GE RESEARCH

Richard Arthur

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GE COLLABORATIONS WITH DOE AT THE EXASCALE



GE Research... an innovation engine

connecting to GE businesses, government agencies & strategic partners



(4)

Generating 1/3 of world's electricity



Ō

Powering Takeoff every 2 seconds

Curing 16,000+ scans every minute





Drivers of needed Confidence & Reliability

86)

Fielded Product Characteristics

Critical Infrastructure

safety / failure consequence surface for cyberattack

Long field life

durable to extended use & changes to environment / mission

Capital intensive

maintenance contracts for uptime cost-effective sensor monitoring





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Modeling & Simulation well-established at GE / GE Research

Computational Science & Engineering

Modeling (Form & Function) & Simulation (Credibility & Confidence)

TO SEE TO UNDERSTAND TO PREDICT





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TO SEE



Computational model as scientific instrument



MICROSCOPE

Interrogate extreme detail

MACROSCOPE

Perceive system-wide interactions



HYPERSCOPE

Explore vast dimensionality









Computational Fluid Dynamics – Used throughout today's GE products

Widely Applicable

- Aerodynamics, heat transfer, aeromechanics, aero-acoustics, combustion
- Aviation, Energy, Renewables

Long term investment in Software

- Solvers, meshing, post-processing
- ~50 years of investment

Sustained investment in HPC Infrastructure

- Significant in-house capabilities
- Compete for peer-reviewed grants to access Leadership Compute facilities





Hydro



Power



Wind



Aircraft Engines – Pushing the state of the art to reduce fuel burn and CO₂ emissions



GE / Safran CFM56

First flew in 1979 and continuously improved

GE / Safran LEAP

Next generation single aisle (2016) ... B737, A320 Architecture, material, advanced components 15% reduction in fuel burn

GE / Safran RISE Demonstrator

20% reduction in fuel burn SAF and Hydrogen Capable 20% -100% reduction in CO2 emissions





THE CHALLENGE – Design engine with sufficient propulsive efficiency to enable use of hydrogen as zero CO₂ emission fuel



Sustainable Propulsion

- Path to zero CO₂ emissions requires hydrogen as a fuel.
- But economic factors impose barriers such as:
 - 1. Price of fuel source **per km** traveled.
 - 2. Reduced **passenger load** (4x fuel volume per joule)
 - 3. Reduced aircraft range (onboard fuel capacity)
- > Must improve propulsive efficiency.



a 50-50 joint company between GE and Safran Aircraft Engines

RISE program: Open fan design is key.



[infographic]



Blade

Multi-blade / Blade Row

Multi-row / Full Stage



Full Annulus / Multi-stage

Computational View from mid 2000's



GPUs ~2005



FPGAs ~2002



STI Cell ~2007



SONY TOSHIBA IBM

Heart of PlayStation3



GPUs ~2005



High Integrity

Application Software Integrity provide by the platform Processor Processor System Bus

Breakthrough multi-core architecture and ultra high-speed communications capabilities for high-performance workloads

787 Core Compute System

Revolutionizing medical and molecular imaging systems with Cell Broadband Engine technology



The role of maging will change hom a test, or detend by the physician and performed by a peciality. In a May Insignated change is a May Insignated change is a market of anticonce, prevail a detail with a second of the origination of the second workfows, perform information will be accessible at all levels of care. from weightbook childres to perform the market of the second based on the second of the second from the physical based on the second based on the second on the second from the physical based on the second based on the second on the second based on the second on the second from the physical based on the second based on the second on the second based on the second on the second on the second on the second the second on the second on the second on the second the second on the second on the second on the second the second on the second on the second on the second the second on the second on the second on the second the second on the second on the second on the second the second on the second the second on the second o

IBM

The problem of reconstructing medical images from measurements of the electromagnetic radiation around the body of a patient belong to the class of mathematical problems called inverse problems. These tornographic image reconstruction methods are central to many of the new applications in medical imaging and they are very computationally demanding. In the past, Digital Signal Processors (DSPs) and the implementation of specific

Image reconstruction

architectures, connecting Application Specific Integrated Circuits (ASICs) or Field Programmable Gate Arrays



(FPGAs) to the memory through dedicated high-speed busses were used to solve these problems. However, these hardware architectures are expensive, take a long time to develop, and can be quite difficult to program/modify.

