Virtual Foundry: Parameterized Reduced-order Models for Predicting Distortion in Additive Manufacturing

DSSI DATA SCIENCE INSTITUTE

August 6th, 2024

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LLNL-PRES-867437

This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under contract DE-AC52-07NA27344. Lawrence Livermore National Security, LLC

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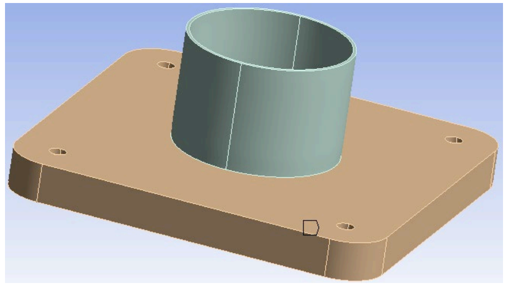
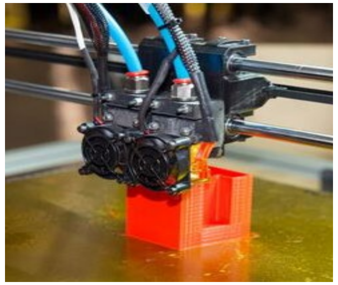
Motivation

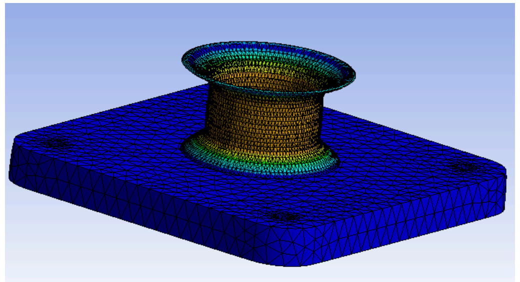


Input Geometry

Source: web



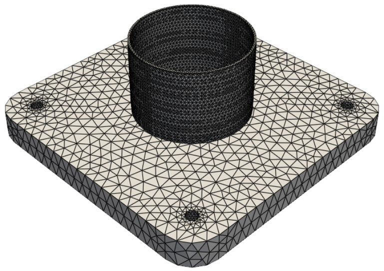
3D Printing



Printed Part

- Distortion in printed parts
- Need multiple trial geometries
- Time consuming
- Prohibitively expensive

Virtual Foundry: Simulating 3D Printing on Computers

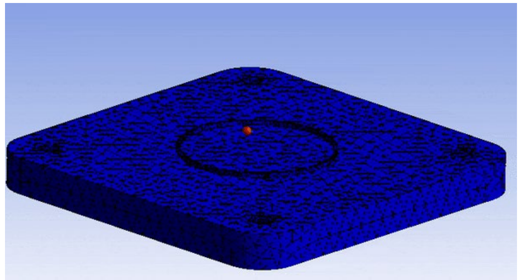


Discretized mesh
~200k elements

$$\frac{\partial F}{\partial t} + (\mathbf{V} \cdot \nabla) F = 0$$

$$k \frac{\partial T}{\partial \mathbf{n}} = \frac{\eta (P_{\text{laser}} - P_{\text{atten}})}{\pi R^2} - h_c (T - T_\infty)$$

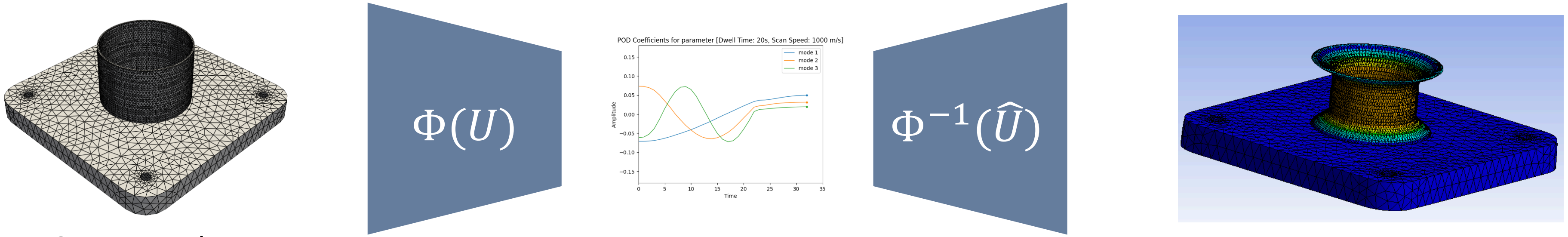
Representative PDE



Simulation

- 8-12 hours, 256 Cores
- Slow computational speed
- We need to increase the computation speed

Methodology: Reduced-order Modeling



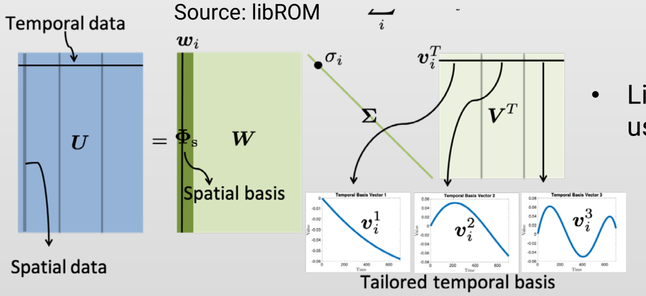
Coarse mesh
~48K nodes
μ : *machine parameters*

