

# NCSA Industry Overview with Computational Breakthroughs and Synergies with Artificial Intelligence

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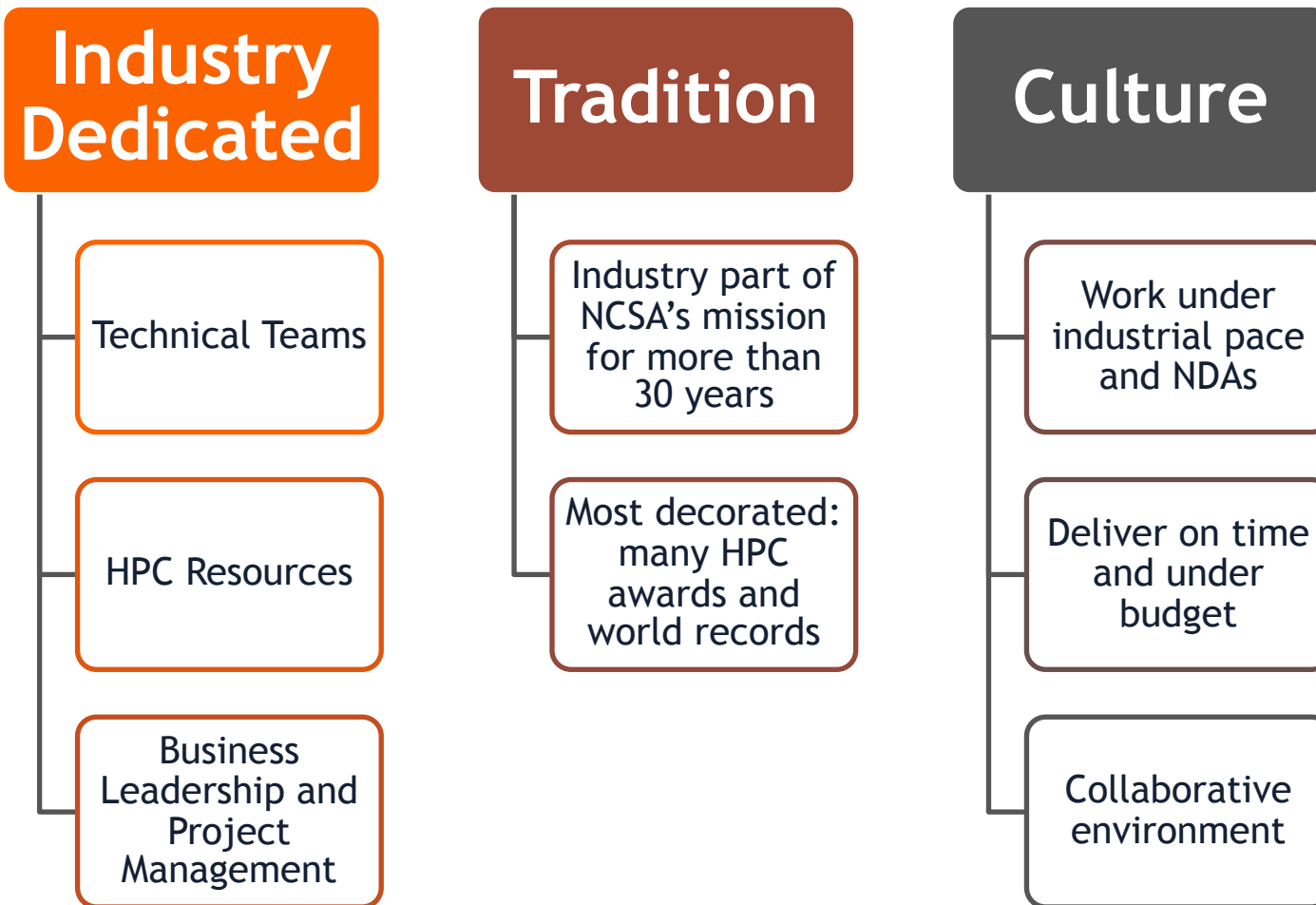
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Supercomputing Applications**

UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

# With NCSA: Six Months Ahead of Competition



Largest and Oldest Industrial HPC Program in the World



# Industry Partners – 1 of 3





# Industry Partners – 2 of 3





# Industry Partners – 3 of 3



**Barcelona  
Supercomputing  
Center**  
Centro Nacional  
de Supercomputación



The Digital Manufacturing Institute



# Legacy Partners



# History

1986 – Program founded with first industry partner, Eastman Kodak

1992 – First Grand Challenge Award: Eli Lilly

1993 – Caterpillar joins, wins Grand Challenge Award

2004 – Boeing recognized with Grand Challenge Award

2011 – iForge industrial cluster becomes available

2014 and 2017 – Winner of HPCwireTop Supercomputing Achievement

2017 – ExxonMobil sets sector world record

- Oil reservoir model: 3 months to 10 minutes, 719000 cores, \$1B+ ROI

2020 – Majority of Industrial engagement becomes AI-oriented





# Engagement Model: Current Partners

## Discover

Initial meetings  
Identify needs  
Define scope  
Set timelines  
Define budget  
Create work plan

## Build

Design solutions  
Develop  
Test  
Loop as  
necessary

## Deliver

Implement  
Interview  
stakeholders  
Evaluate  
effectiveness  
Calculate ROI

# Engagement Model: Prospective Partners

- Identify **challenges for companies** that match team skills



- Be **consultative**: listen to needs and challenges
- **Match needs with specific skills** within team or with strategic partners
- Define **value** proposition: what company gets from engagement

# NCSA Industry Technical Team Expertise

Modeling and Simulation

Bioinformatics and Genomics

“Big” Data Analytics, GIS, and AI

Code Profiling and Optimization

Rapid User Support and Domain/HPC Training

Cyberinfrastructure and Security

Visualization

Much more at NCSA and the University of Illinois





# National Petascale Computing Facility

## World-Class Data Center

- Dept. of Energy-like security
- 88000 sqft
- 25 MW of power; LEED Gold
- 400+ Gb/sec bandwidth

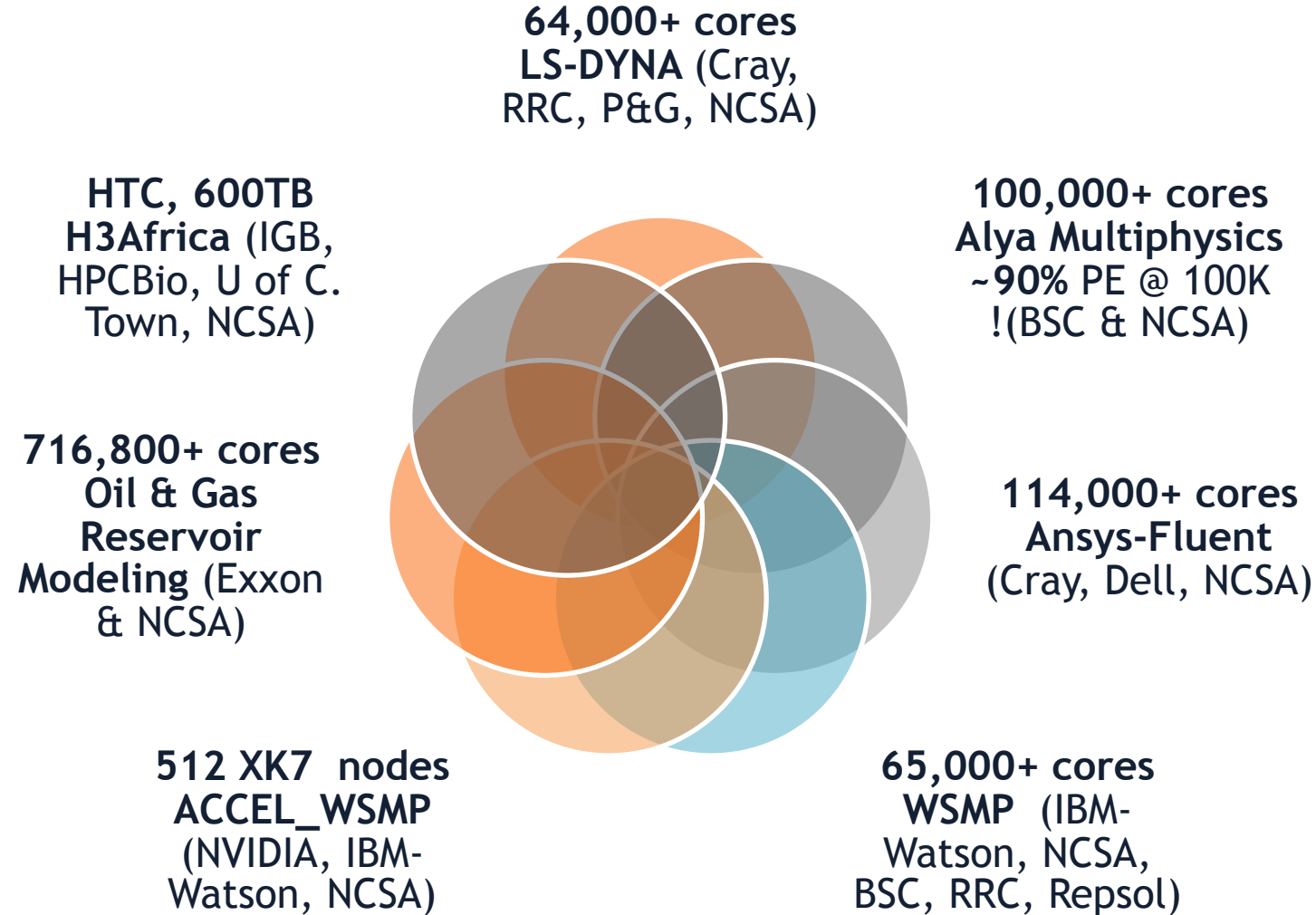
## Hosting Benefits to Industry

- Low-cost power & cooling
- 24/7/365 Help Desk
- Adjacent to and aligned with UIUC Research Park