GE Research gains a 16x improvement on MRI image reconstruction

Recently, a team at GE Global Research implemented three MRI image reconstruction algorithms on the IBM BladeServer QS20 with Cell/B_E. processors. Each algorithm was implemented and compared



Homodyne

-- Opteron -- Cell Blade (16 SPEs)

Acced

0.09

Full K-Shace

FPGAs ~2002



STI Cell ~2007



Heart of PlayStation3













Never Before Seen



- Unobservable physically
- Relevant to engineering design
- 2012 IDC award:



Result on OLCF Jaguar Cray XT5 (2010): Unsteady analysis with wake from strut



Prior State of the Art:

Steady Analysis

(GE Internal HPC)



Separated flow poor air flow control loss of efficiency



TO SEE





GE Global Research acquires a Cray Supercomputer



Symbol

CRAY

CRAY

10am

Recommend

On Tuesday June 21, 2011, 5:59 am EDT

🍽 Tweet 🖂 Email 🔒 Print

Companies: Cray Inc. | General Electric Co.



12pm

2pm



-6.30 -6.25 -6.20

4pm

Cray Inc. (NasdaqGS:CRAY) announced the company has sold a



that could not be simulated using standard commodity clusters.





Early promise to predict performance vs. physical test (Aeroacoustics)



2011 Exascale Panel @Capitol



Supercomputing for Science & Competitiveness

American Chemical Society March 17th, 2011

Potential Problem Size



23 July 14, 2022

Full wheel aircraft engine (each "spoke" on each "wheel" is a "blade")

- 1,000 blades
- x 5M geometric points per blade (w/ cavities)
- x 9 (double precision) variables (degrees of freedom)
- x 60,000 time steps
- = 2.7x10^14 (2.7 Peta-calculations¹) per case
- Output file = 500 time steps = 180 Tb file **per case** • This is just CFD
- imagination at work

(1) Each "calculation" = many FLOP/s





2015 Chapter: GE's Journey to Supercomputing

Industrial Applications of High-Performance Computing

Best Global Practices

Chapman & Hall/CRC Computational Science Series

> Edited by Anwar Osseyran Merle Giles



A. Osseyran & M. Giles, *Industrial Applications of High-Performance Computing: Best Global Practices*, (pp. 253-277). London, England: Chapman & Hall/CRC Press (2015)

Chapter by Richard Arthur, GE Research Case study in full chapter by Masako Yamada, GE Research

© CRC Press

April 2016 National Lab Day Poster (2022 Update) Argonne LABORATORY Fan Exhaust OAK RIDGE Combustor National Laboratory Lawrence Livermore National Laboratory **High Pressure Turbine** Low Pressure Turbine National Laboratory

National Laboratory



TO UNDERSTAND











Super Collaboration

Smoky Mountains Computational Sciences and Engineering Conference



GE Power igust 28, 2018

GE Energy Executive

Joe Citeno

Issue: Combustion Turbulence Thermo-acoustic Instability on **GE's Next-Generation Gas Turbine**

Acknowledging computational support from Dept of Energy Office of Science, Oak Ridge National Laboratory, Argonne National Laborator

Combustion in gas turbines

12 Combustors in a 7HA Gas Turbine, **each one** consumes **in just 1 minute....**



GE 7HA: World's Most Efficient 60Hz Gas Turbine





Understand observed thermo-acoustic instability; beyond-state-of-the-art (single combustor) simulation capability



Never seen before simulation: Multi-combustor dynamics interactions

GE & Oak Ridge Received the 2016 HPCwire Reader's Choice Award for Best HPC Application in the Energy Industry



