

High performance computing & data sciences for reactor systems

Workshop on Computational Nuclear Science and Engineering

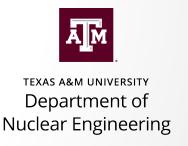
Jean Ragusa,

jean.ragusa@tamu.edu

Nuclear Engineering / Institute for Scientific Computation / Center for Large Scale Scientific Simulations / **Center for Exascale Radiation Transport**

Texas A&M University

July 16, 2021 **IAEA** (online)





Outline

- Brief (picturesque) bio
- High-performance computing (HPC)
 - Some history
 - Some well-recognized software used in nuclear engineering
 - A few application examples:
 - Thermal-hydraulics (from Argonne Nat'l Lab)
 - Neutron Transport (from Argonne Nat'l Lab)
 - Neutral-particle Transport (from Texas A&M U.)
 - Multiphysics simulations of molten salt reactor (from CNRS/Texas A&M U.)
- Data sciences with HPC
 - Motivations (multi-query problems)
 - Data-driven model-order reduction
 - Application to multiphysics simulation of molten salt reactor (from Texas A&M U.)
- Conclusions and Outlook



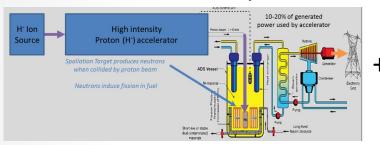


← That's me (on GitHub 😯)



← That's me (in real life)

Accelerator-driven production of tritium

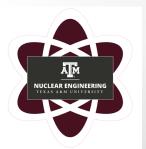


7LiF - BeF2 - 233UF4



Near-real-time PWR accident simulator for crisis management
 Reactor physics and Applied Math Department

2004-present: Nuclear engineering, Texas A&M U.
 Computational radiation transport, Multiphysics, and
 Predictive science https://multiphysics.engr.tamu.edu/



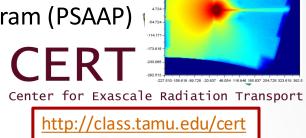
INP Grenoble

My research interests

Radiation transport

Predictive Science Academic Alliance Program (PSAAP)







Multiphysics software development (RELAP-7, RattleSNake, Pronghorn)



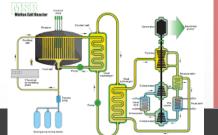
Data sciences and machine-learning

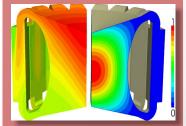
Nuclear radiation effects



Multiphysics model reduction

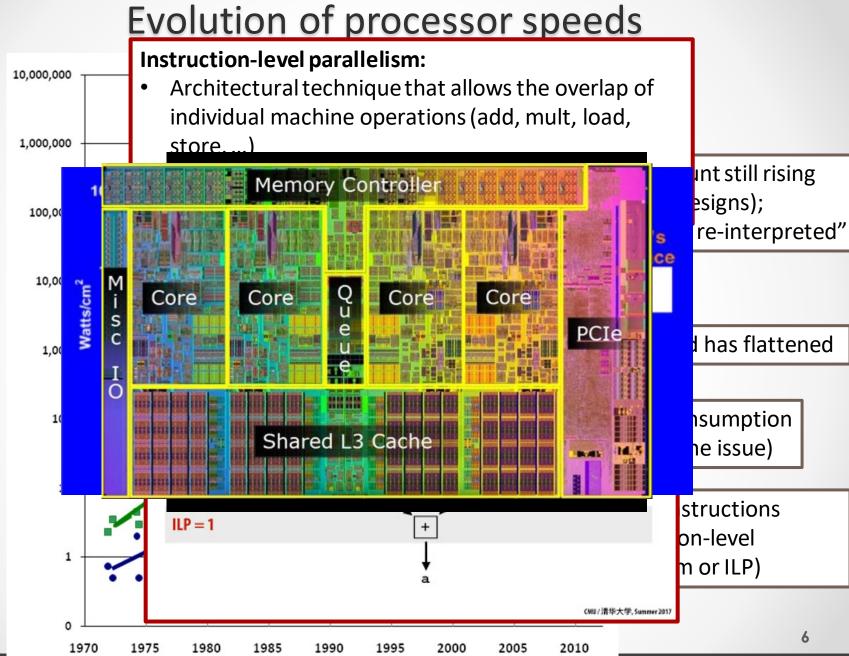






Outline

- Brief (picturesque) bio
- High-performance computing (HPC)
 - Some history
 - Some well-recognized software used in nuclear engineering
 - A few application examples
- Data sciences with HPC
 - Motivations (multi-query problems)
 - Data-driven model-order reduction
 - Application to multiphysics simulation of molten salt reactor
- Conclusions and Outlook

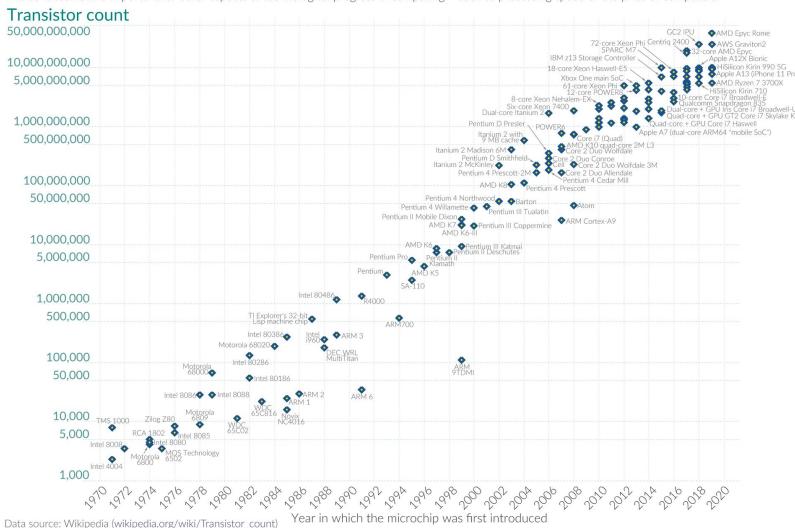


Moore's law: ~straight line on semilog scale

Moore's Law: The number of transistors on microchips doubles every two years Our World

in Data

Moore's law describes the empirical regularity that the number of transistors on integrated circuits doubles approximately every two years. This advancement is important for other aspects of technological progress in computing – such as processing speed or the price of computers.

