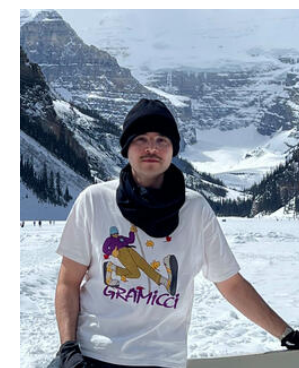


Operator Learning for Power Systems Simulation



Matthew Schlegel, Matthew E. Taylor, Mostafa Farrokhabadi

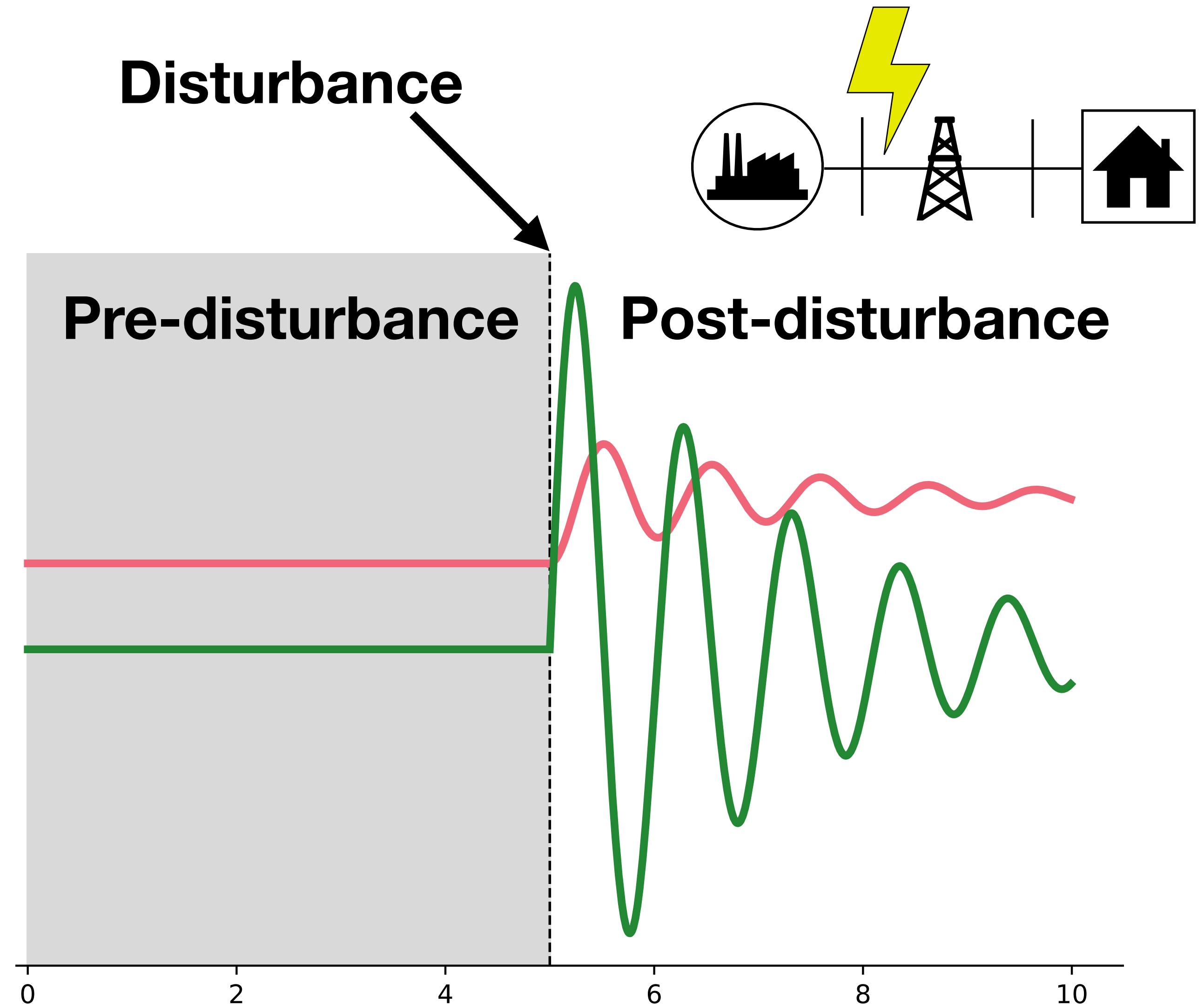
Tackling Climate Change with Machine Learning, NeurIPS 2025



Our aim is to accelerate time-domain power system simulation with operator learning for scalable, resolution-invariant modeling in renewable-rich grids.

