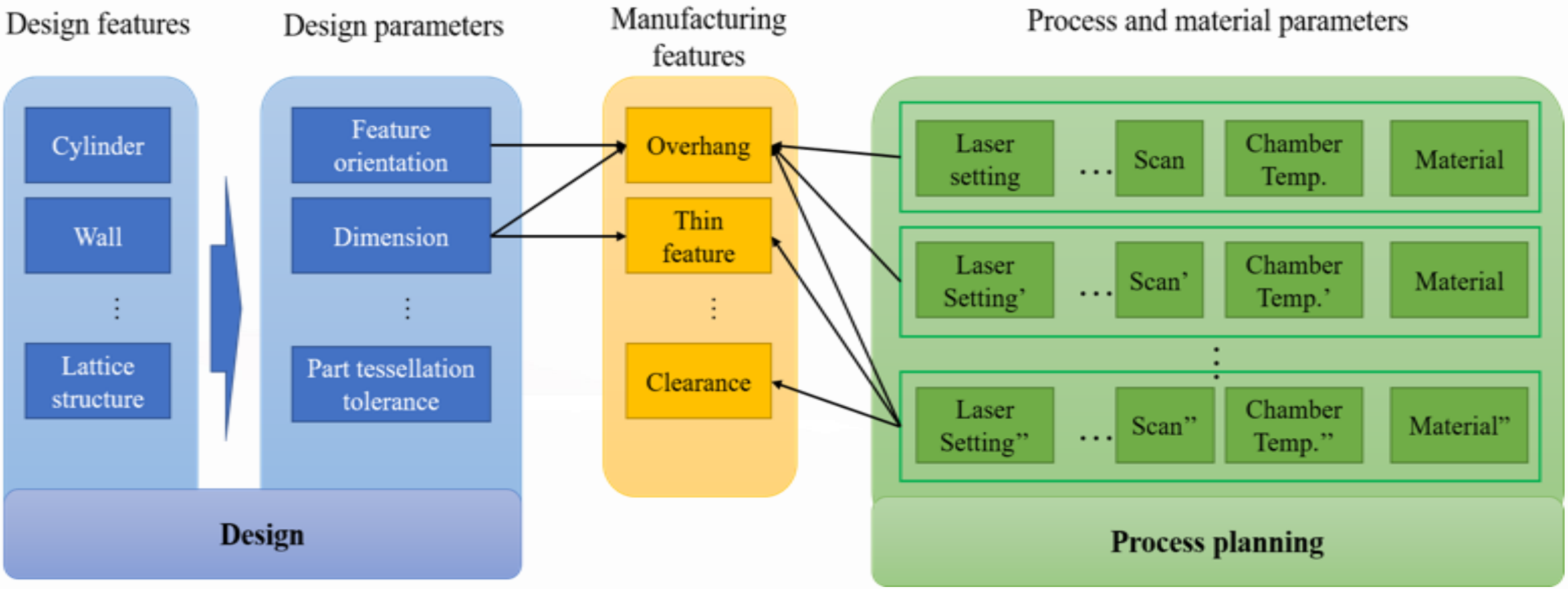
Topics

- Industry drivers
- Research challenges
- Scientific and engineering approaches
  - Machine learning - Continuous learning
  - **Formal representations and structure**
  - Surrogate / Predictive modeling
  - Adaptive databases – Advanced query methods

Design for Additive Manufacturing (DfAM) - Drivers

- Provide manufacturers a systematic approach to derive or capture design rules when using AM processes utilizing formal representations.
- Provide the required structure and formalism to ensure consistency while deriving design rules in a computer-interpretable way thus enabling effective communication, discussion making, and exchange of AM information.
- Support the development of tools to improve decision support capabilities in AM while facilitating the development of an information base for best practices and standard procedures.

Design for Additive Manufacturing (DfAM) - Ontology

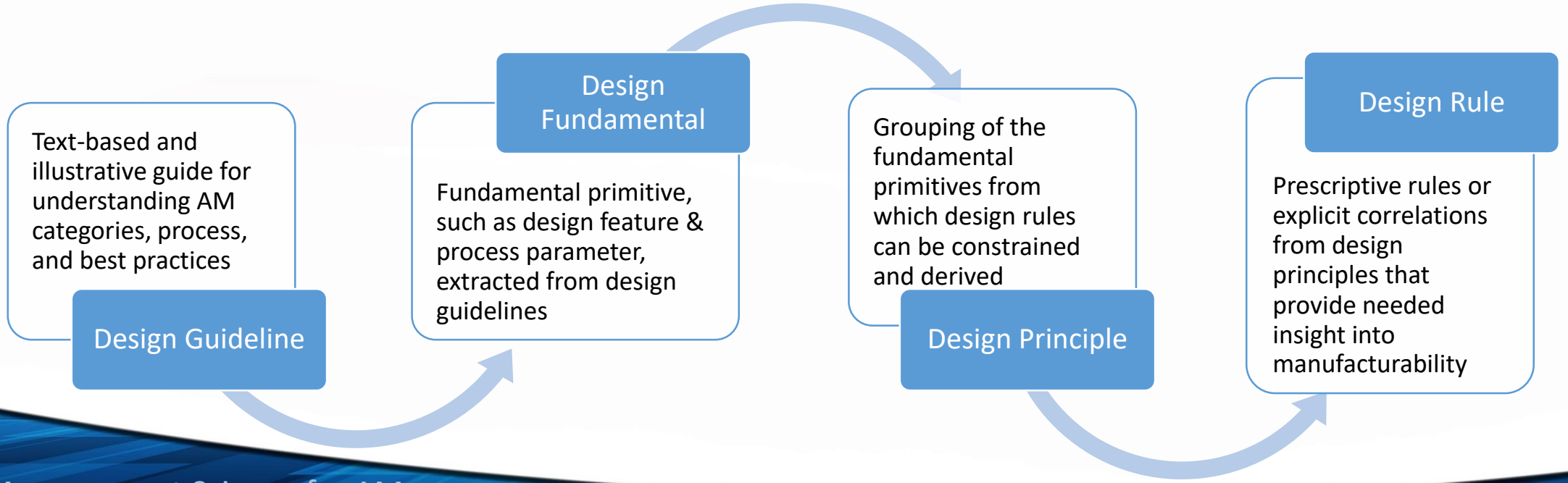


Kim, S., Ko, H., Witherell, P., Rosen, D.W., "A Design for additive manufacturing ontology to support manufacturability analysis," ASME Design Automation Conference, Quebec City, Canada, Aug. 26-29, 2018.

Design for Additive Manufacturing (DfAM) - Standards

Guide for Principles of Design Rules in Additive Manufacturing (WK54586)

- To standardize fundamental design-process-material correlation through the use of design rules within AM processes
- To provide the needed reference when additively manufactured through the design rules based on elemental design features
- Guide-to-Principle-to-Rule (GPR) Methodology



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