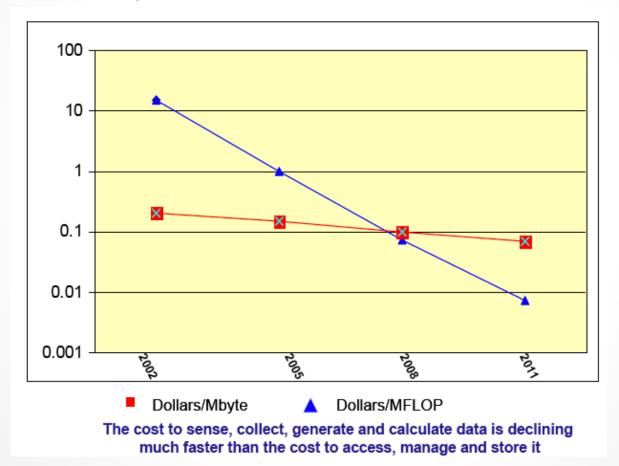


OurWorldinData.org - Research and data to make progress against the world's largest problems.

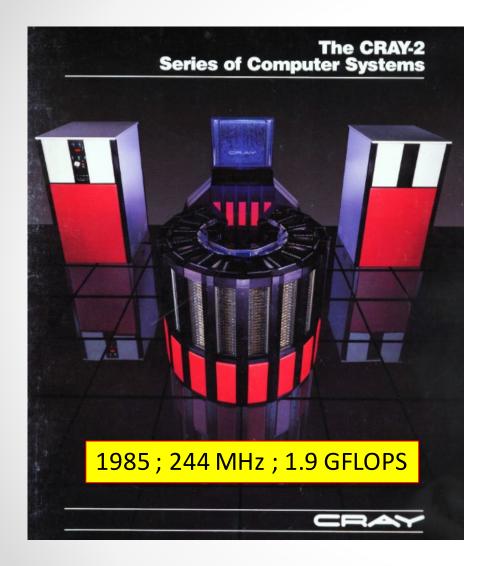
FLOP costs decreasing faster than RAM costs

 Our ability to sense, collect, generate and calculate on data is growing faster than our ability to access, manage and even "store" that data

Source: David Turek, IBM



Perspective





2010; 800 MHz; 1.6 GFLOPS



Top 500 list

Rank	System	Rank	System		
1	Sunway Sunway Nationa	1	Supercomputer Fugaku - Supercomputer Fugaku, A64FX 48C 2.2GHz, Tofu interconnect D, Fujitsu RIKEN Center for Computational Science		

(TFlop/s) (TFlop/s) (kW)
442.010.0 537,212.0 29.899

Rmax

Cores

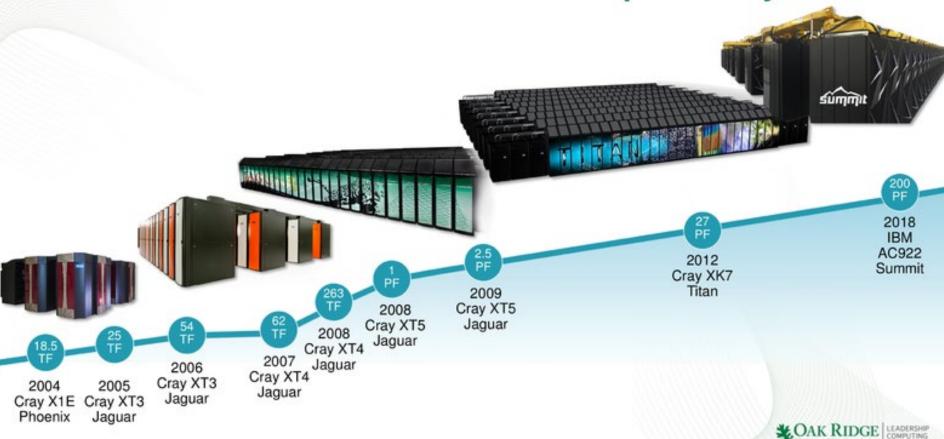
7,630,848

Power (kW)

pp/s) (kW)

435.9 15,371

The Oak Ridge Leadership Computing Facility has enabled us to field a series of leadership-class systems





Joint C Japan

Japan

United States

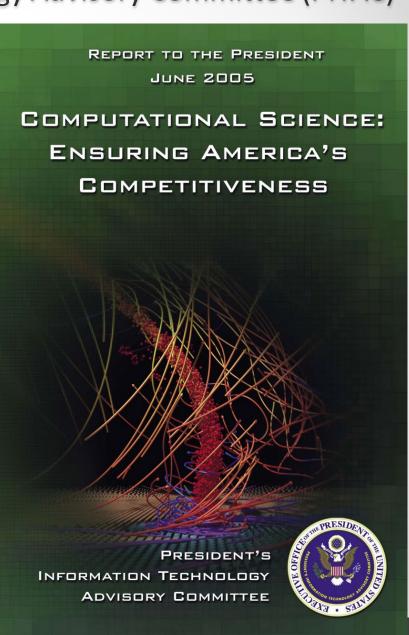
U.S. Presidential Information Technology Advisory Committee (PITAC)