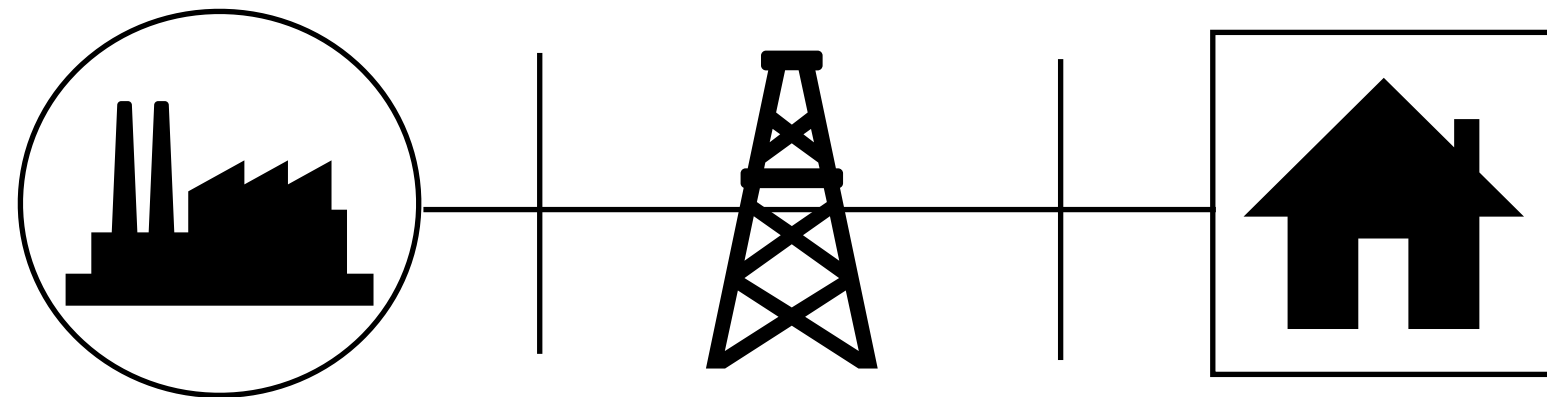
Why simulate the power grid?

- Simulations help assess the stability of the grid after disturbances (e.g., faults, sudden generation loss, renewable fluctuations).
- Modern power systems require high resolution simulation to capture the fast, novel dynamics associated with renewables.