GE Breakthrough Scale & Fidelity with DOE Leadership Computing

AEROACOUSTIC ANALYSIS COMBUSTION ANALYSIS UNSTEADY WAKE ANALYSIS Jaguar Cray XK7 Mira IBM BlueGene/Q **Titan Cray XT4** Cascade LES Solver GE In-house RANS Solver AFRL LES Solver Brian Mitchell, GE Umesh Paliath, GE Joe Citeno, GE Argonne National Laboratory National Laboratory LABORATORY

LEAP AVIATION ENGINE

9X AVIATION ENGINE

7HA2 GAS TURBINE





Understand wind turbine wake impact on wind farm performance





GE Research received the 2018 HPCwire Editor's Choice Award for Best Use of HPC in Manufacturing



Goal: Optimize wind farm design to improve energy generation efficiency of turbines





CONCEPTLASER

CHALLENGE -

Understand sources of manufacturing defects in materials and processes to improve first-time yields

GE Additive Manufacturing New Business for Novel Capabilities

Highly complex and relatively new manufacturing process

GE Additive company

- Wide spectrum of length scales (from powder grains to solid parts)
- Very long process times (kilometres of scanning)
- Complex physics from the melt pool to the final workpiece
- Complex parts and supports structures (lattice-type e.g.)

Leveraged HPC4EnergyInnovation program

24 hours



ATT 1 cm

2009-2017 OVER 1 BILLION CORE-HOURS AWARDED TO GE IN PEER-REVIEWED COMPETITIVE GRANTS

- ~14 INCITE + ~22 ALCC + ~6 HPC4Manufacturing
- Multiple pan-lab engagements



- Gas Turbine, Wind Turbine & Aviation
 - Combustion (Atomization, Interactions)
 - Unsteady Aerothermal & Aeroacoustics
- Ice Formation (nucleation) & Adhesion
- Alloy Solidification (part castings)
- Additive Manufacturing (metal powder)



2019 ECP Annual Meeting Poster





Wind Turbine Blade Acoustics



Inlet Distortion Flow Impact On Engine Fan



Multiscale Modeling of Manufacturing & Materials to Improve Performance

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Example: Combustor + High-Pressure Turbine





CHALLENGE - Understand impact of coastal low-level wind-jets on offshore wind farm performance and reliability







TO PREDICT









Øresund wind farm (Baltic sea)

Liligrund wind farm (Sweden)







Design objectives: Efficiency and Durability over various operating conditions



Understand flow behavior changes due to selection of Reynolds number:



Laminar-to-turbulent transitions (*reduced energy capture*) Flow structures in wake (*reduced performance*)

Acoustic wave propagation from trailing edge (*reduced stability*)

High-fidelity datasets as training repository to create surrogate models able to substitute for complex effects in lower-fidelity simulations.

ALCC 2021-2022 Project CFD153 (Osusky)

Applying Machine Learning to Reynolds Number Impact on HPT Flow







THE CHALLENGE — Design engine with sufficient propulsive efficiency to enable use of hydrogen as zero CO₂ emission fuel

RISE™: **R**evolutionary Innovation for **S**ustainable **E**ngines



GE / Safran RISE Demonstrator

20% reduction in fuel burn SAF and Hydrogen Capable 20% -100% reduction in CO2 emissions





CFM <u>RISE</u>^{™*} industry program to enable sustainable aviation

 $\textbf{RISE}^{\texttt{TM}}: \textbf{R} evolutionary \, \textbf{Innovation for Sustainable Engines}$

* RISE is a registered trademark of CFM International, a 50-50 joint company between GE and Safran Aircraft Engines





Predict flight test performance from models validated on TRL4 rig tests





Discovering new ways to control the **challenging flow physics** that limit improvements in **noise and efficiency** Product-scale flight Reynolds number: **only possible via Frontier**