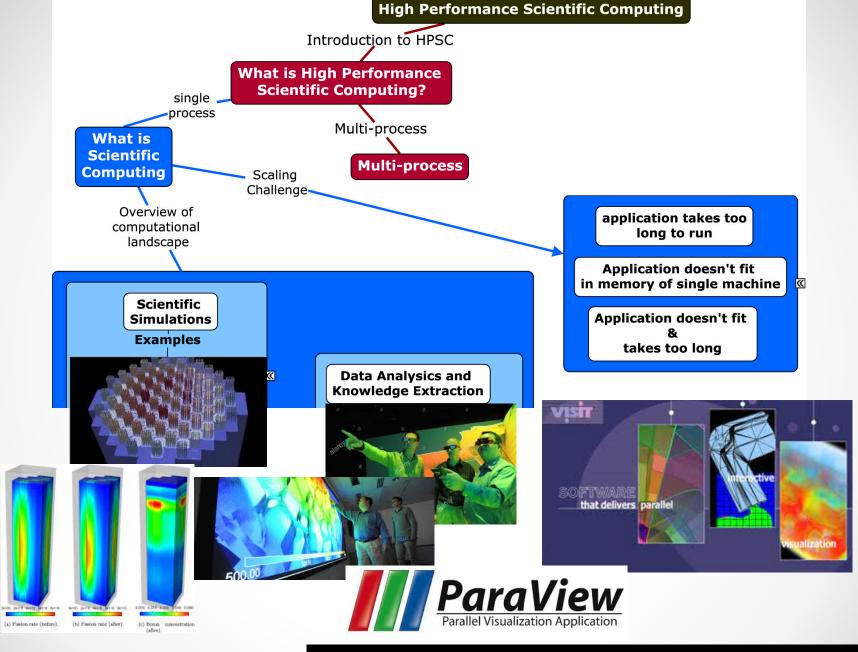
Computational science is a rapidly growing multidisciplinary field that uses advanced computing capabilities to understand and solve complex problems.

Requires advances in hardware and

software.







Partially adapted from the Lincoln Laboratory Supercomputing Center (MIT)



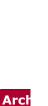


Introduction to HPSC

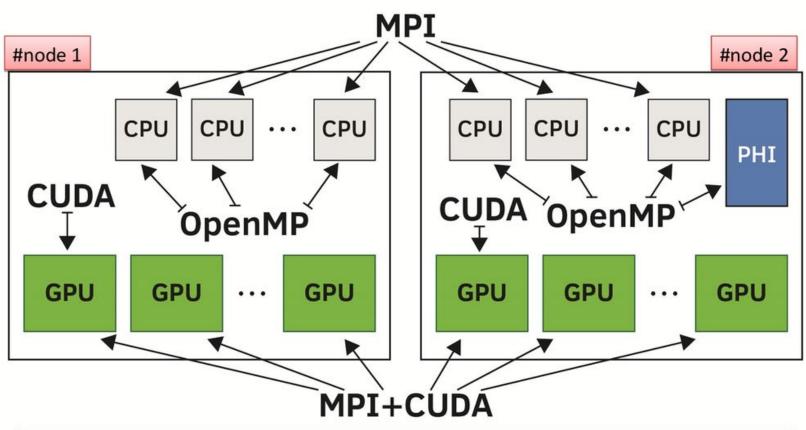
Parallel technologies: levels of parallelism





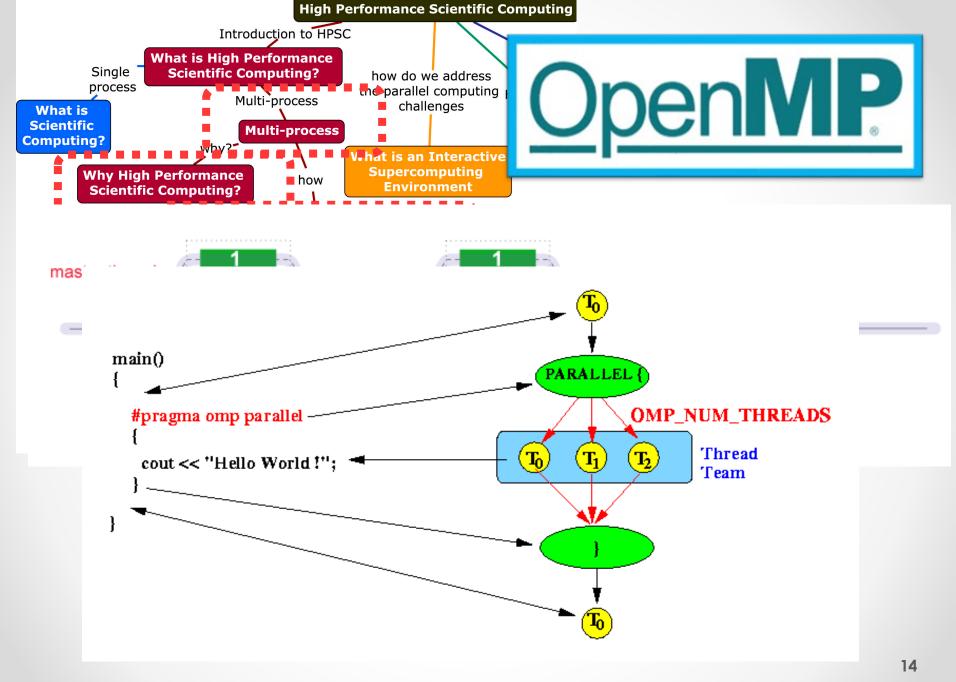


cor



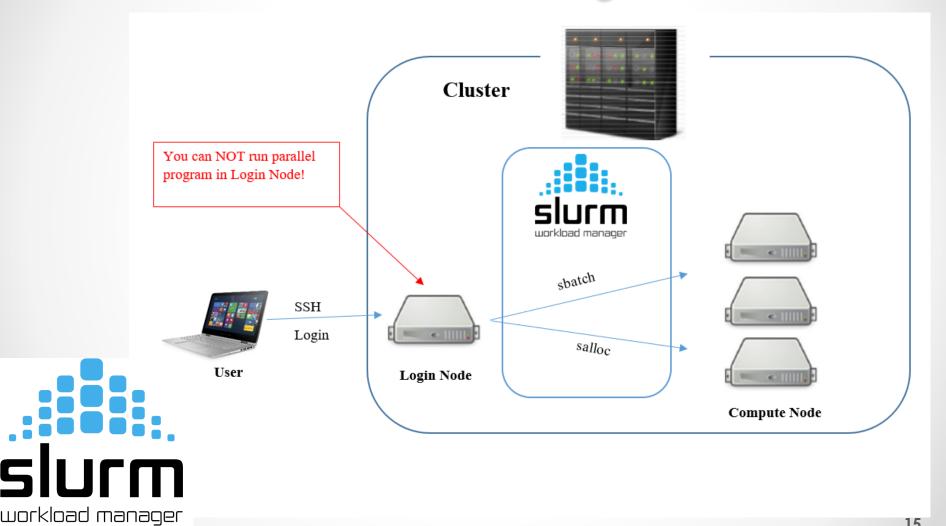


How to control hybrid hardware: MPI – OpenMP – CUDA - OpenCL ...