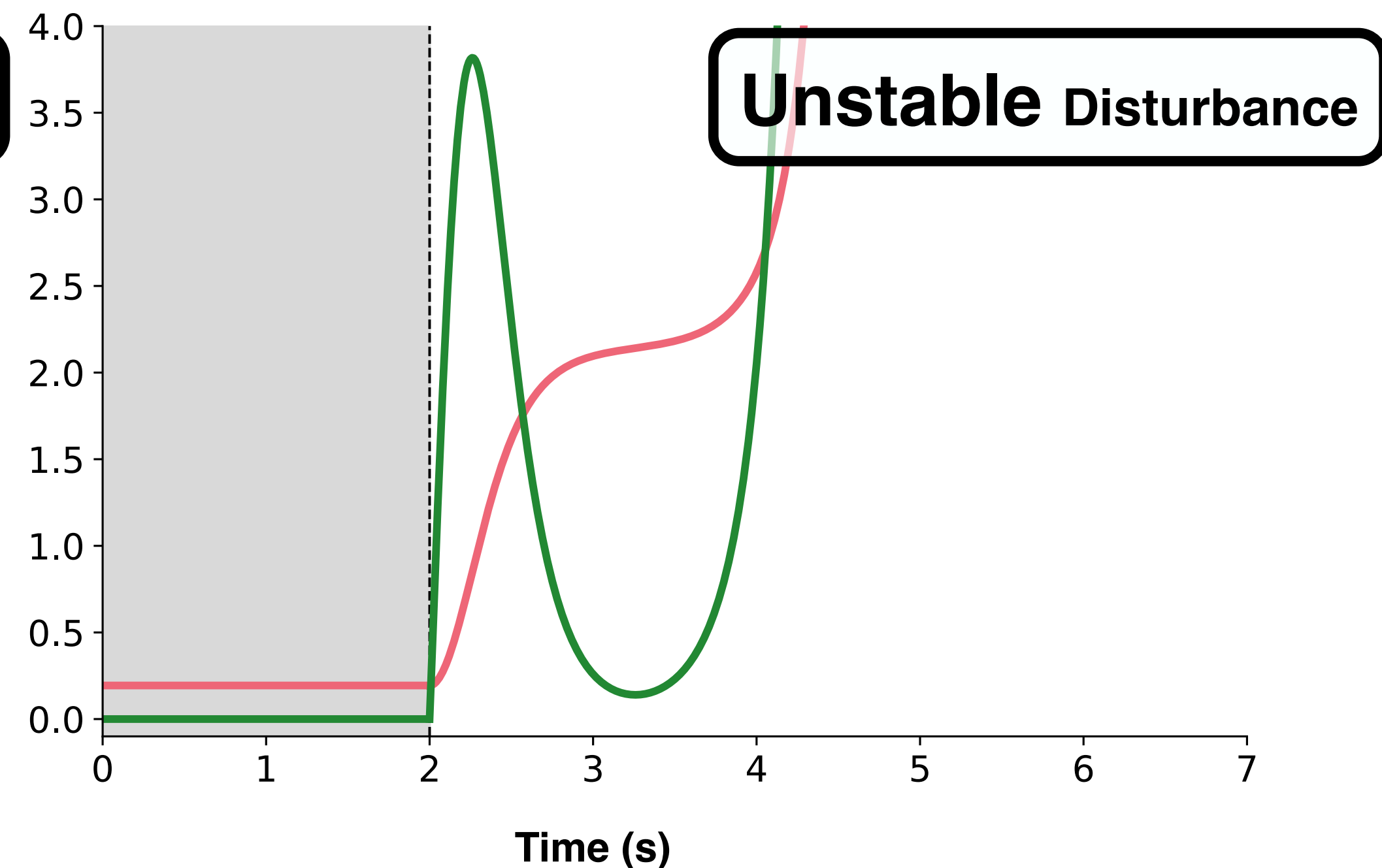
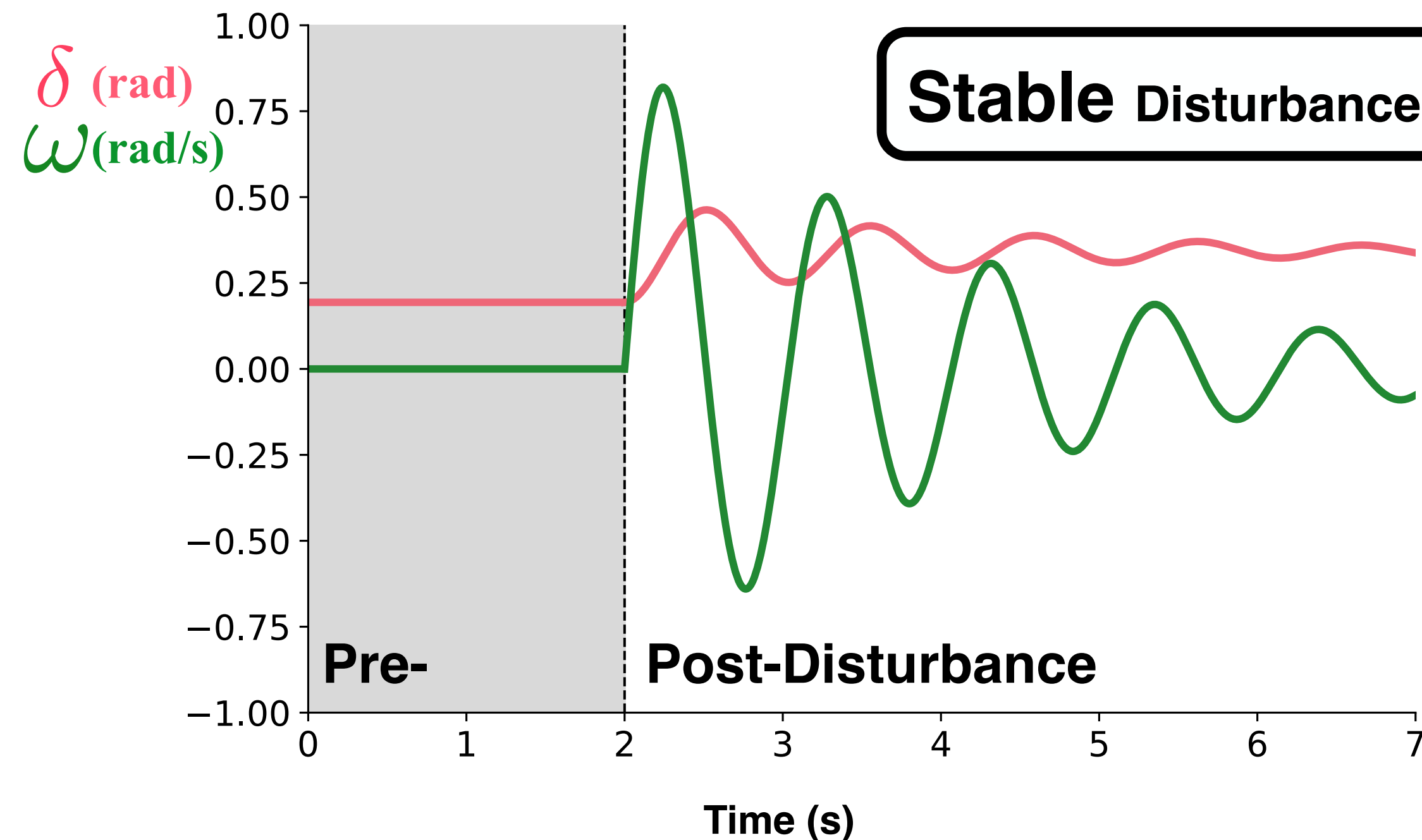
Data Generation

