

ML Based CFD Model Reduction for Rapid Computational Screening

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CCSI²: Carbon Capture Simulation for Industry Impact





Machine Learning





History of ML in CCSI





How do we use ML for CCSI²?

CFD is critical for the fundamental understanding, to inform process and system level modeling.

- Need local information on transport
 phenomena to understand driving forces
- Can be incorporated into design
 optimization to optimize the device

Simulation time is a bottleneck that impedes high-level modeling.

Machine learning surrogates, such as Deep Fluids (DF) and MeshGraphNets (MGN), can reduce the computational burden of timeconsuming simulations.





Fast Surrogates for CFD Simulation Model





Computational approaches to screening parameters



Metric	Computational Fluid Dynamics (CFD)	Machine Learning (ML) Surrogates
Speed	<i>Slow</i> : 2D model takes 1 hour to simulate	<i>Fast</i> : 2D model takes 1 second to simulate
Effort to construct	<i>High</i> : Equations, assumptions, numerical methods, software packages, …	<i>Low</i> : Common architectures across problems reduce effort required for a 'good' model
Accuracy	<i>Variable:</i> Depends on the model/effort	Variable: Depends on accurate CFD training data and surrogate's ability to bridge from "toy" problems in literature to our large-scale data
Downstream modeling/problems	<i>Ill-suited:</i> Generally, too slow to scale to large, 3D simulations	<i>Well-suited:</i> Scaling made feasible by speed of reduced models



Growth in Machine Learning and the Physical Sciences



DeeperFluids

- Builds on Kim et al., 2019
- Interpolates CFD mesh onto regular grid
- Uses image-processing ML techniques
- Published in IAAI 2022 (Bartoldson et al., 2022)
- Included as a plugin for FOQUS
- Code: https://github.com/CCSI-Toolset/DeeperFluids

MeshGraphNets

- Builds on Pfaff et al., 2021
- Uses same mesh as CFD
- More faithful to physics than DF
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Ground truth

Prediction



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Image source: Heldebrant et al., 2019

Carbon capture systems have many parameters to tune



Image source: Heldebrant et al., 2019



Potential approach: Run a CFD simulation to understand effect of each parameter...





Screen parameter settings to optimize efficiency---interfacial area (IA), liquid holdup, pressure drop, etc.





Problem: CFD is too slow to fully explore parameter space

Computational fluid dynamics (CFD) modeling

 $\frac{\partial \rho}{\partial t} + \nabla \cdot \rho \mathbf{u} = 0$

$$\frac{\partial(\rho \mathbf{u})}{\partial t} + \nabla \cdot (\rho \mathbf{u} \mathbf{u}) = -\nabla p + \mu \nabla^2 \mathbf{u} + \rho \mathbf{g} + \mathbf{F}_{\sigma}$$

 $\frac{\partial \alpha}{\partial t} + \nabla \cdot (\mathbf{u}\alpha) = 0$

Numerical methods/software for CFD







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Surrogates learn from CFD data, are tested against CFD data



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Deep Fluids (DF)

Forward pass in latent space







LLNL's Deeper Fluids Surrogates

Building on the original surrogates...

		Error _{IA}				
Н	w=20	50	150	200	300	499
1024,512	0.33 (0.14)	0.08 (0.00)	0.09 (0.00)	0.10 (0.00)	0.11 (0.00)	2.53 (0.26)
128, 128, 128	0.64 (0.11)	0.08 (0.01)	0.08 (0.00)	0.07 (0.00)	0.06 (0.00)	2.25 (0.18)

We find better performance!

		Er	$\mathrm{Error}_{\mathrm{IA}}$		$\mathrm{or}_{\mathrm{VF}}$
LIN	s	$L_{\rm RE}$	RMSE	$L_{\rm RE}$	RMSE
ARC	1	0.12	0.09	0.53	0.55
	6	0.15	0.14	0.51	0.53
LSTM	1	0.12	0.06	0.56	0.54
	6	0.09	0.09	0.52	0.54
MLP	1	0.07	0.07	0.53	0.55
	6	0.08	0.12	0.49	0.52
Transformer	1	0.08	0.04	0.53	0.55
	6	0.06	0.22	0.53	0.80



And big speedups!

LIN	$\mathrm{Error}_{\mathrm{IA}}$	$\mathrm{Error}_{\mathrm{VF}}$	S_W
ARC	0.07 (0.00)	0.49(0.00)	4800
LSTM	0.08(0.01)	0.49(0.01)	2700
MLP	0.06 (0.00)	0.47 (0.00)	5400
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t = 0









Input

A patch within the original frame





Input

A *mesh* within the original frame

Encoding *E*

Each node and edge has its own embedding.

Message Passing M

Neighboring edges and nodes exchange info to update embeddings.

Decoding D

Updated embeddings are decoded, which represent the gradient in physical space.

Forward pass *F* Via forward Euler



Implemented the first public version of MGN in PyTorch







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MGN Surrogate Innovations for Scaling to PNNL Data





MGN Surrogate Innovations for Scaling to PNNL Data





MGN Surrogate Innovations for Scaling to PNNL Data





Physics-informed surrogates





Momentum Model Input



0.0001

-0.0001

Work in progress

- MGN extensions/improvements
 - Improving scalability
 - Architectural improvements
 - Training/optimization improvements
 - Curriculum learning
 - Incorporating physics constraints/expert knowledge
 - Explainability methods
- Surrogate models with CMU/PNNL data
- Design optimization
 - Integrate MGN into FOQUS





https://github.com/CCSI-Toolset/MGN

Acknowledgements

CCSI² Machine Learning Team





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Jay Xu PNNL



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