Interacting with a supercomputer:

Job scheduling



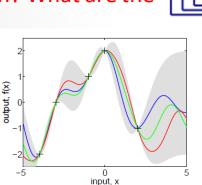
15

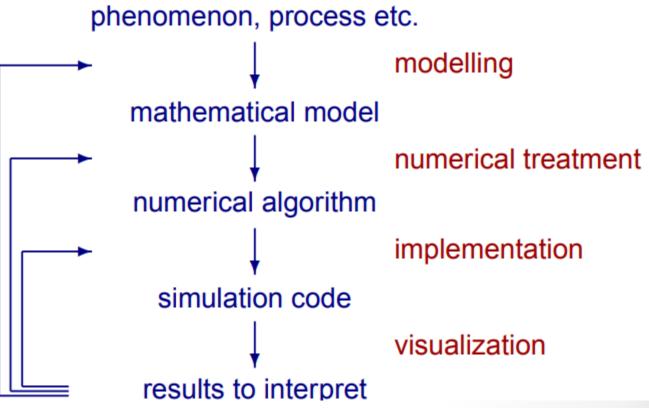
HPC for Scientific computing (SC)

Verification (Am I solving the equations correctly?)

Validation (Am I solving the correct equations?)

Uncertainty
Quantification
(What is the goal of my simulation? What are the Qol's?)





FastMath: Frameworks, Algorithms and Scalable Technologies for Mathematics





Portable, Extensible Toolkit for Scientific Computation

Toolkit for Advanced Optimization

PETSc								
	Matrices							
Vectors	Compressed Blocked Com Sparse Row Sparse Ro (AIJ) (BAIJ)		ssed Block Diagonal (BDIAG)	Dense	Others			
Linear Solvers								
GMRES CG CGS BiCGSTAB TFQMR Richardson Chebychev Others								
Preconditioners								
Additiv Schwart			ILU	ICC	Others			
Non-linear Solvers Time Steppers								
Line Search	Trusted Regi	on Others	Euler Backw Eule		Others			



Example-1: Computational fluid dynamics



Nuclear Energy

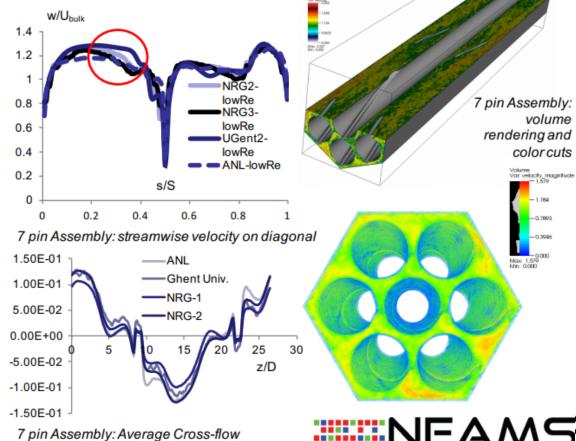
User case: Using higherresolution approaches to inform lower-resolution methods - 1

For complex geometries CFDgrade data is often not available.

 RANS approaches can benefit from comparison with DNS/LES

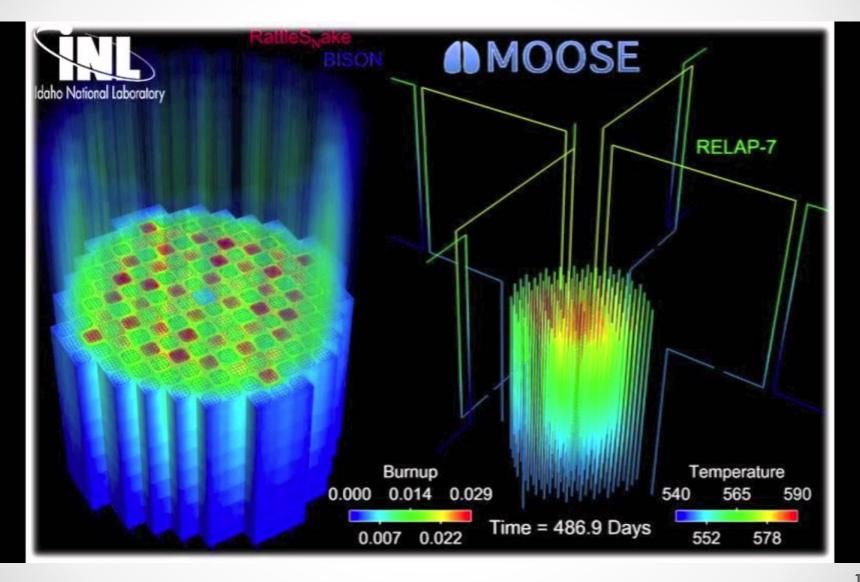
International collaboration (INERI) centered on wirewrappers.

- Comparison between commercial codes and Nek5000
- Results are being used in the design of advanced reactors in Europe



[SFR]

Example-2: MOOSE, a Multiphysics HPC platform

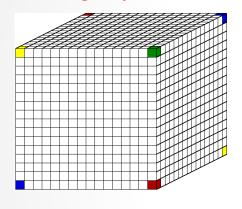


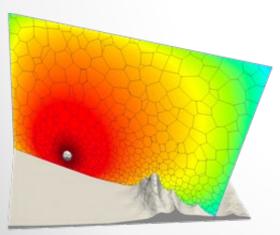
Example-3: Massively parallel radiation transport