# Engineering Application Breakthroughs on Blue Waters 2013-2020

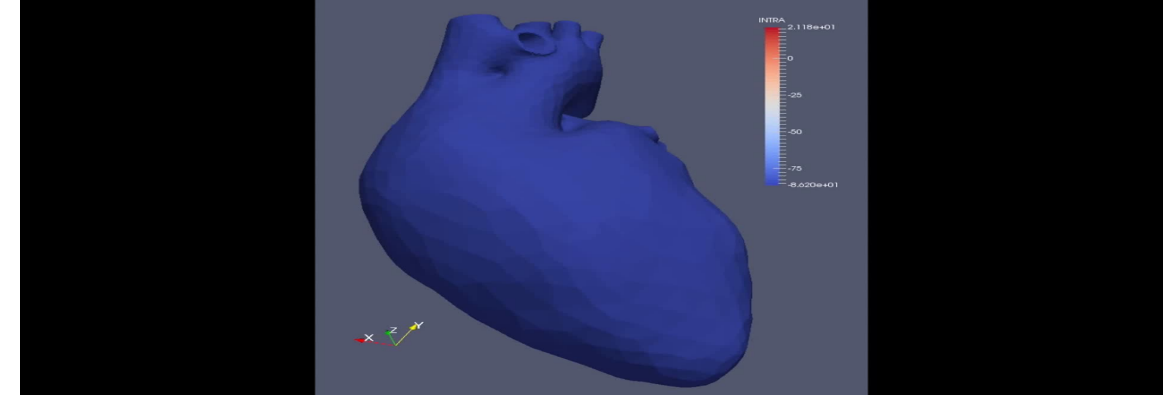




# Two Real-World Cases Solved with Alya Multiphysics Code from BSC on NCSA's Blue Waters

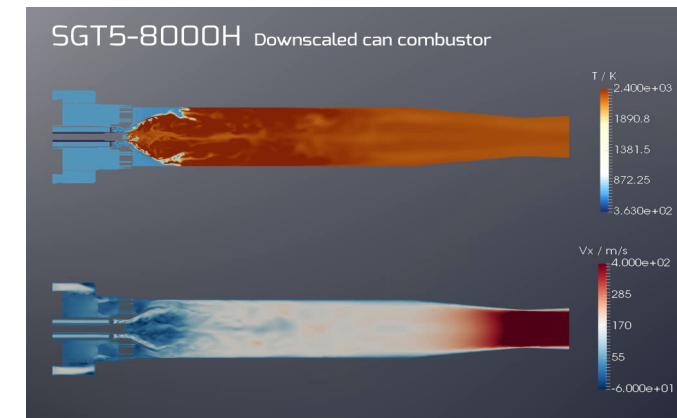
## Human Heart

Non-linear solid mechanics  
Coupled with electrical propagation  
3.4 billion elements, scaled to 100,000 cores

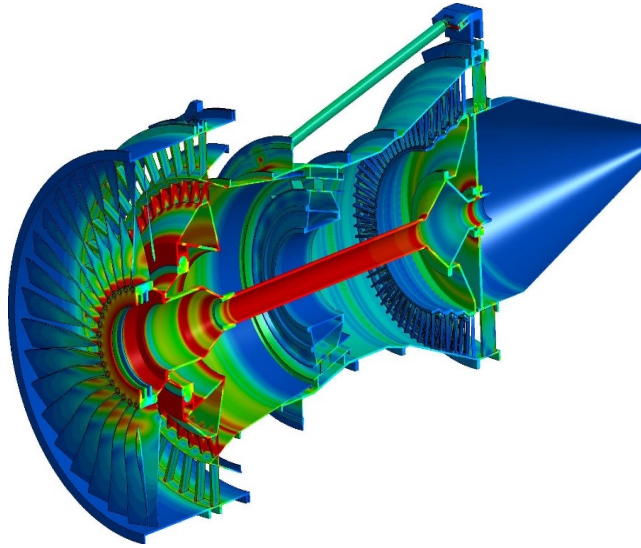


## Kiln Furnace

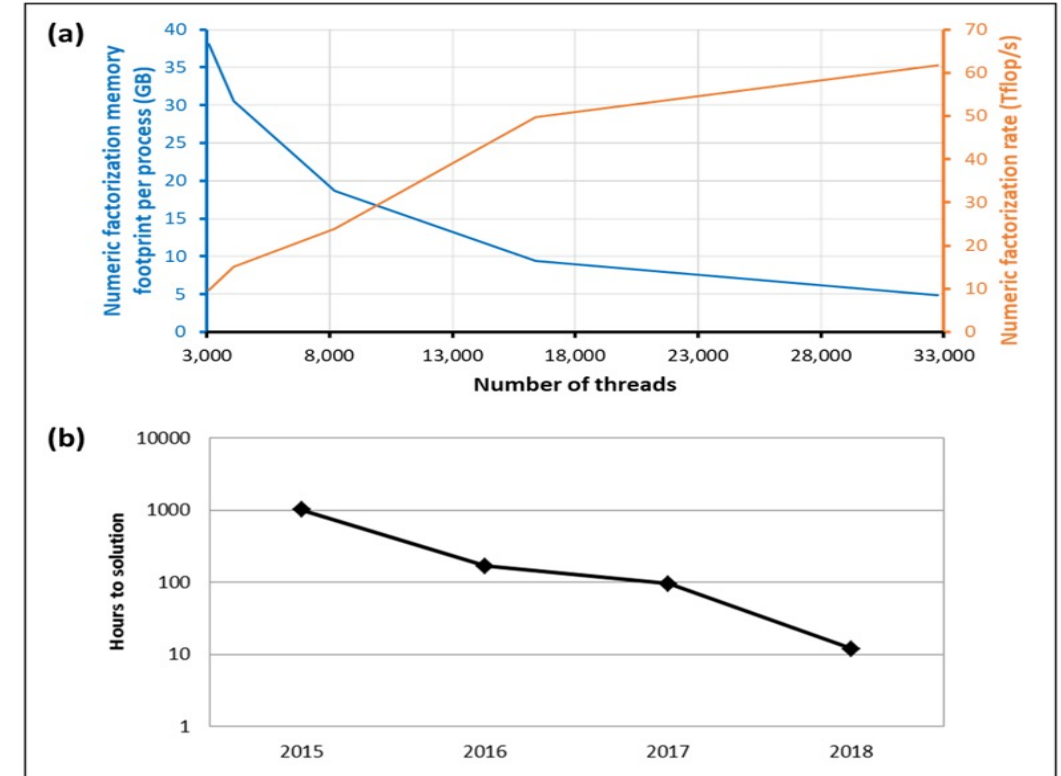
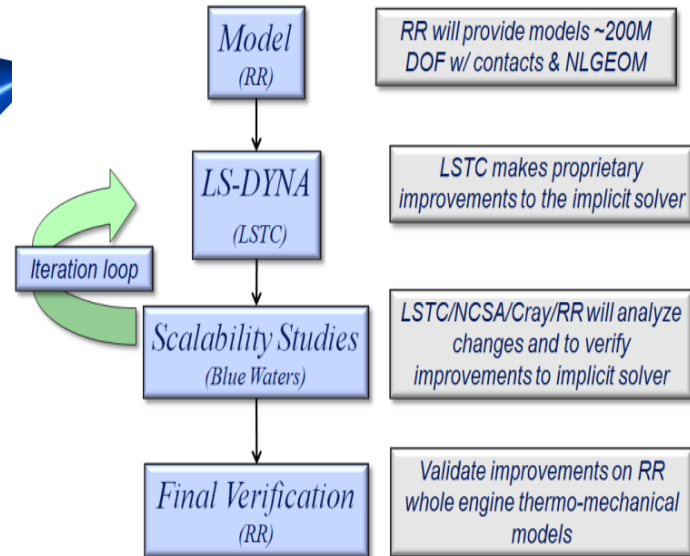
Transient incompressible turbulent flow  
Coupled with energy and combustion  
4.22 billion elements  
Scaled to 100,000 cores @90% parallel efficiency  
**17.4 years** on a serial PC down to **1.8 hours** on BW