Novel ScientificML Workflow: Bespoke Surrogate Model Factory





Tallman, ORNL AIRES Worship '20

Post-Grant Publications



Application of Cascade model towards development of DLN2.6e technology 🔶 Numerical methods behind Cascade 🔶 Premixed Combustion Model & acoustics prediction 🔶 Application Paper for prediction of thermoacoustics & other quantaties and comparison with lab and engine 🔶 LES & thermoacoustic prediction of combustion process in lean premixed gas turbine with Staged Fuel Injection 🔶 Using a New Entropy Loss Analysis to Assess the Accuracy of RANS Predictions of an HPT Vane 🔶 The Current State of High-Fidelity Simulations for Main Gas Path Turbomachinery Components and Their Industrial Impact 🔶 High-Fidelity Simulations of Low-Pressure Turbines: Effect of Flow Coefficient and Reduced Frequency on Losses 🔶 High-Fidelity Simulations of a Linear HPT Vane Cascade Subject to Varying Inlet Turbulence 🔶 Machine learning for turbulence model development using a high-fidelity HPT cascade simulation 🔶 Transition investigations based on large eddy simulation of high-pressure turbines vane at realistic Reynolds and Mach numbers 🔶 Highly Resolved LES of a Linear HPT Vane Cascade Using Structured and Unstructured Codes 🔶 Multiple invited seminars given based on this work - Can pull that list together 🔶 Application of High Performance Computing for Simulating Cycle-to-Cycle Variation in Dual-Fuel Combustion Engines 🔶 Unsteady adjoint of pressure loss for a fundamental transonic turbine vane 🔶 Fluid Dynamics Effects on Microstructure Prediction in the Laser Additive Manufacturing Process 🔶 Fluid Dynamics Effects on Microstructure Prediction for the Single-track Laser Additive Manufacturing Process 🔶 Effect of Particle Spreading Dynamics on Powder Bed Quality 🔶 Fluid Dynamics Effects on Microstructure Prediction in Single-Laser Tracks for Additive Manufacturing of IN625 • Effect of Particle Spreading Dynamics on Powder Bed Quality in Metal Additive Manufacturing • Quantification of Powder Bed Structure for Metal Powder Bed Additive Manufacturing Using Discrete Element Method 🔶 Wall-modeled LES study of surface roughness effects from additive manufacturing for gas turbines 🔶 Near Wall resolution Requirements for High-Order FR/CPR Method for Wall-Resolved Large Eddy Simulations 🔶 GPU accelerated Turbomachinery LES using DG methods 🔶 Large Eddy Simulation for Jet Installation Effects 🔶 Investigation of Noise Generated by a DU96 Airfoil 🔶 Large eddy simulation of a wind turbine airfoil at high angle of attack 🔶 Large eddy simulation of airfoil self-noise 🔶 Report for Workshop: Trailing-Edge noise 🔶 Towards Identifying Contribution of Wake Turbulence on Inflow Turbulence Noise from Wind Turbines 🔶 Large Eddy Simulation of a Wind-Turbine Airfoil at High Freestream Flow Angle 🔶 Effect of Installation Geometry on Turbulent Mixing Noise from Jet Engine Exhaust 🔶 Large Eddy Simulation for jets from chevron & dual flow nozzle 🔶 Turbulent Mixing Noise from Jet Exhaust Nozzles 🔶 Aerodynamic Noise Prediction for a Rod-Airfoil Configuration using Large Eddy Simulations

B. Jayaraman, E. Quon, J. Li, and T. Chatterjee, "Structure of Offshore Low-Level Jet Turbulence and Implications to Meso-micro Coupling",

TORQUE2022 paper 651, J. Phys.: Conf. Ser. 2265 022064.

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"Wind Farm Response to Mesoscale-driven Offshore Low Level Jets: A Multiscale Large Eddy Simulation Study",

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S. Priebe, D. Wilkin, A. Breeze-Stringfellow, A. Mousavi, R. Bhaskaran, L. d'Aquila,

"Large Eddy Simulations of a Transonic Airfoil Cascade",

GT2022-80683, ASME Turbo Expo 2022, Rotterdam, The Netherlands, June 13-17, 2022.