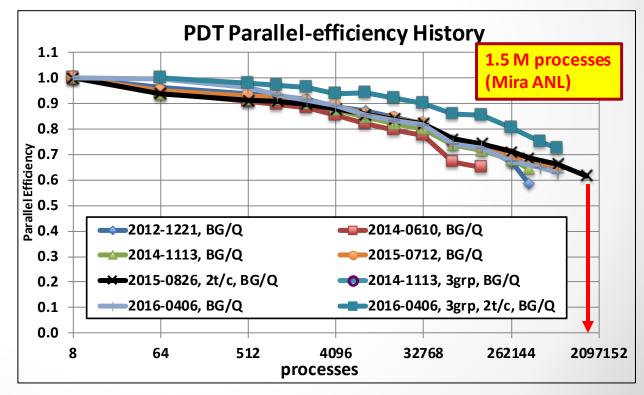
- neutron, thermal radiation, gamma, electron
- steady-state, time-dependent, criticality, adjoint, etc.
- advanced solution techniques
- discretization in space/angle/energy
 - Largest problem we have done: 20.8 Trillion unknowns



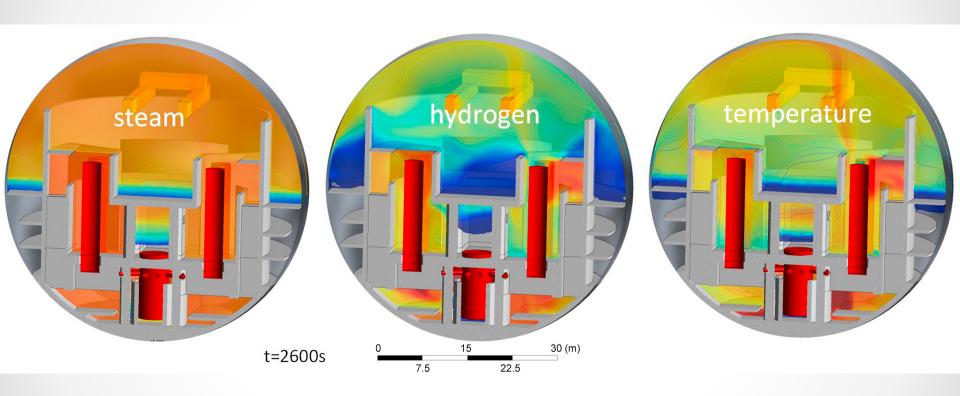








Example-4: Reactor containment

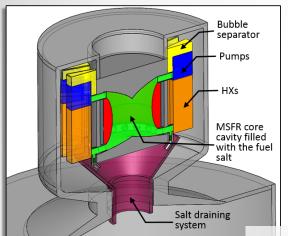


Gas distribution and pressurization inside the containment during an SB-LOCA (Julich, Germany, Kelm et al.).

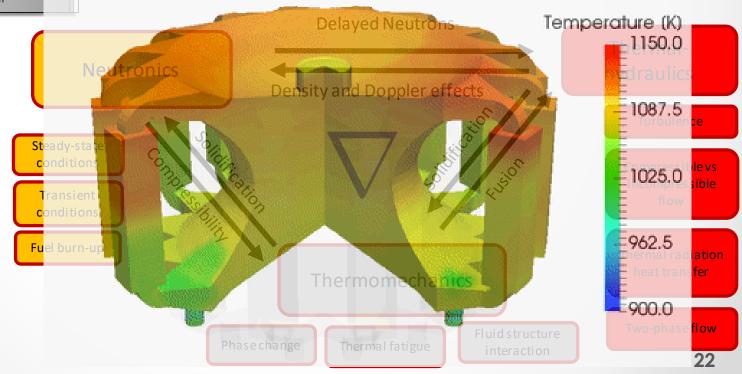
Based on OpenFOAM for CFD



Example-5: Multiphysics of molten salt reactor



Conceptual Design of the MSFR core cavity



NUCLEAR ENGINEERING TEXAS A&M UNIVERSITY

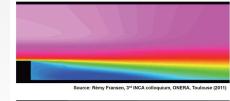
(CNRS, Tano)

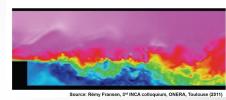
Outline

- Brief (picturesque) bio
- High-performance computing (HPC)
 - Some history
 - Some well-recognized software used in nuclear engineering
 - A few application examples
- Data sciences with HPC
 - Motivations (multi-query problems)
 - Data-driven model-order reduction
 - Application to multiphysics simulation of molten salt reactor
- Conclusions and Outlook

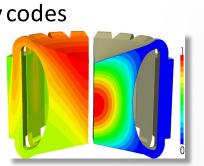
What is SC/HPC for?

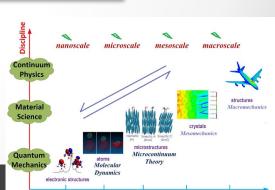
- Increase insight and understanding of physical phenomena
 - DNS > LES > RANS > lumped-parameter TH
- Provide layers in a <u>hierarchy</u> of increasingly complex models
 - O Are we capturing the right physics?
 - First-principle simulations to ascertain the range of applicability of (cheaper) low-order models
 - New designs/configurations not handled by legacy codes
- Scaling bridging:
 - Material science <-> continuum FEM
 - NSF's Material Genome Initiative (MGI)
- Experimental design
 - o simulation-informed experiments
- Sometimes, too costly/dangerous experiments:
 - Accidents (core meltdown), disasters, NW, ...





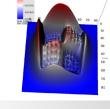








What is SC/HPC not for?



- Pretty pictures (the "viewgraph" norm = useless simulations).
- More demanding, complex simulations that do NOT increase your ability to predict the outcome (the quantities of interest)

increased accuracy in prediction resources spent (\$)

- Kord Smith (ANS M&C 2003)
 - PWRs: 3D reaction rates 3% pin power, axially integrated power: 1%
 - +/-10 ppm critical boron at start-up = "close to perfect"
- Uncertainties in some physics (e.g., XS evaluations, fuel thermo-mechanics, TH, ...) may overwhelm the accuracy of a solver for instance.

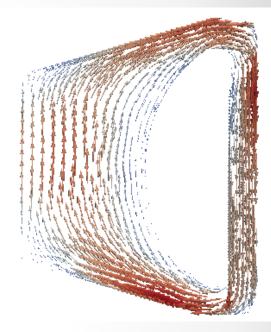
How about a much quicker turnaround for quality

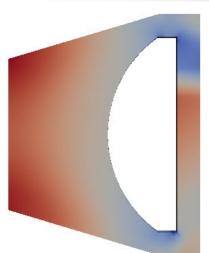
design calculations?