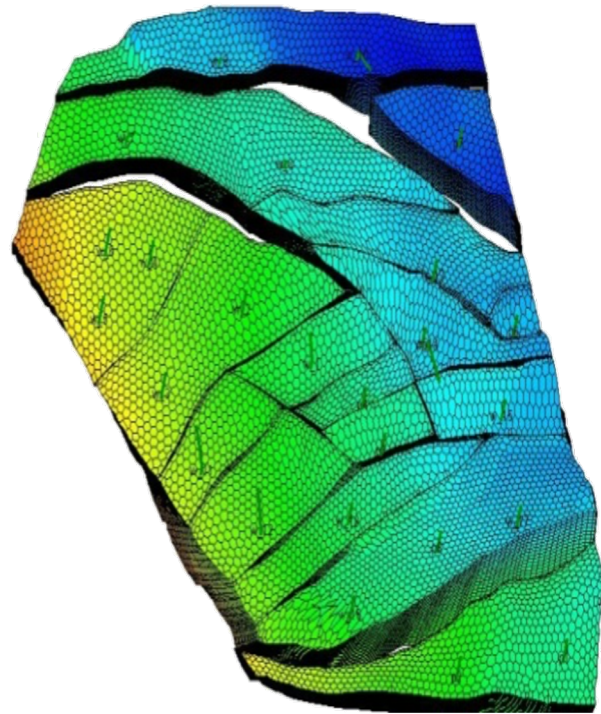
# Reducing the Time-to-Solution for High Fidelity Finite Element Analysis of Gas Turbine Engines - from Months to Hours, 2015-2018



Rolls-Royce engine model for thermo-mechanical analysis, >200M DOFs



# Massively Parallel Modeling in Oil & Gas & ROI



**ExxonMobil**

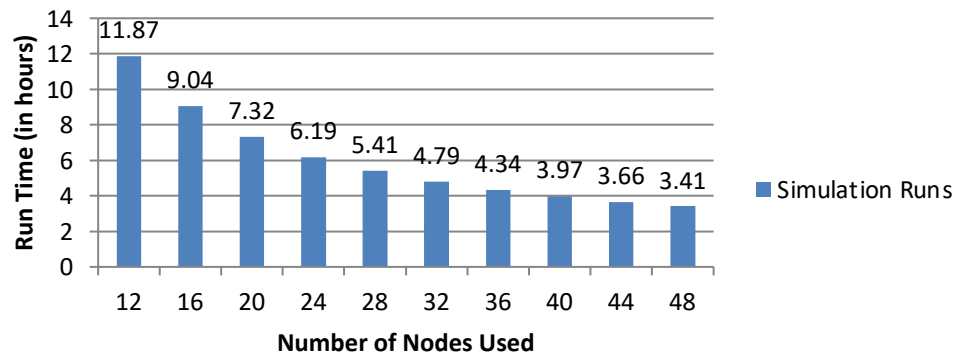
- Reservoir simulation models the complex subsurface flows of fluids in oil and natural gas reservoirs
- Previous runtime: 3.5 months on prem
- Optimized: 10 minutes on Blue Waters
- 716800 MPI processes, was the entire engineering sector world record for degree of parallelism
- Minimized costs and environmental impact
- ROI: USD\$1+B



# Large Scale Statistical HPC Analysis in Agriculture



Simulation Run using Different Number of Nodes on iForge

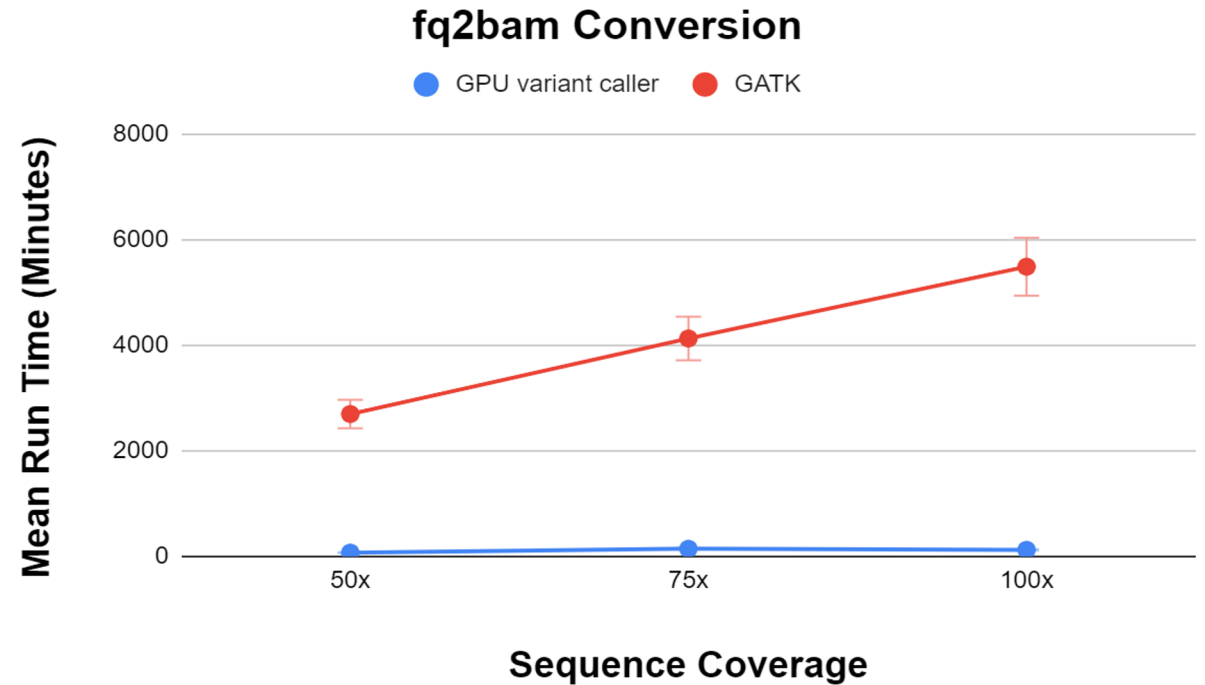


- Power statistical analysis uses massive data collected from farm field trials to allow an agriculture partner of NCSA to assess quality of their experimental designs
- NCSA has developed an efficient and scalable implementation in **R** to perform massive simulation using multi-node parallelization and variable instantiation techniques
- Our new implementation decreases the size of the program from over 50,000 lines to less than 100 lines, reduces the processing time for a simulation with over 70,000 cases from **175 days (@partner) to less than 3.5 hours) (@HPC/iForge)**

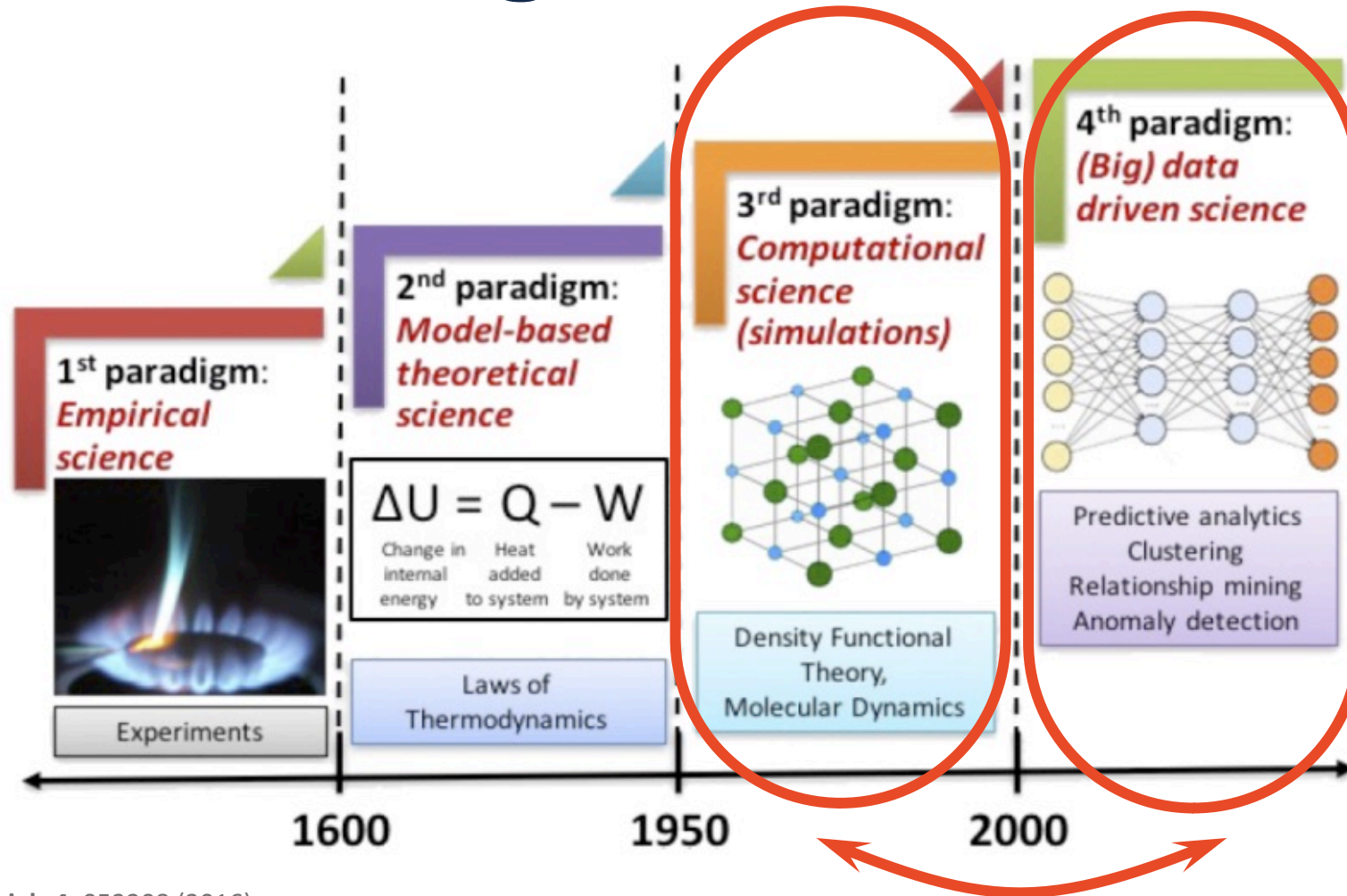
Courtesy of Dr. Dora Cai and an Industrial Partner of NCSA

# Benchmarking of new variant calling tools on GPUs

- Benchmarked a new genomic variant calling software which **runs on GPU only**
- Tested **multiple tools within the suite**, determined the speed up of this software with respect to the industry standard GATK
- Evaluated the **biological accuracy** by comparing results to GATK, the gold standard of variant calling.
- Tested the **scalability** of this software with different sizes of genomic data to determine its robustness.
- Worked with our **industry partners** to test against their variant calling tools.