Single-Machine Infinite-Bus



Swing Equation:

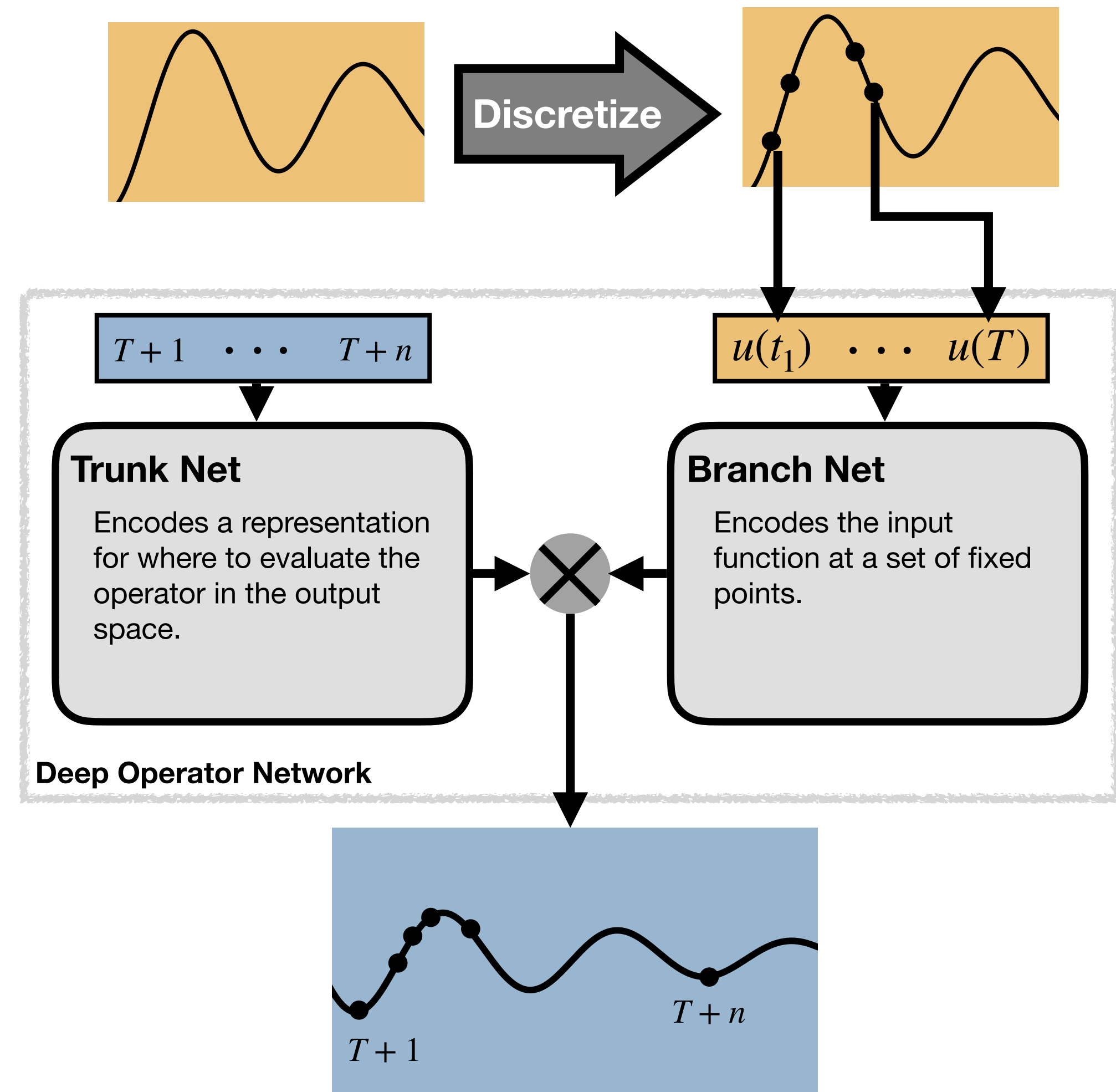
$$\frac{\partial^2 \delta}{\partial t^2} = \frac{\pi f_0}{H} \left(P_m - D \frac{\partial \delta}{\partial t} - \frac{|E||V|}{X} \sin \delta \right)$$