- High-dimensional (high-order/first-principles) models:
 - Generate a wealth of data
 - Require high-end HPC platforms
 - May need to be repeated for every change in the input parameter space.
- Multi-query HPC problems (repeated calculations with changes in the input) can become expensive
 - Design optimization
 - Uncertainty quantification
- Data Sciences:

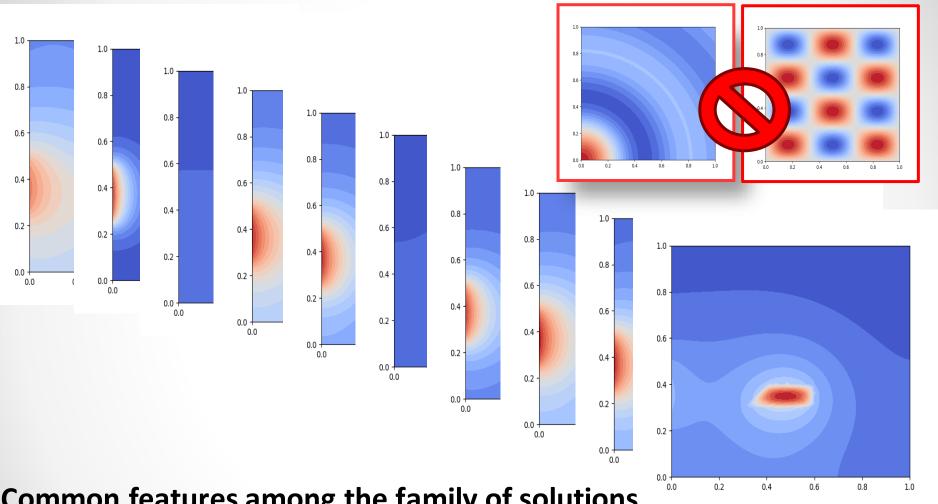
Learn from HPC simulations to predict new cheap HPC-quality simulations

→ Think data assimilation ("image/video compression")





Many simulations with parametric variations



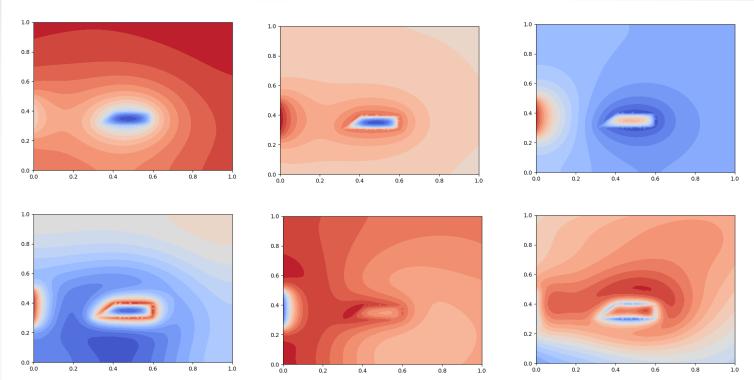
Common features among the family of solutions

Can we learn from that? → data-driven subspace discovery

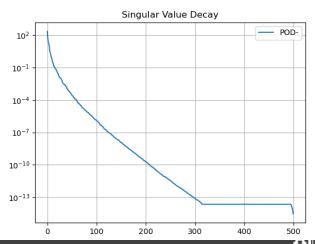




Discovered subspace from learned data



- Obtained via Singular Value Decomposition of the snapshots (learned data)
- Reduction comes from the low number of modes needed



Model Order Reduction: to reduce the computational complexity

Definition

- Model order reduction (MOR) is a set of techniques aimed at reducing the computational complexity of mathematical models in numerical simulations.
- Description of reality (model) + problem input data $(in) \longrightarrow PDEs \longrightarrow discretization \longrightarrow large-scale model with a large number of unknowns (degrees of freedom, DoFs) <math>N$.

Full Order Model (FOM): Solve
$$\dot{x} = f(x(t), in(t))$$
 with $x \in \mathbf{R}^N$

ullet Model order reduction aims at lowering the computational complexity of such problems by reducing the # of DoFs $(r \ll N)$

Reduced Order Model (ROM): Solve
$$\dot{c} = f_r(c(t), in(t))$$
 $c \in \mathbf{R}^r$ with $r \ll N$

such that

$$||x - Uc|| \le C_r ||in||$$
 with $\lim_{r \to N} C_r = 0$

U: reconstruction operator.

Key points:

• Full Order Model (FOM)

 $x \in \mathbf{R}^N$

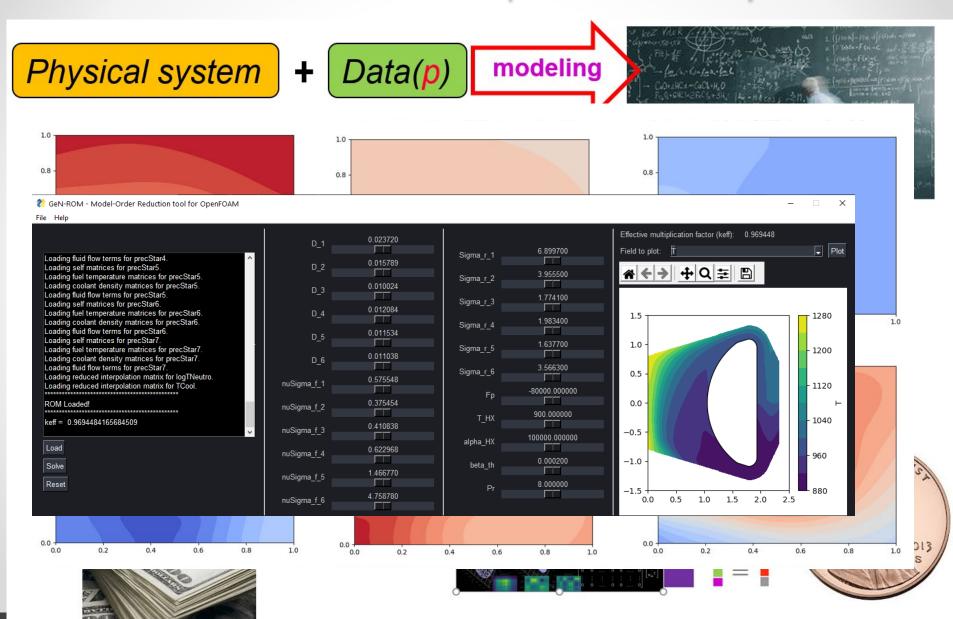
Reduced Order Model (ROM)

 $c \in \mathbf{R}^r$ with $r \ll N$

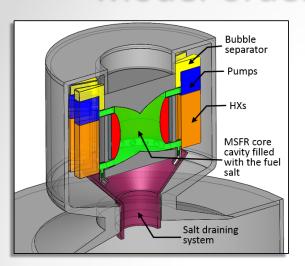
• Reconstruction: $x \approx Uc$ where U (size $N \times r$) is a data-driven discovered basis.