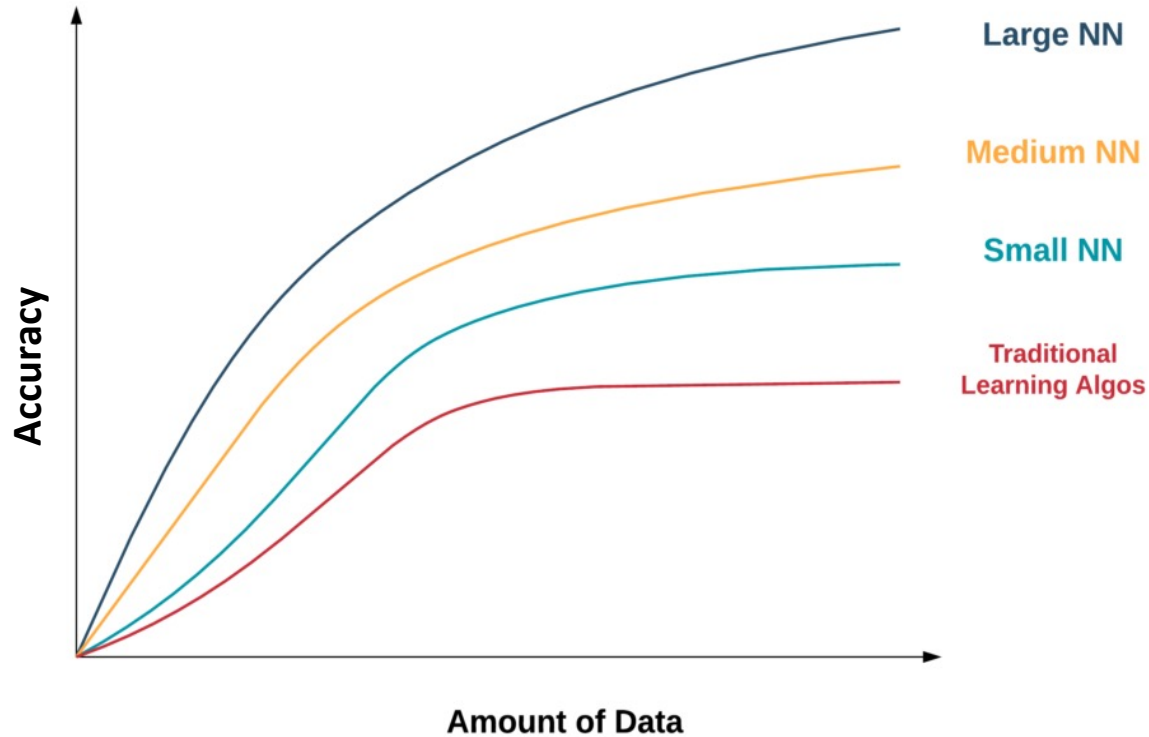
# Four Paradigms in Science and Engineering



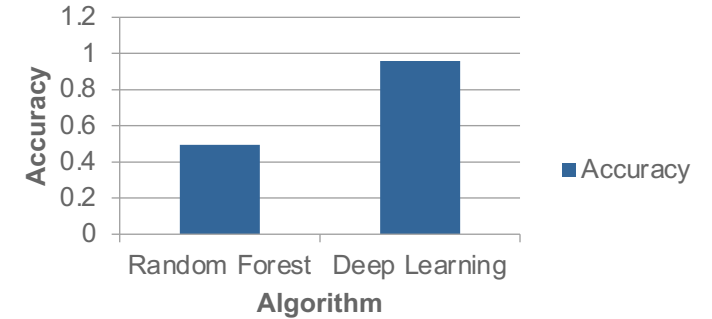
“AI is the new electricity”  
Prof. Andrew Ng, Stanford,  
Coursera founder

APL Materials 4, 053208 (2016)