R. Bhaskaran, R. Kannan, B. Barr and S. Priebe,

"Science-Guided Machine Learning for Wall-Modeled Large Eddy Simulation,"

2021 IEEE International Conference on Big Data (Big Data), 2021, pp. 1809-1816, doi: 10.1109/BigData52589.2021.9671436.

S. Priebe, T. Wood, J. Yi and A. Mousavi,

"Large Eddy Simulation of an Open Rotor Fan Blade",

Paper GT2022-80538, ASME Turbo Expo 2022, Rotterdam, The Netherlands, June 13-17, 2022.

(Presentation) B. Mitchell, KAUST Conference: Flow Simulation at the Exascale, March 28-30, 2022

GE Support for Leadership Computing & Exascale



HPC: Computational Science & Engineering Partnerships – THANK YOU!





Building a world that works

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Background materials follow...



DAVE KEPCZYNSKI

Chair, ECP Industry Council



Exascale Computing Project (ECP) Industry Council Chair Brunon (Dave) Kepczynski serves as Chief Information Officer, General Electric (GE) Global Research Centers and the Engineering Product Leader for GE's Digital Technologies. His missions are the scaling and maturing of digital thread technologies and engineering horizontal products across the enterprise to deliver outcomes in technical velocity, cost, and quality. In a previous role at GE, he was Engineering Chief Information Officer for GE Oil & Gas where his teams drove digital transformation.

Before GE, he spent more than 25 years with General Motors, leading teams in Global Systems Development & Business/IT Transformation, Global Design Execution & Operations, Vehicle & Powertrain Product Development, Assembly Operations, and Manufacturing Engineering. His teams developed and deployed solutions enabling the design, validation, and manufacture of world-class automotive products.

Dave has been an active member of the ECP Industry Council since its inception and became chair in April 2018.



2020 Computational Methods Workshop 2022 GE Simulation Symposium





Whitney Symposium 2015

Physics & Big Data for Customer Outcomes

Whitney Symposium 2012

Analytics, Modeling and Simulation in the Age of the Industrial Internet

Whitney Symposium 2016

Al: The Promise of Limitless Industrial Opportunity

Making Simulation Pervasive

Online: June 22, 2022



2022 GE Simulation Symposium

2020 Computational Methods Workshop



Discipline Lead – Materials and Structures Transformational Tools and Technology Program NASA Glenn Research Center

Mike Heroux

Director – Exascale Computing Project (ECP) Software Pillar Senior Scientist – Advanced Simulation & Computing (ASC) Sandia National Laboratories, U.S. Department of Energy

Sr. Manager – Product Lifecycle Management

Greg Laskowski

Director of Fluid Mechanics Alumnus of Sandia, GE Aviation Dassault Systèmes

Dan Seal

Ed Kraft



Boeing Defense, Space & Security Retired – Chief Technologist for Ground Testing

One of Principal Architects for Air Force Digital Thread/Digital Twin initiative Air Force Test Center, Arnold Air Force Base

- Steven Levine, Sr. Dir. Virtual Human Modeling, Dassault Systèmes
- Eric Stahlberg, Dir. Cancer Data Science, Frederick National Lab
- Laurence Sampson, Sr. Dir., Siemens Digital Industries Software
- Amanda Randles, Biomedical Engineering, Duke University
- Marc Horner, Distinguished Engineer, Ansys, Inc.
- Eric Bogatin, University of Colorado, Boulder

General Electric (Internal)

- Patrick Harrington, Sr. Mechanical Engineer
- Kyle Reiser, Mechanical Architect
- Emma Cusack, Mechanical Engineer
- Gunaseelan Murugan, Sr. Systems Engineer, GE Healthcare
- Rick Arthur, Sr. Director, Computational Methods, GE Research
- Ann Buneo, Product Leader, HPC, GE Research
- Doug Grant, Sr. Mechanical Engineer, GE Healthcare
- Jonathan Bruss, Sr. Engineer, Mechanical Engineering, GE Healthcare