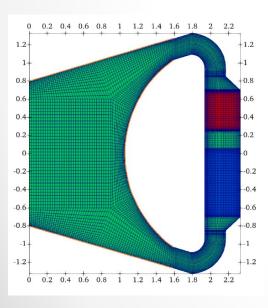
Need to determine the expansion coefficients c (as functions of the input parameters)

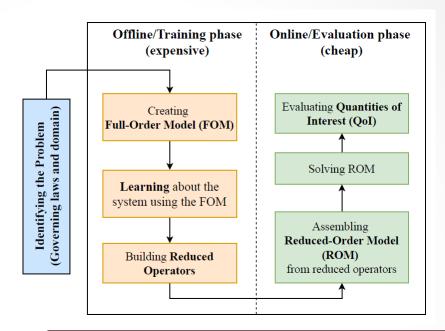
Data-driven sub-space discovery



Model-order reduction for advanced reactors







The reduced equation system

$$\rho \mathbf{M} \dot{\mathbf{c}}^{u_D} + \rho \mathbf{c}^{u_D, T} \underline{\underline{C}} \mathbf{c}^{u_D} - \mathbf{c}^{\eta, T} \underline{\underline{T}} \mathbf{c}^{u_D} - \eta \mathbf{D} \mathbf{c}^{u_D} + \mathbf{P} \mathbf{c}^{\rho} + \Gamma (\mathbf{B} \mathbf{c}^{u_D} - |\mathbf{u}_{D,in}| \mathbf{S}_r^{BD})$$

$$- \sum_{z=1}^{Z} \left(|\mathbf{F}_{p,z}| \mathbf{S}_{p,z} - \mathbf{S}_{fr,z} \mathbf{c}_{\mathbf{z}}^{\mathbf{F}_{fr}} \right) - \rho \beta_e (\mathbf{A} \mathbf{c}^T - T_{ref} \mathbf{S}_T) = 0, \quad (16)$$

$$\rho \mathbf{G} \mathbf{c}^{u_D} = 0 \quad (17)$$

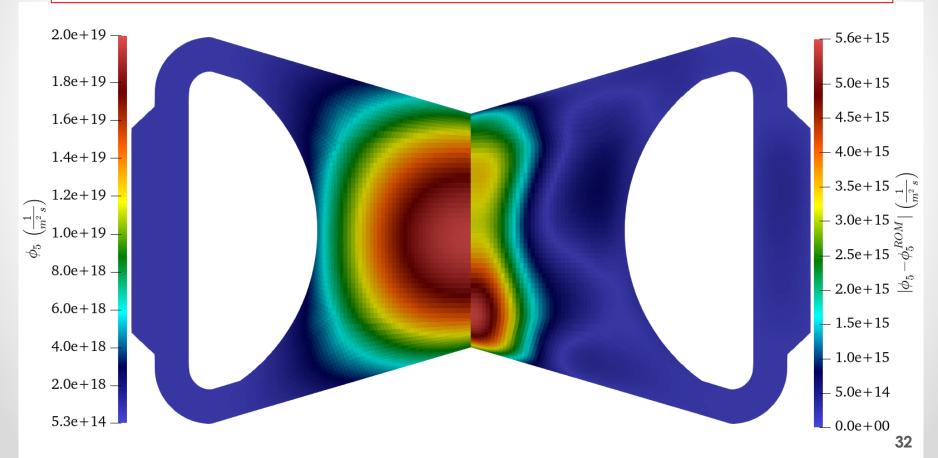
Some of the reduced operators

$$\begin{aligned} \boldsymbol{M}_{i,j} &= \left\langle \psi_{i}^{\boldsymbol{u}_{D}}, \psi_{j}^{\boldsymbol{u}_{D}} \right\rangle_{\mathcal{D}} & \underline{\underline{\underline{C}}}_{i,j,k} &= \left\langle \psi_{j}^{\boldsymbol{u}_{D}}, \frac{1}{\gamma} \nabla \cdot \left(\psi_{i}^{\boldsymbol{u}_{D}} \otimes \psi_{k}^{\boldsymbol{u}_{D}} \right) \right\rangle_{\mathcal{D}} \\ \boldsymbol{D}_{i,j} &= \left\langle \psi_{i}^{\boldsymbol{u}_{D}}, \nabla \cdot \left[\nabla \psi_{j}^{\boldsymbol{u}_{D}} + (\nabla \psi_{j}^{\boldsymbol{u}_{D}})^{\mathsf{T}} \right] \right\rangle_{\mathcal{D}} & \boldsymbol{P}_{i,j} &= \left\langle \psi_{i}^{\boldsymbol{u}_{D}}, \gamma \nabla \psi_{j}^{\boldsymbol{p}} \right\rangle_{\mathcal{D}} \\ \boldsymbol{B}_{i,j} &= \left\langle \psi_{i}^{\boldsymbol{u}_{D}}, \psi_{j}^{\boldsymbol{u}_{D}} \right\rangle_{\Gamma_{in}} & \boldsymbol{S}_{\boldsymbol{p},\boldsymbol{z},i} &= \left\langle \psi_{i}^{\boldsymbol{u}_{D}}, \gamma \frac{\delta_{\boldsymbol{z}}(\boldsymbol{r}) \boldsymbol{F}_{\boldsymbol{p},\boldsymbol{z}}}{|\boldsymbol{F}_{\boldsymbol{p},\boldsymbol{z}}|} \right\rangle_{\mathcal{D}} \\ \boldsymbol{S}_{r,i}^{BD} &= \left\langle \psi_{i}^{\boldsymbol{u}_{D}}, \frac{\boldsymbol{u}_{in}}{|\boldsymbol{u}_{in}|} \right\rangle_{\Gamma_{in}} & \boldsymbol{G}_{i,j} &= \left\langle \psi_{i}^{\boldsymbol{p}}, \nabla \cdot \psi_{j}^{\boldsymbol{u}_{D}} \right\rangle_{\mathcal{D}} \end{aligned}$$