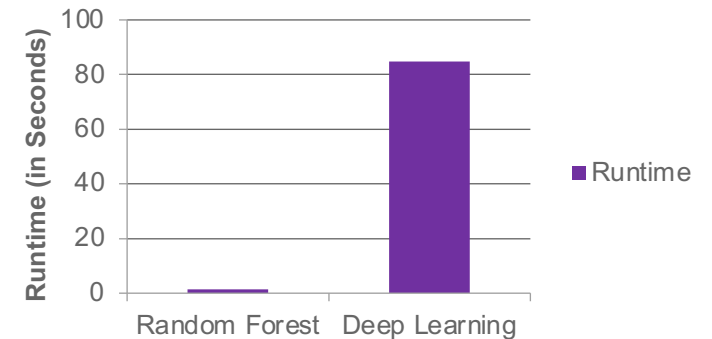
# Big Data and HPC Driven Deep Learning



## Accuracy Comparison

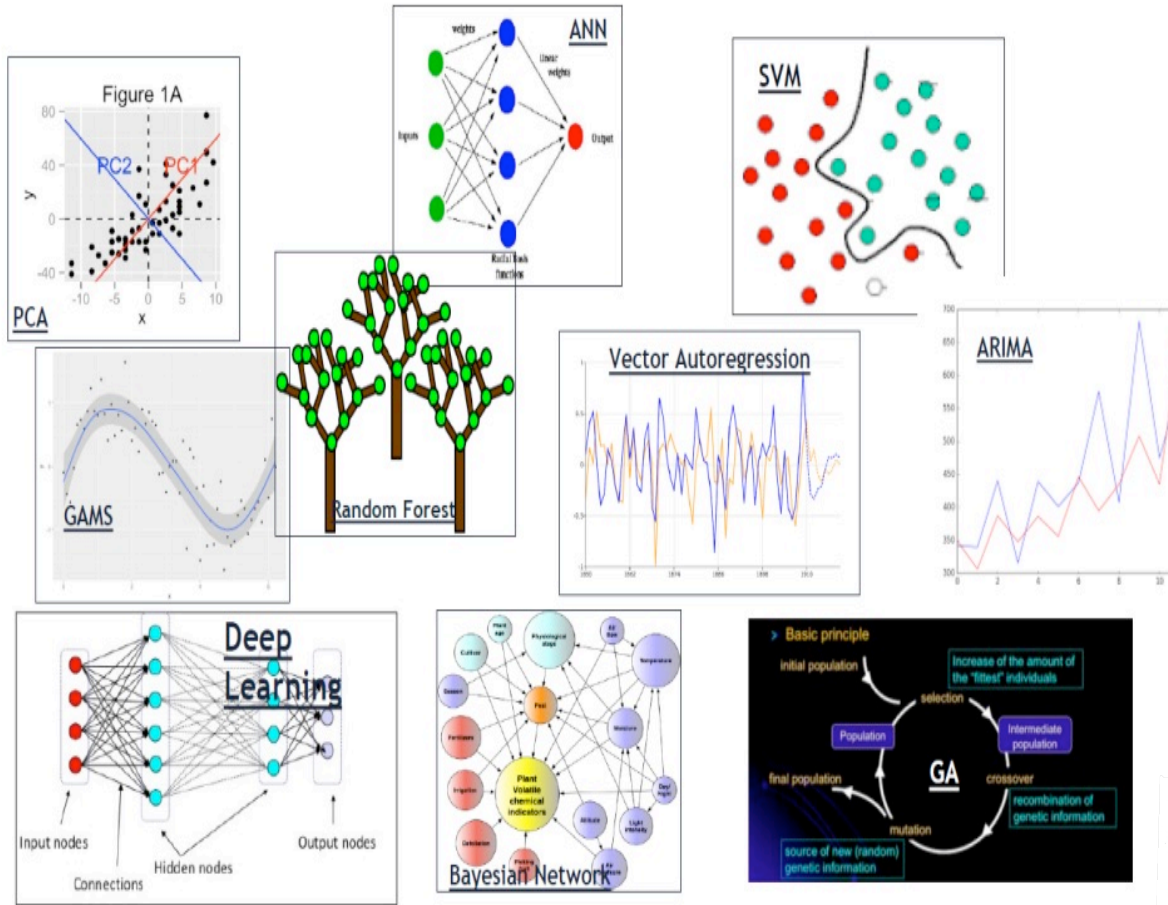


## Runtime Comparison

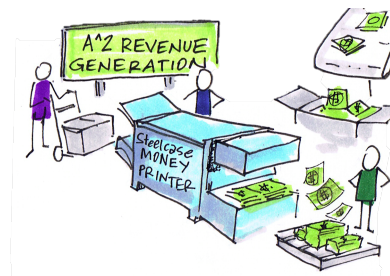




# Choosing and Applying Best Machine Learning Algorithm

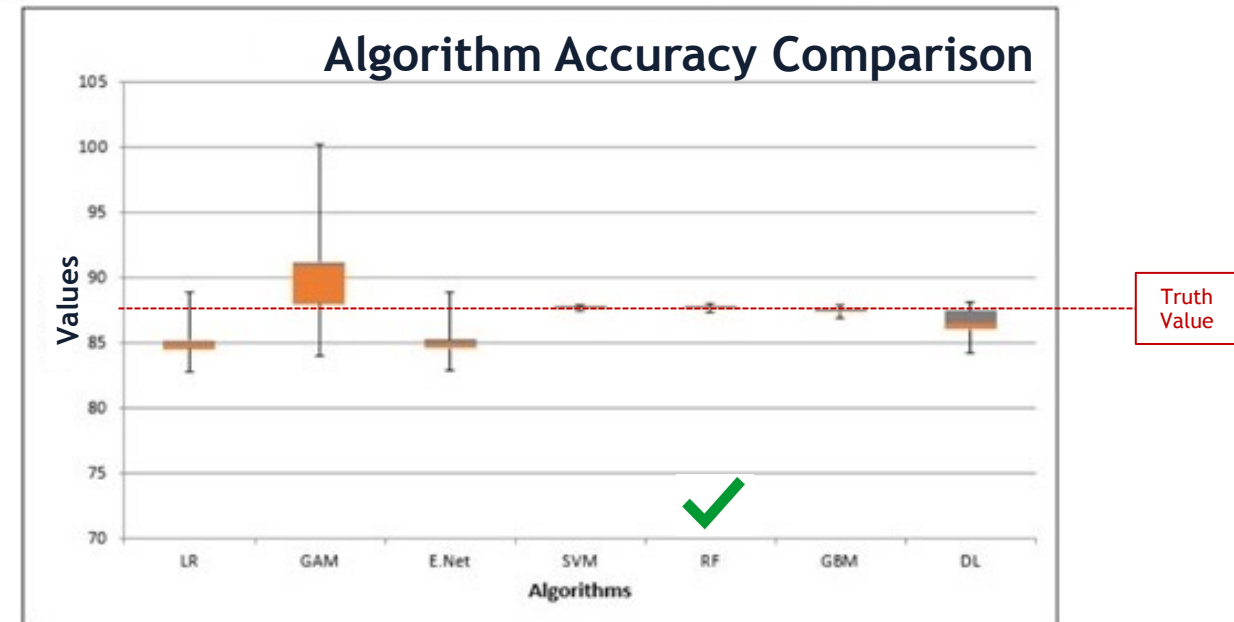
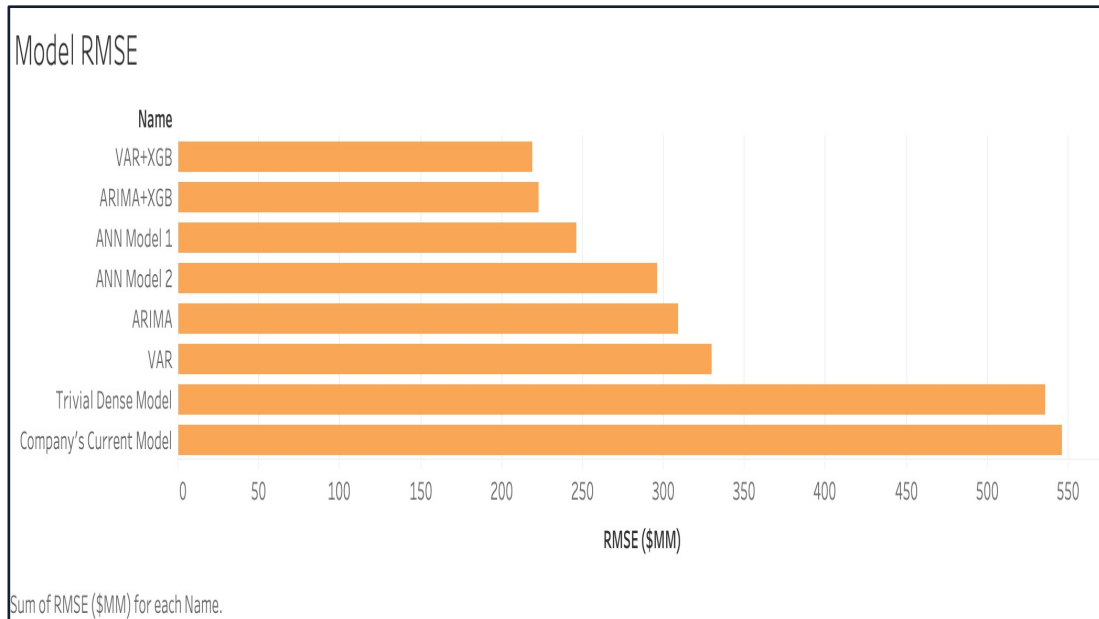


**OPTIMIZING PORTFOLIO**  
**FORECASTING DAILY ORDER LOADING**  
**PREDICTING NEW PRODUCT MARKETS**  
**FORECASTING PRICE VOLATILITY**  
**FORECASTING MULTIPLE TIME HORIZONS (DAILY, WEEKLY, MONTHLY)**  
**FORECASTING PRICE**  
**DATA MINING CUSTOMER LIFE CYCLE ESTIMATION**  
**FORECASTING SINGLE SOURCE OF TRUTH HIERARCHICAL DEMAND**  
**FORECASTING EARLY DEMAND SIGNALS**  
**PREDICTING PRICES**  
**NEW PRODUCT RISK**  
**FORECASTING STREET ESTIMATE ERROR BARS**  
**PREDICTING NEW PRODUCT MARKETS**  
**PREDICTING PRICE VOLATILITY**  
**TEXT MINING MEGA TRENDS**  
**FORECASTING ECONOMIC ACTIVITY BY MARKET AND GEOGRAPHY**  
**OPTIMIZING MARKETING CAMPAIGNS**  
**PREDICTING CUSTOMER RETENTION/ATTRACTION**  
**TEXT MINING COMPETITOR, SUPPLIER, CUSTOMER**  
**DATA MINING CUSTOMER BUYING PATTERNS**  
**MARKET TRENDS**  
**TEXT MINING**  
**PREDICTING CROSS SELLING**  
**FORECASTING SINGLE SOURCE OF TRUTH HIERARCHICAL DEMAND**  
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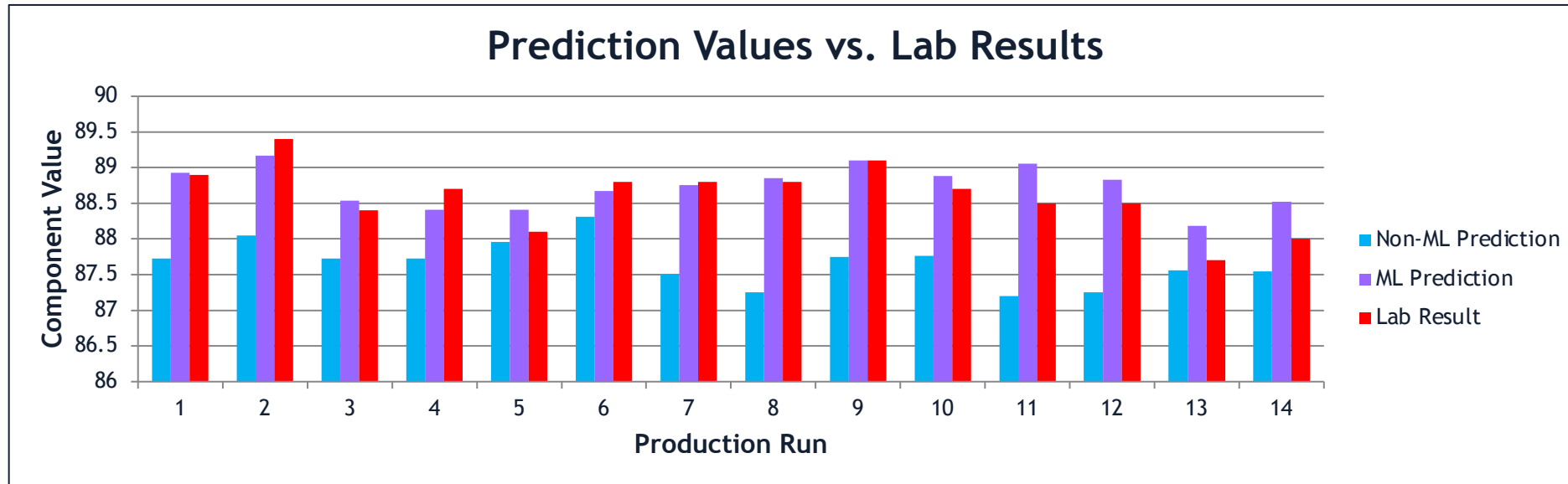