Operator Learning

Mapping from function space to function space

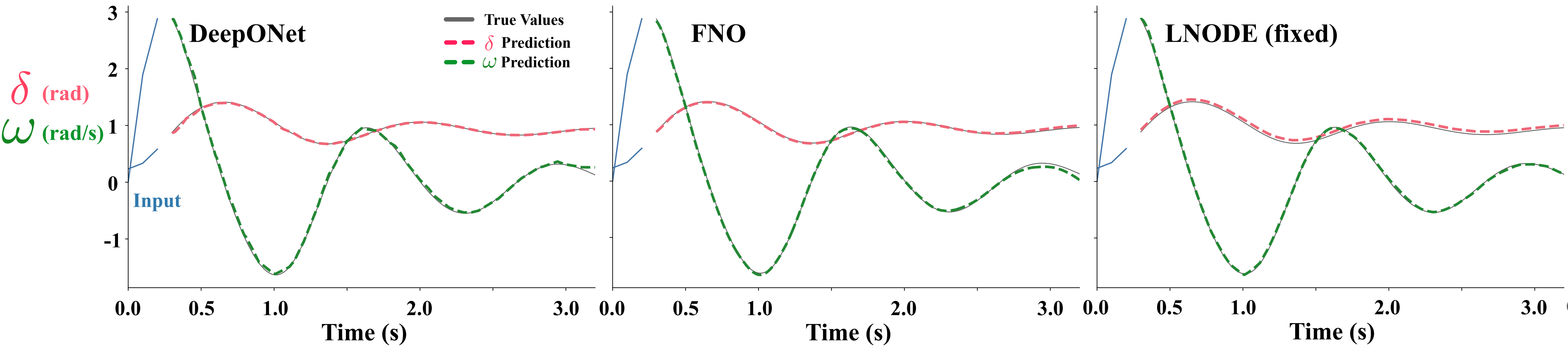
- Neural Operators map between two function spaces, enabling resolution-invariant inference.
- **Deep Operator Networks (on the right):** An explicit operator with dual networks for history encoding and point evaluation
- **Fourier Neural Operators:** An implicit operator that learns mappings in the Fourier domain using spectral convolutions
- **Latent Neural ODEs:** An explicit operator encoding history into a latent space, where a learned NODE evolves states decoded to match outputs