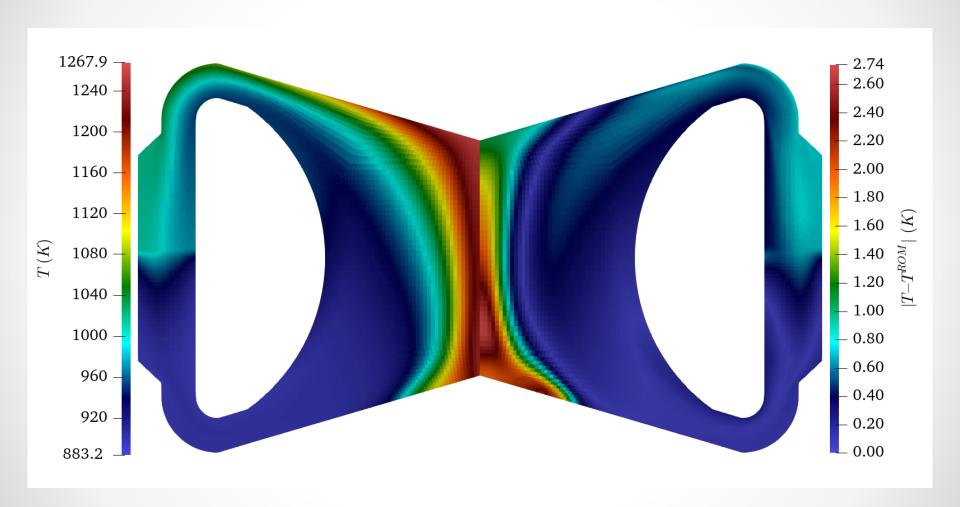
Reconstructed Flux (left) - Reconstruction Error (right)

Uncertain parameters (23 total):

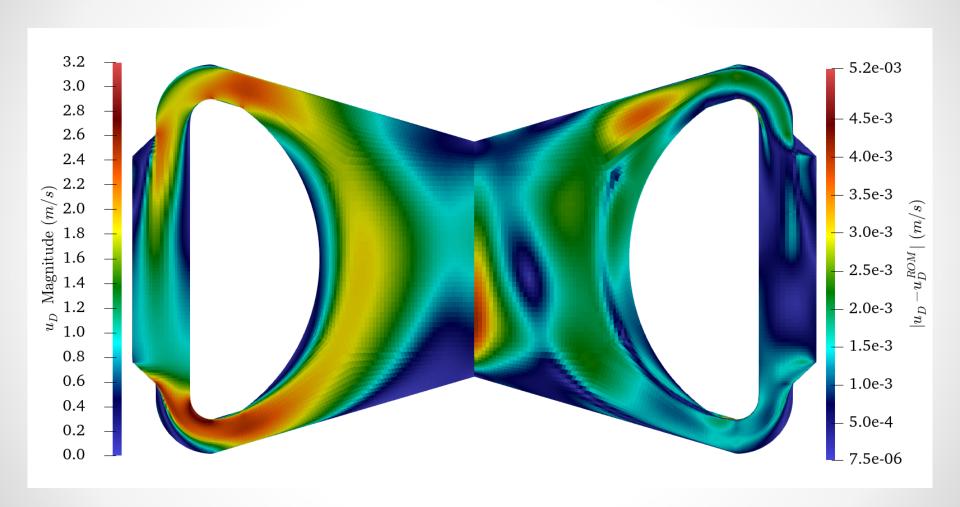
- \bullet Diffusion coefficients, fission and removal cross sections (\pm 10% around the nominal values)
- Pumping force, external coolant temperature, Heat transfer coefficient,
 Pr-number, thermal expansion coefficient



Reconstr. Temperature (left) – Reconstr. Error (right)

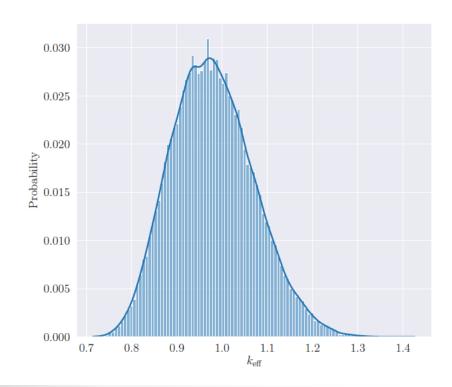


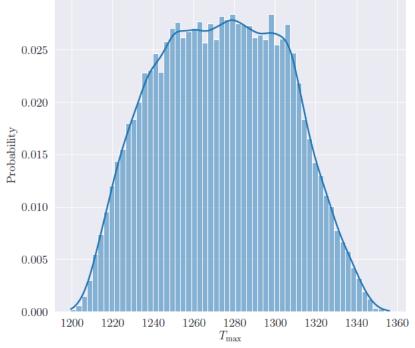
Reconst. Velocity (left) - Reconstruction Error (right)



Model-order Reduction: huge speed ups

- Quantities of interest:
 - Effective multiplication factor (k_{eff})
 - Maximum temperature of the system (T_{max})
- Propagation of uncertainties: Monte Carlo approach with 50,000 samples
- Speedup in the UQ including training: approximately factor of 1,500







35

Graphical User Interface Demo



Conclusions and EOF



- Intro to HPC for scientific computing in nuclear engineering and sciences
- Focus SC/HPC efforts where gains are visible/tangible
- Emphasize Predictive Science (VVUQ) and whether the simulation efforts will have an impact?
- Seek certifiable reduced-order models for quick design cycle
 - Borrow from machine-learning and big-data science.