# Choosing Best Machine Learning Algorithm

- Based on Root Mean Square Errors (RMSE)
- Based on Median Values and Standard Deviation



# Reduce Production Cost using Machine Learning



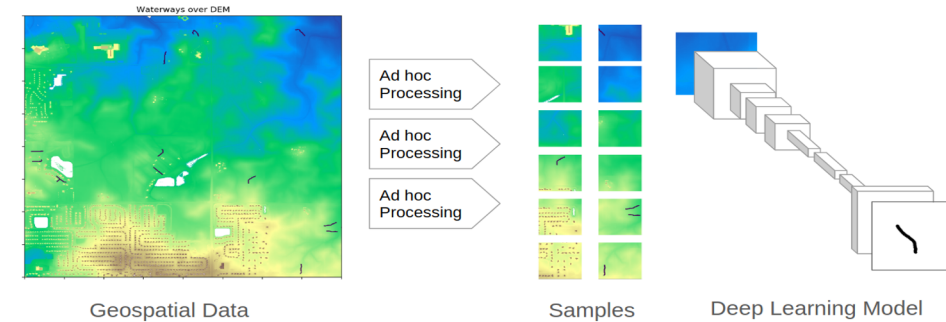
- Optimize ingredient recipes using Machine Learning predictive models
- Make the predicted values closer to the real lab test results (ground truth)
- Reduce *Mean Absolute Errors (MAE)* from 0.73 to 0.43
- ROI: **USD\$18 million annually** by reducing the production cost

# Connecting Industrial Geospatial and AI Communities

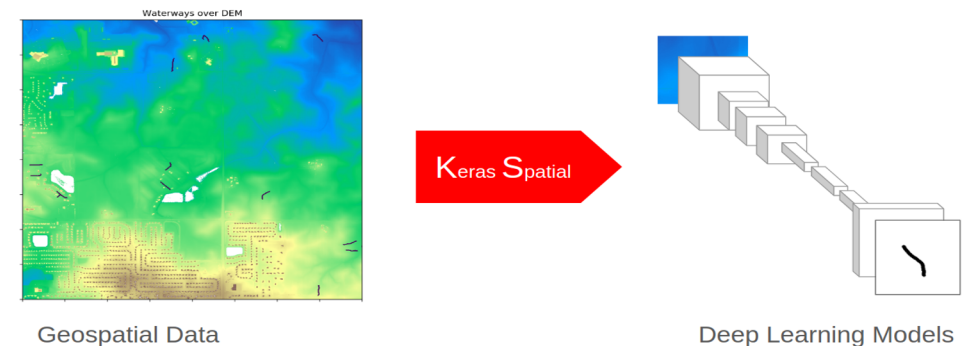
## Novel Spatial Data Generators to connect TensorFlow models with geospatial data :

- Handles geospatial data in consumable formats by AI models without worrying about their specs such as projection, resolution, etc.
- Harmonizes multiple data sources and feeds them directly to the same AI model during the training phase.
- Scales processing of archives of geospatial data during the prediction phase.

### Separate Worlds

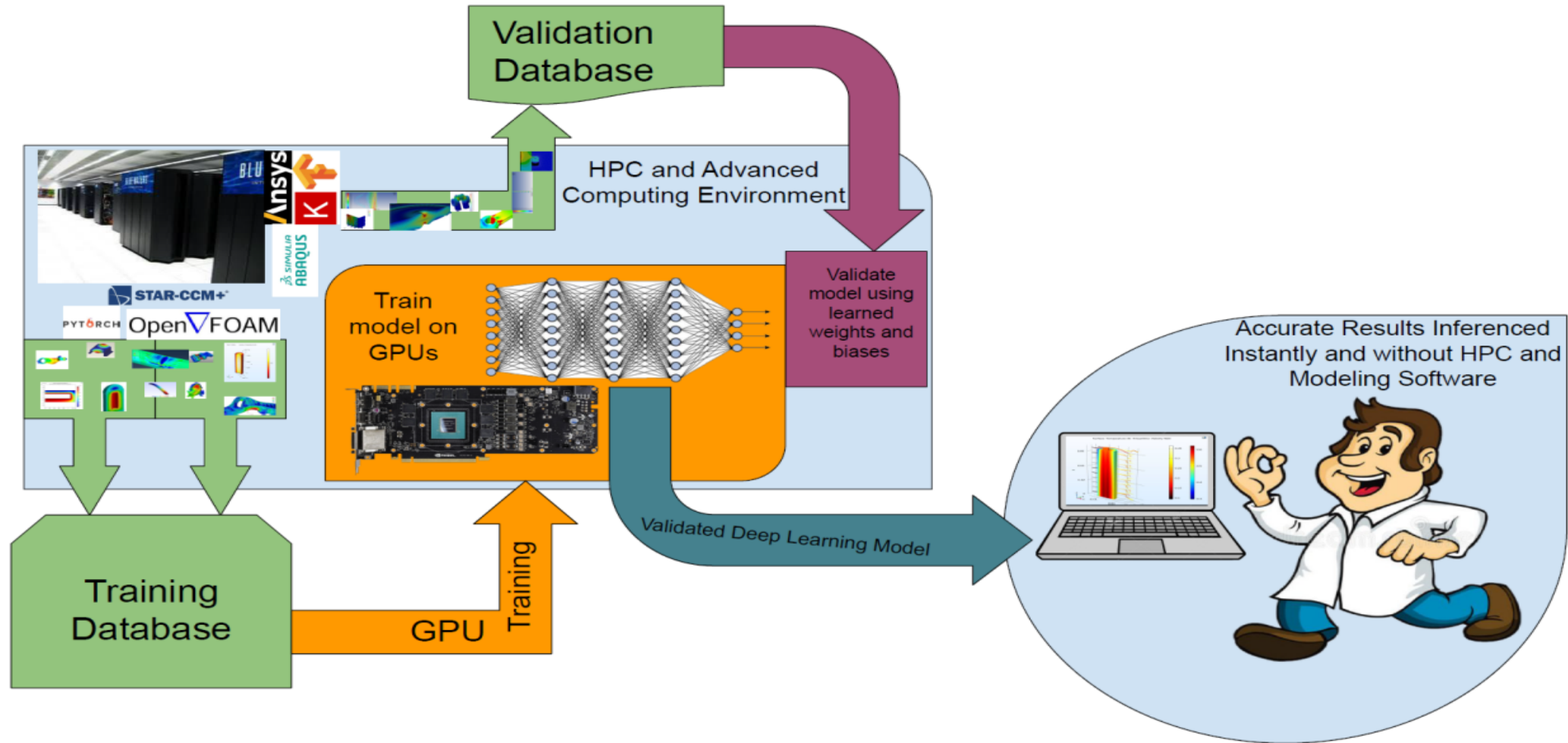


### Connecting Two Worlds

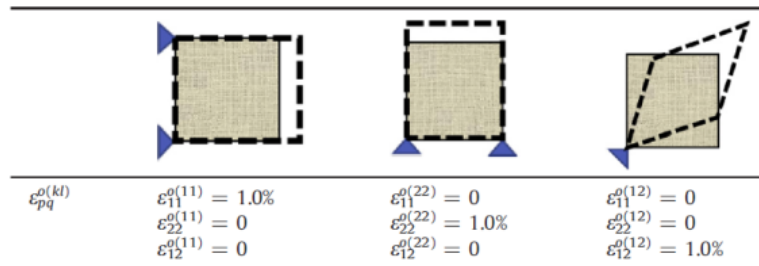




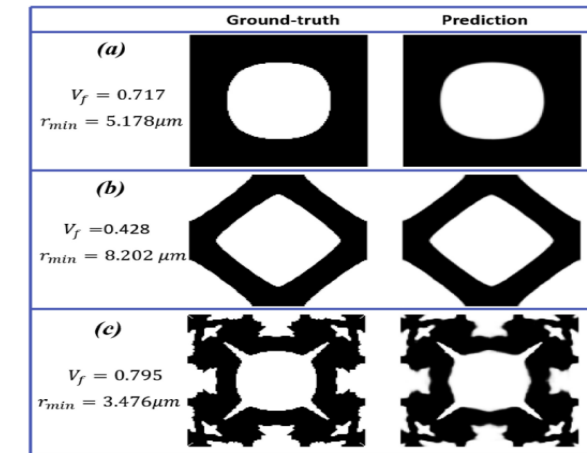
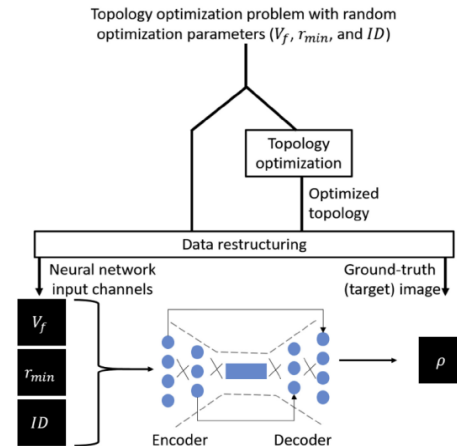
# Surrogate Data-Driven Deep Learning Model