Online: June 22, 2022

Making Simulation Pervasive

Modeling Maturity Rubric

Real	Model Competence	Realism	Completeness of	
		Accuracy	Validity within	Model's
Flexibility	Accuracy Confidence Robustness Productivity ntation	Confidence	Error bounding within	Competence
		Robustness	Stability & Assertability of	
Scalability		Productivity	Cognitive	& Waste Reduction
itectu		Sustainability	Augmentation	& Architecture Quality
Sustainability		Scalability	Capable & High Performance	
Produce Cognitive Augmentation		Flexibility	Modular, Extensible, Interoperable	



Additional Reference: PCMM Adaptation by GE Digital Twin Model Maturity Team:



Per Asset Based Models	L0: Empirical Trial & Error	L1: Expertise-driven	L2: Model-assisted	L3: Model-driven
Model Representation What features are neglected because of simplifications or stylizations?	Little or no representational fidelity requirements established for the model geometry, material properties, and process conditions (parameters, initial conditions (IC's), and/or boundary conditions (BC's))	Significant assumptions of the model geometry, material properties, and process conditions (parameters, initial conditions (IC's), and/or boundary conditions (BC's))	Limited assumptions of the model geometry, material properties, and process conditions (parameters, initial conditions (IC's), and/or boundary conditions (BC's))	Real time process and quality assurance data used to refine model assumptions and develop physics based and data driven reduced order models
Process Physics Fidelity How fundamental are physics & material models + degree of model calibration?	Empirical data-driven models and/or judgment used to define important parameters of the asset of interest	Some physics based models exist for key parameters of the asset of interest	(Suite of) physics based models exist for the key parameters of the asset of interest	Real time predictions of physics based process performance enable enterprise decisions made within process takt time
Code/Algorithm/Model Integration Do algorithm deficiencies, software errors, and poor SQE practices corrupt results?	Minimal or no testing of any commercial off the shelf (COTS) or custom software elements with little of no configuration management procedures specified or followed	Source code and algorithms are either COTS software or managed by configuration management procedures with limited comparisons to established algorithm benchmarks	Customized and/or modified algorithms are tested and compared to benchmark data and/or solutions to determine impact on numerical convergence and physics	Integration of algorithms with machine controls and multi-physics data fusion
Solution Verification Are numerical solution errors and procedural human errors corrupting the simulation results?	Modeling assumptions have an unknown effect on the accuracy and/or precision of the numerical model predictions	Alternative model builds considered; Numerical, discretization, and model assumption induced errors qualitatively estimated based on model input/output for each use case; Qualitative assessment of model limitations and weaknesses provided.	Alternative model builds have been considered; Numerical, discretization, and model assumption induced errors quantitatively estimated across validation envelope and used to establish best practices; Quantitative assessment of model limitations and weaknesses provided.	Real time comparison of predictions with process data
Model Validation How is accuracy of simulation & experimental data assessed over the validation hierarchy?	Judgment and/or limited experimental data exists to validate model predictions	Industry standard use cases and benchmark experimental data sets exist and used to calibrate models at one or more distinct validation points	Data from actual enterprise and/or customer/supplier processes used to calibrate model predictions and establish validation envelopes	Model predictions are used to adapt process parameters for real time control
Uncertainty Quantification How thoroughly are uncertainties and sensitivities characterized and propagated?	Model prediction uncertainties and sensitivities to key input parameters are not assessed as part of the simulation	Prediction uncertainties inferred from benchmark experimental use case validation data with limited sensitivity studies conducted for key parameters	Prediction uncertainties segregated and propagated by source (geometry, material properties, and process conditions (parameters, initial conditions (IC's), and/or boundary conditions (BC's)) etc.) with detailed sensitivity analyses conducted	Uncertainty and confidence estimates made for all predictions using physics based data- driven reduced order models
Peer review	Absent	Informal / ad-hoc peer review	Peer review conducted as process	Formal independent peer review process