Compress — Latent-space dynamics — Decompress — Distortion Prediction

Two Approaches

Projection + Gaussian Process Regression

Source: libROM



- Linear projection using SVD

❑ Predict temporal basis coefficient using Gaussian Process

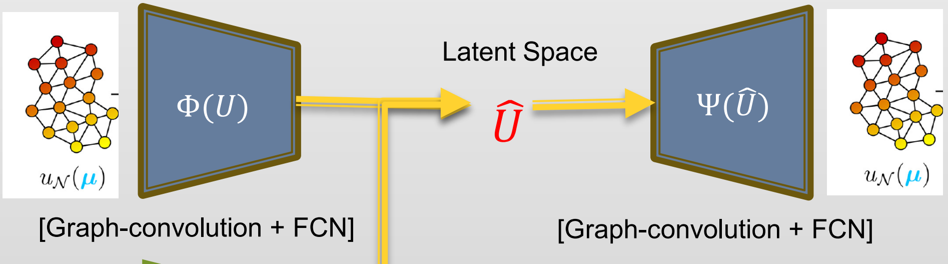
$$V_j^{\mu_i} = GP_j(\mu_i)$$

Where μ_i *is machine parameter and* $V_j^{\mu_i}$ *coeff. for jth mode*

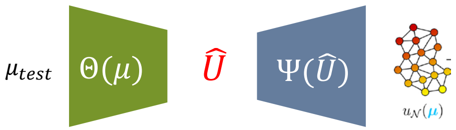
❑ We train r independent GPs for each mode.

Parameterized Graph Convolution

Training:



Testing:

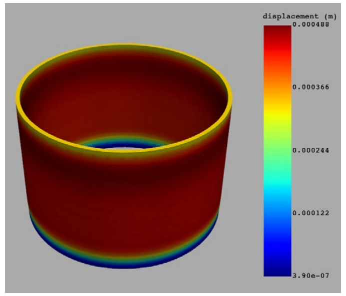


Results

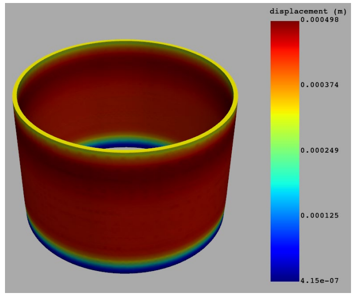
- $\mu : Dwell\ time\ (s)$
- $\mu_{train} = [20,25,35,40,50,55,65,70,80]s$
- $\mu_{valid} = [30,60]s$
- $\mu_{test} = [45,75]s$

Ansys Numerical Simulation

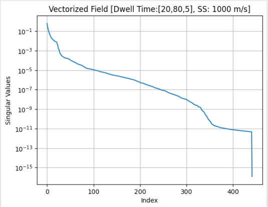
DT = 45s



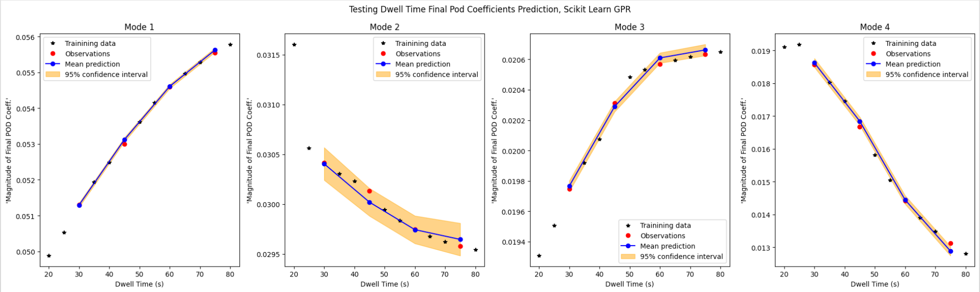
DT = 75s

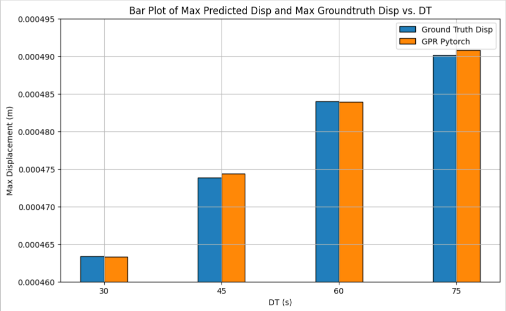


Approach 1:



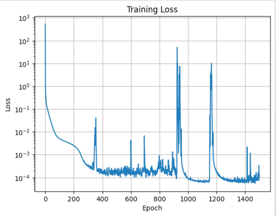
- 99.99 % energy in 129 modes
- Compresses from 48k degrees of freedom to 129 dof.
- Use GPR to predict coefficients of basis



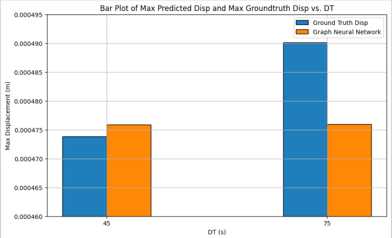


- Maximum nodal displacement for test and validation.
- Desired accuracy is $\pm 0.1\ mm$
- Our method predicts within $\pm\ 0.001\ mm$
- Decreases the computation time from 2 hours to 4 seconds for ~48k nodes
- Speedup = x1800

Approach 2:



- Denoising training with early stopping
- Latent space is 12 dimensional
- Compresses from 48k nodes to 12 dof
- Parameter network uplifts the parameter to 100 dimensional space and then project to latent space.



- Only 9 training data points
- Graph Net is failing to generalize on testing set
- Why care for GCN then?
- Graph architecture allows to generalize for varying geometry and mesh
- Needs further validation of GNN

Conclusion and Future works:

- Projection + GPR showed generalization, speed-up of 1800 times and desired accuracy of $\pm 0.001\ mm$
- Generate more data and varying geometry for training GNN
- Test advanced architecture like w-LaSDI for ROM