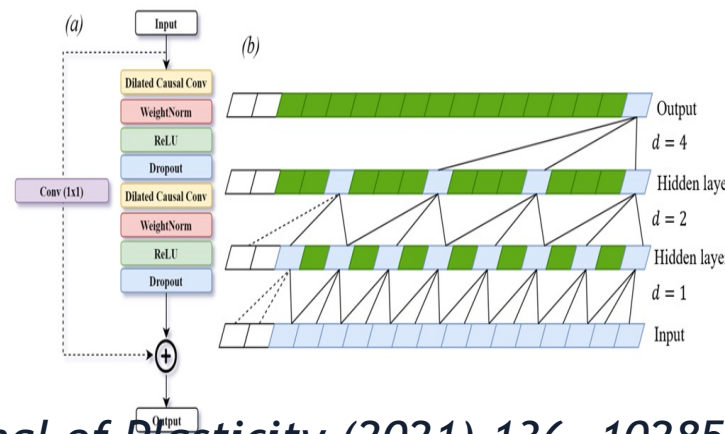
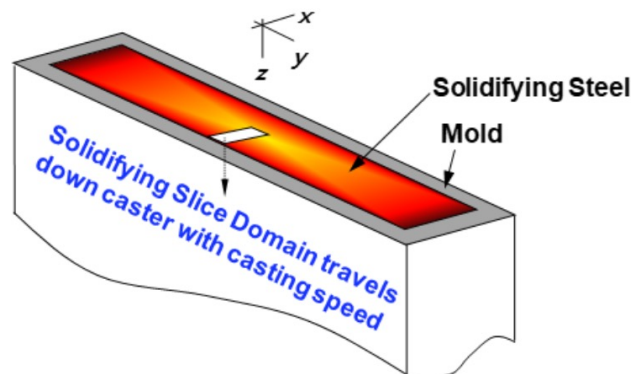
# Deep Learning for Topological Optimization of Metamaterials



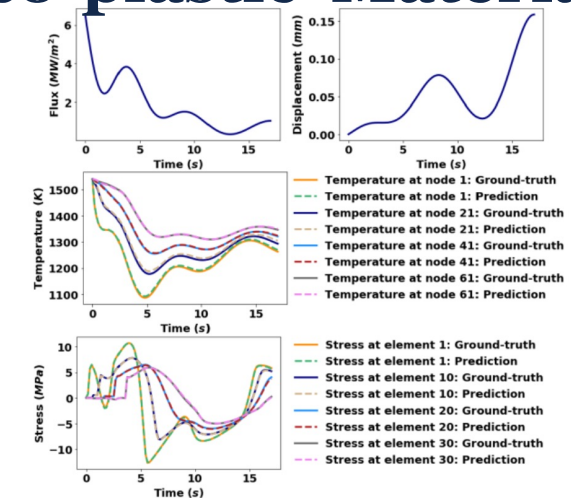
Kollmann et al., *Materials & Design* (2020), 109098



# Deep Learning for Multiphysics Modeling of Visco-plastic Materials



Abueidda et al., *International Journal of Plasticity* (2021) 136, 102852



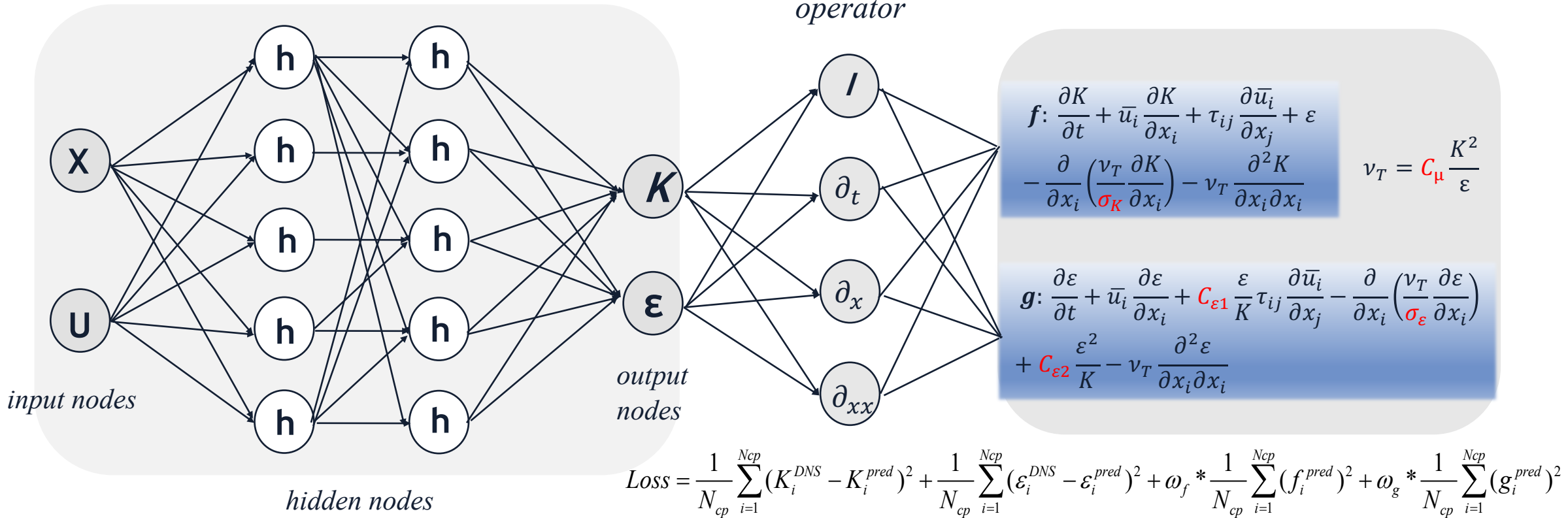
# Physics Informed Neural Network (PINN)

## Tuning K-ε Turbulence Model

*Feedforward neural network*

*Fluid physics constraints*

*operator*



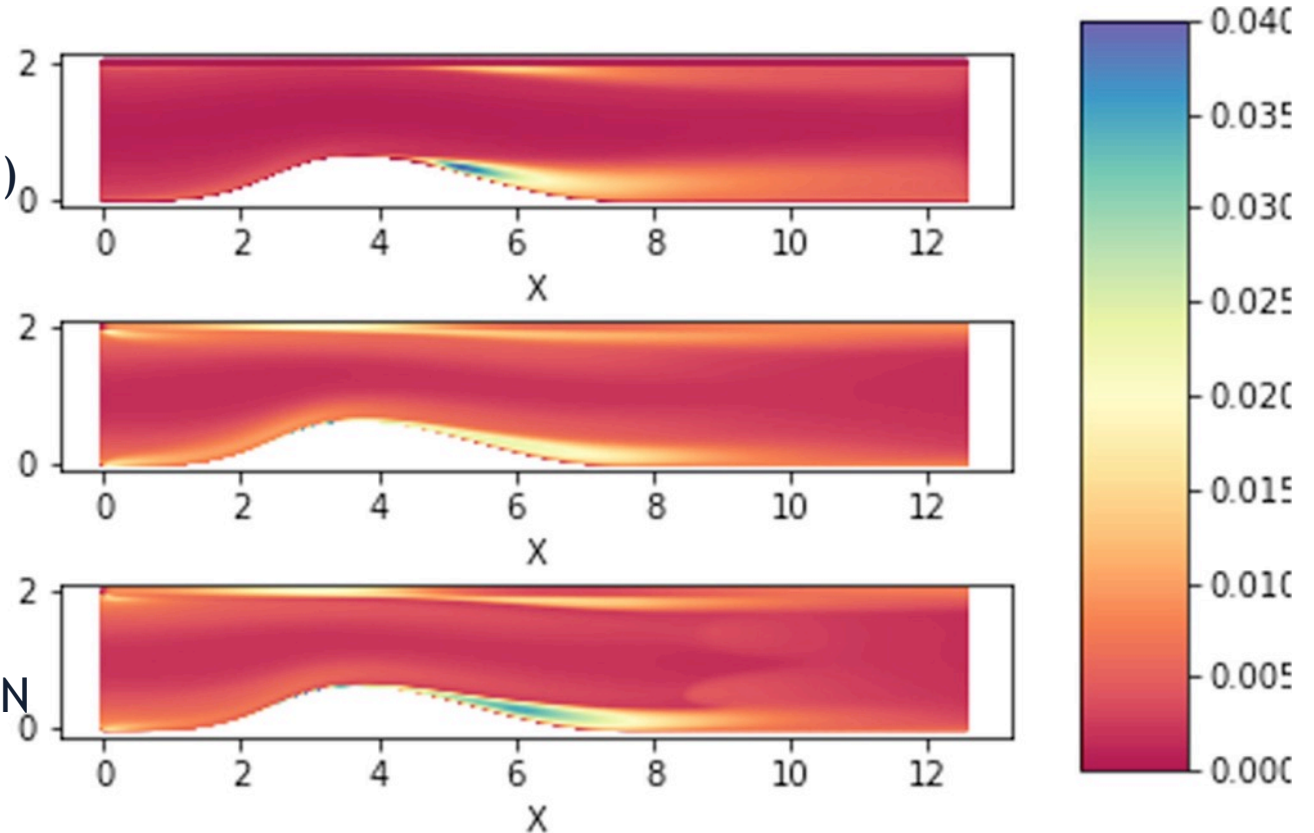
Luo et al., International Supercomputing Conference (ISC) 2020