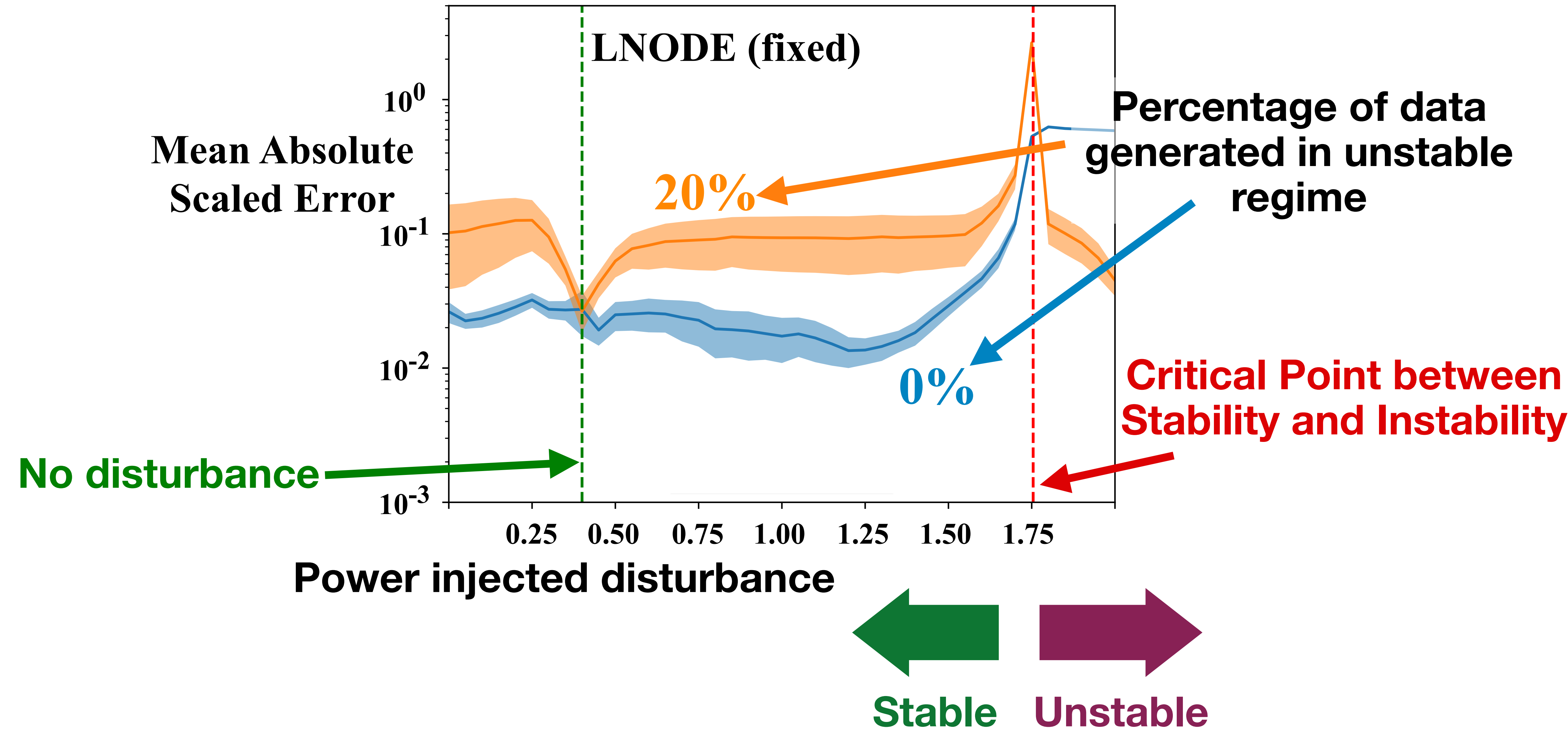
Zero-shot Super-Resolution

Train on Coarse, Generate at Fine Resolution

Model Name	Coarse Resolution	Fine Resolution	%Difference (95% CI)
DeepONet	0.0220 ± 0.0001	0.0348 ± 0.0002	45.2% (39.0, 51.3)
FNO	0.0186 ± 0.0001	0.0302 ± 0.0001	47.5% (39.9, 54.8)
LNODE (Fixed)	0.0280 ± 0.0006	0.0305 ± 0.0006	8.6% (0.5, 33.6)
LNODE (Adaptive)	0.0275 ± 0.0003	0.0296 ± 0.0003	7.3% (0.4, 19.7)