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Physical system models with predictive **REALISM**



COLLABORATIVE MULTI-DISCIPLINARY MODEL INTEGRATION

GEOMETRIC DIMENSIONING & TOLERANCING PRECISION

MULTI-SCALE MATERIALS MODELS

COUPLED MULTI-PHYSICS& CO-SIMULATION



Physically validate predictive ACCURACY

Garbage In Garbage Out

"RIG" TEST

Experimental Measurement Targeted Field Sampling

DIGITAL TWIN

VERIFICATION & VALIDATION

CALIBRATION & UNCERTAINTY QUANTIFICATION

to trust critical model results & bound assertable CONFIDENCE





Decision Space Mapping: Guided Validation & Calibration



Geometry Ecosystem: Gaps & Failure Modes

- 1. Labor-intensive complex mesh generation and validation ("are we sufficiently confident with the geometry spec to take the next step?" – the step being to send to manufacturing or even simply to use to instantiate CFD/FEM analyses ~ flow, thermal, stress/strain, etc.")
- 2. Elegantly and robustly handle tolerances (including consistency & coherence/feasibility in design tolerances vs. manufacturing tolerances)
- 3. Handling imperfect or formulaic geometry (gaps/overlaps/shards)
- 4. Geometric change propagation across adjacent parts
- 5. Mapping / calibration with point cloud measurement (*including evaluating tolerance deviation/acceptance*)
- 6. Load-balancing/adaptive refinement/scalability in highly complex (*especially evolving/sliding and dynamic physics*) meshes







Geometry Ecosystem: EMERGING Gaps

7. Sufficiently authoritative and comprehensive specification of a single source reference for deriving geometries for all potential uses (i.e., end-use context-driven)

- a. automated mesh generation guided by embedded domain knowledge
- b. (e.g., performance flow vs. cooling flow vs. conjugate heat transfer vs. solid thermal flow vs. stress/strain thermal cycling and crack propagation vs. tensile strength / etc.)
- c. (or manufacturing GTD@room temperature vs. performing GTD@operational temperature / etc.)
- d. (and systems modeling inclusion of kinematics / articulation information),
- e. with sufficient fidelity to reduce physical testing-for-certification with virtualized certification-by-analysis
- f. as well as geometry simplification (including high-order analyses),
- g. (with in-situ reflective/introspective learning (of principles, simplification opportunities, etc.) during meshing.)

8. Sufficiently support capabilities for advanced manufacturing use cases including

- a. nonuniform materials (gradient composition, designed microstructures, etc.),
- b. surface tagging in complex internal geometries (such as micro-trifurcating core structures in heat exchangers) and geometries resulting from generative design (fully exploiting additive degrees of freedom & biomorphic shapes),
- c. specification for geometric fit by functional intent rather than explicit shape (generatively/programmatically derived),
- d. assessment of opportunities for multi-part consolidation,
- e. auto-propagate novel manufacturing capability up the toolchain to design decisions (e.g., via design assistants),
- *f.* inclusion of intermediate geometries for manufacturing (such as mid-process geometries or temporary bit holds) and process guidance (such as surface roughness, crystal orientations, measurement & inspection features)









Strategy: Actions & Assets



Modernization of Science & Engineering: Data as Strategic Asset

- Gap Assessment: legacy tools & practices (e.g., physical testing, certification)
- Modeling Maturity: identify opportunities to pilot feasibility study, reduction to practice
- Continuous Improvement/Exploit ML: automation, virtualization, standardization, FAIR data/workflows, ..

Modeling Infrastructure: Systemic Mindfulness & Knowledge Stewardship

- In-silico Infrastructure: HPC, cloud, software & methods ecosystem (capacity + capability)
- Modeling Literacy/Fluency: executive competency/confidence + workforce development
- > Human-Machine Collaboration: data & decision provenance, continuum mindset