Five Parameters  $C_{\varepsilon 1}$ ,  $C_{\varepsilon 2}$ ,  $C_\mu$ ,  $\sigma_K$ ,  $\sigma_\varepsilon$  tuned by TF as 5 extra Hyperparameters to additionally minimize Loss

# Comparison of the time-averaged Turbulent Kinetic Energy

Five constant	Empirical (Default)	NN-pred Fix $C_\mu$
$C_{\varepsilon 1}$	1.44	1.302
$C_{\varepsilon 2}$	1.92	1.862
$C_\mu$	0.09	0.09
$\sigma_\kappa$	1.0	0.751
$\sigma_\varepsilon$	1.3	0.273

DNS Solver  
(Ground Truth)



Default  
K- $\varepsilon$  Solver

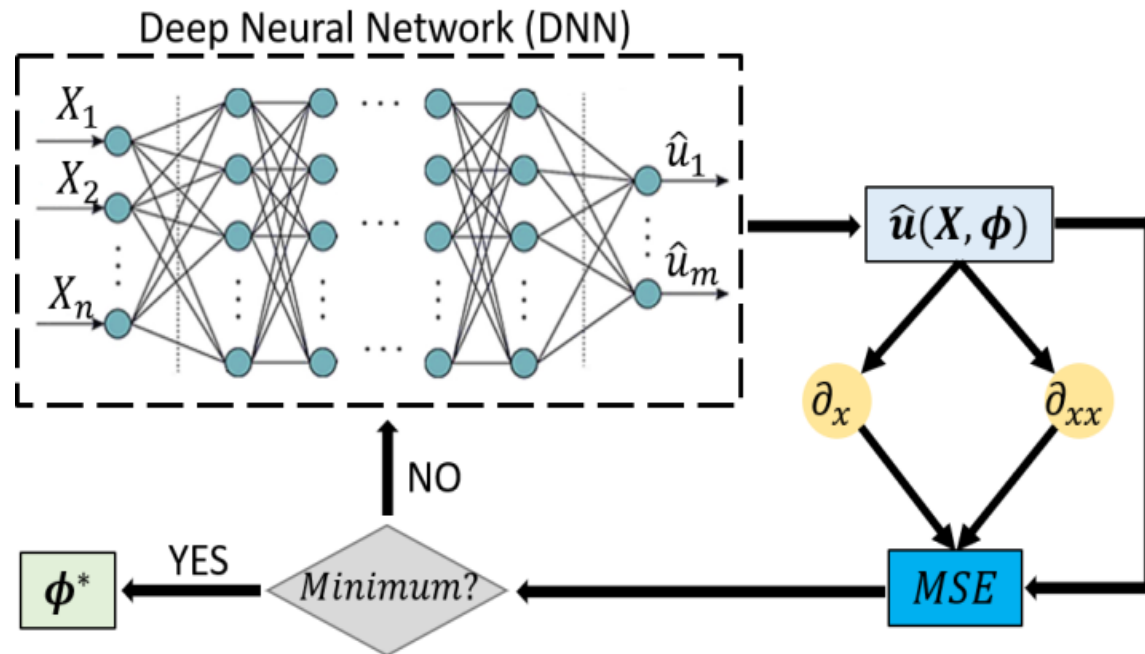
K- $\varepsilon$  Solver  
Tuned by PINN

DNS Simulation ~ Weeks and Months  
K- $\varepsilon$  Simulation ~ Minutes and Hours

*Luo et al., International Supercomputing  
Conference (ISC) 2020*



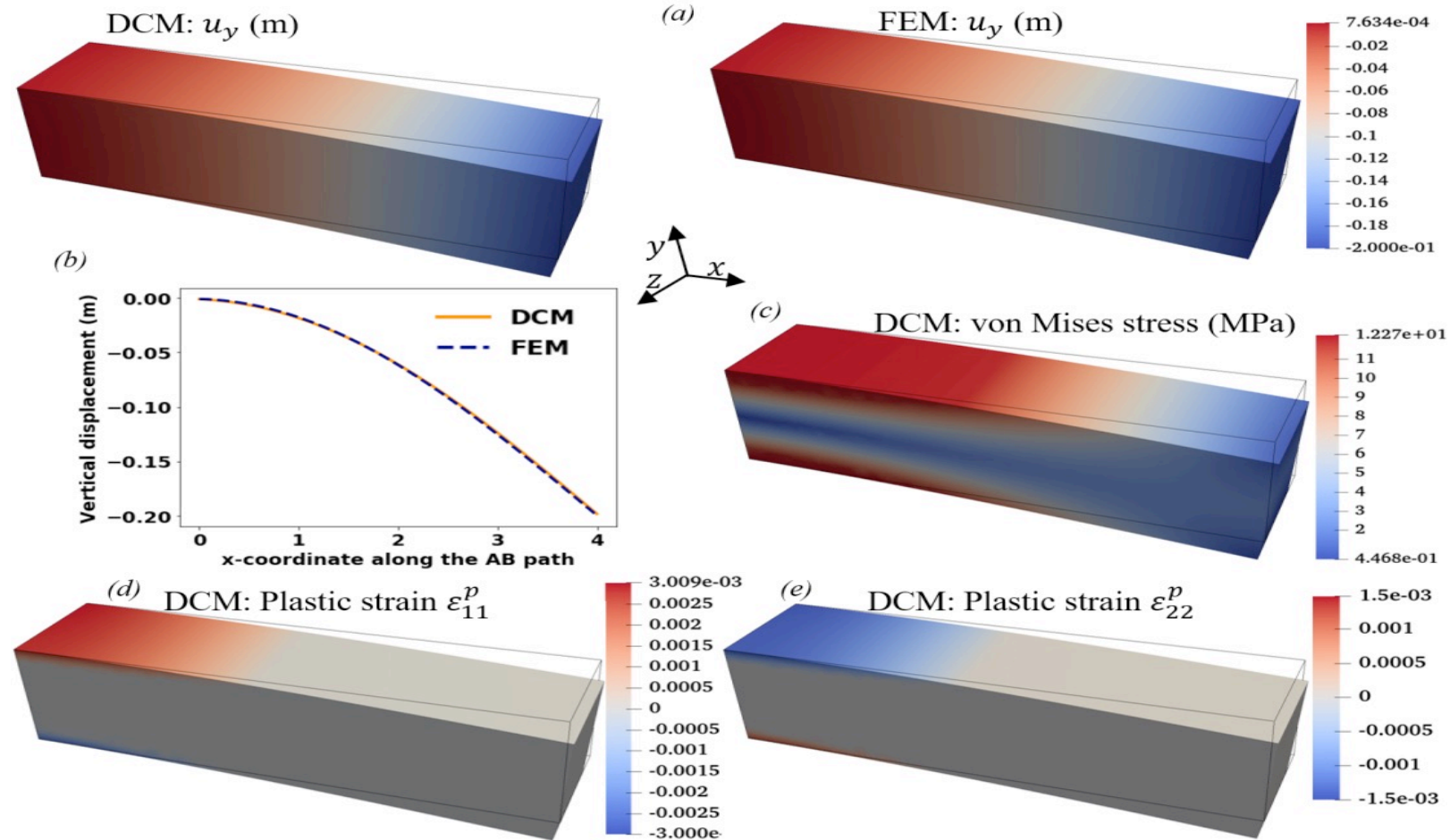
# Meshless Physics Informed Deep Learning Method For 3-D Solid Mechanics



- **Strong Form (Governing PDE) is NN's Loss**, enforced on collocation points in the domain and on essential and natural Boundary Conditions
- **No data generation** is needed, such as in surrogate deep learning models
- Relies on simple linear algebra kernels, which are **better optimized on GPU-s** than sparse direct solvers in implicit Finite Element Method (FEM) and use significantly less memory
- **Easier Discretization** of complex geometries without issues with the aspect ratio of elements, connectivity, and assembling into a global stiffness matrix
- **Globally smoother solution** without discontinuity in displacement solution between lower order elements in FEM

Abueidda et al., *International Journal for Numerical Methods in Engineering*, In Revision, 2021

# Meshless Physics Informed Deep Learning Method For 3-D Solid Mechanics



Abueidda et al., International Journal for Numerical Methods in Engineering, In Revision, 2021

# The Ultimate Singularity in AI?

## AI Reality Checks:

- No, machines can't read better than humans (2018)
  - <https://www.theverge.com/2018/1/17/16900292/ai-reading-comprehension-machines-humans>
- How IBM Watson Overpromised and Under-delivered on AI Health Care, IEEE Spectrum By Eliza Strickland, April 2019
- DeepMind's Latest A.I. Health Breakthrough Has Some Problems, by Julia Powles, August 2019

AI machines can “learn” but not yet “think” (at least not like humans), and it remains to be seen if, how, and when the major AI singularity point of true intelligence will be reached?

# But be careful what you wish for!



Thanks to machine-learning algorithms,  
the robot apocalypse was short-lived.



# Acknowledgements:

- ❖ **IA Confluence Team Members:** Diab Abueidda, Shirui Luo, Nahil Sobh, Hunter Kollmann and Erman Guleyruz
- ❖ Dora Cai, Aiman Soliman, Jeff Terstriep & NCSA Data Analytics Team
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- ❖ NCSA Industry Program
- ❖ AI Center for Excellence at UIUC

# Thank you!

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