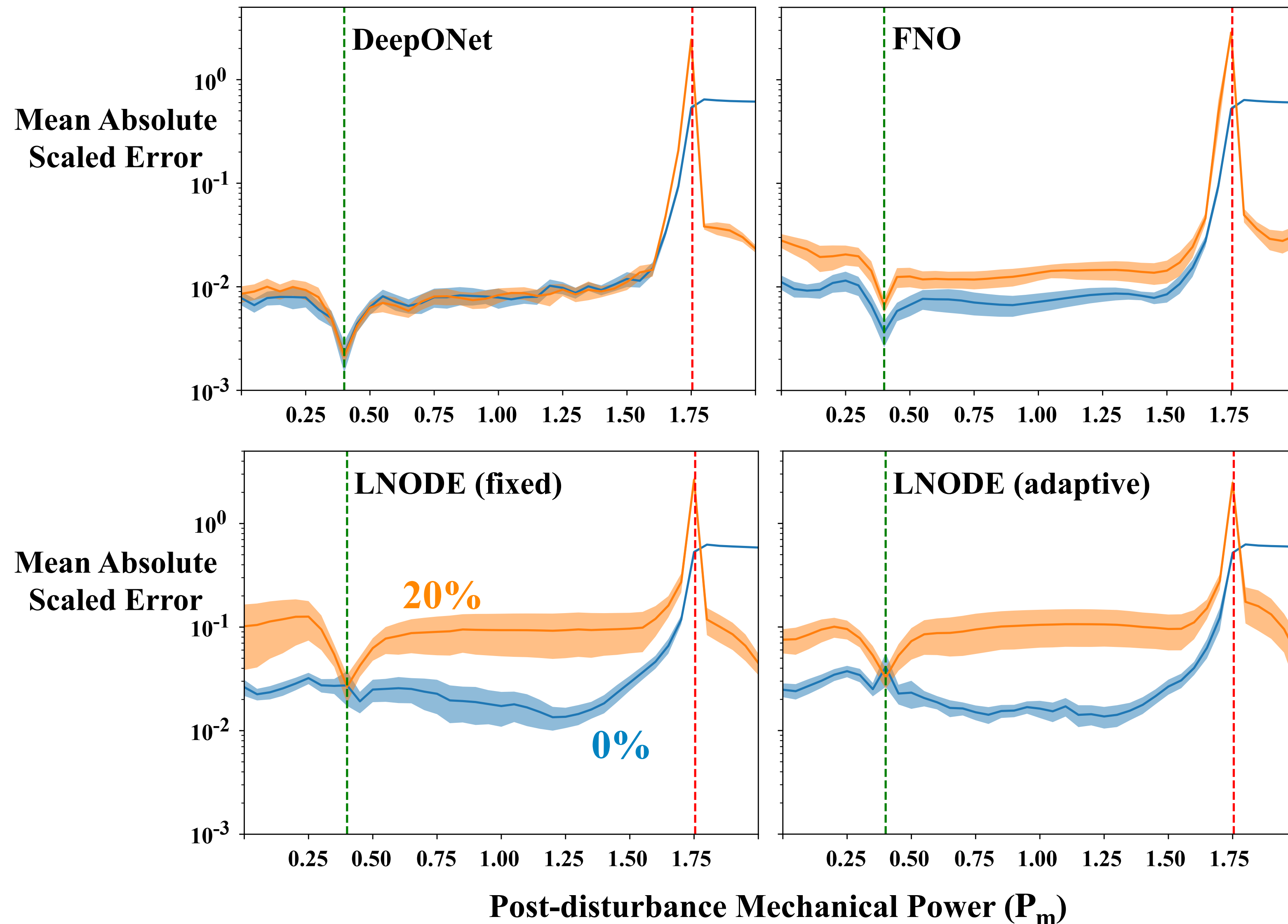


Generalization Across Stability Boundaries



Generalization Across Stability Boundaries

- Neural Operator style networks are better for generalization across dynamical regimes
- LNODEs struggle to robustly manage both regimes simultaneously



Conclusions

Key Takeaway: Operator learning is a promising direction for resolution-invariant grid simulation, but there is a lot of care needed when verifying generated trajectories.

Next Steps: Scale to grids with renewables and more complex disturbance paradigms.



mkschleg



github.com/mkschleg

mkschleg.github.io

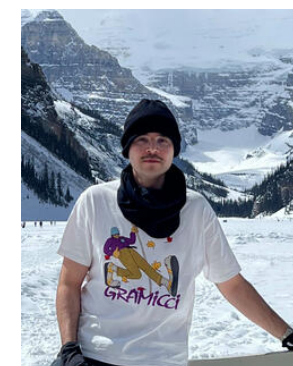


Website



Paper

Thank you!

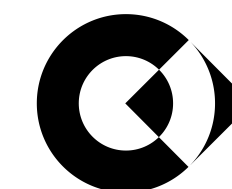


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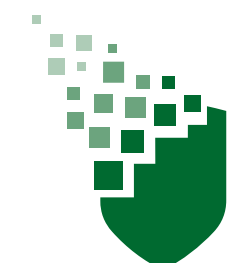
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