# Operator Learning for Power Systems Simulation

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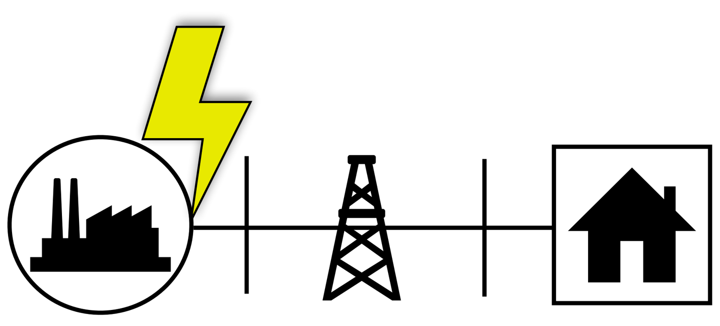
Paper · Website

## Towards accelerating time-domain power system simulation with operator learning for scalable, resolution-invariant modeling in renewable-rich grids

## Problem Setting

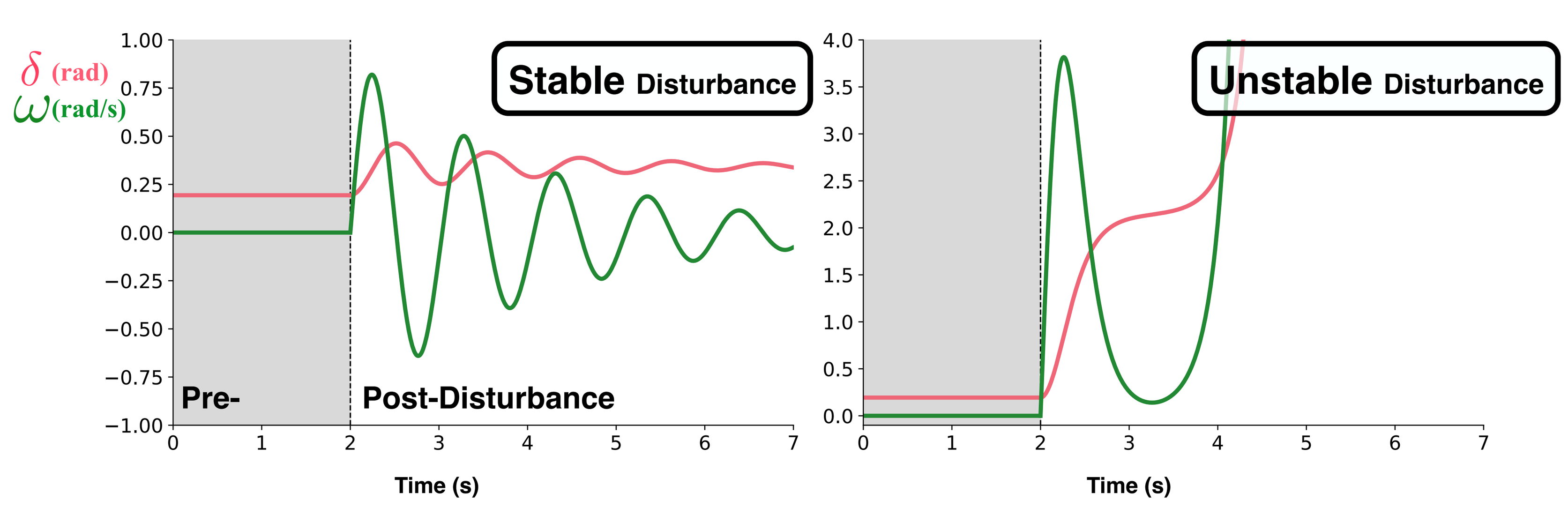
Modern power systems require high resolution time-domain simulations to capture the fast, novel dynamics associated with renewables.



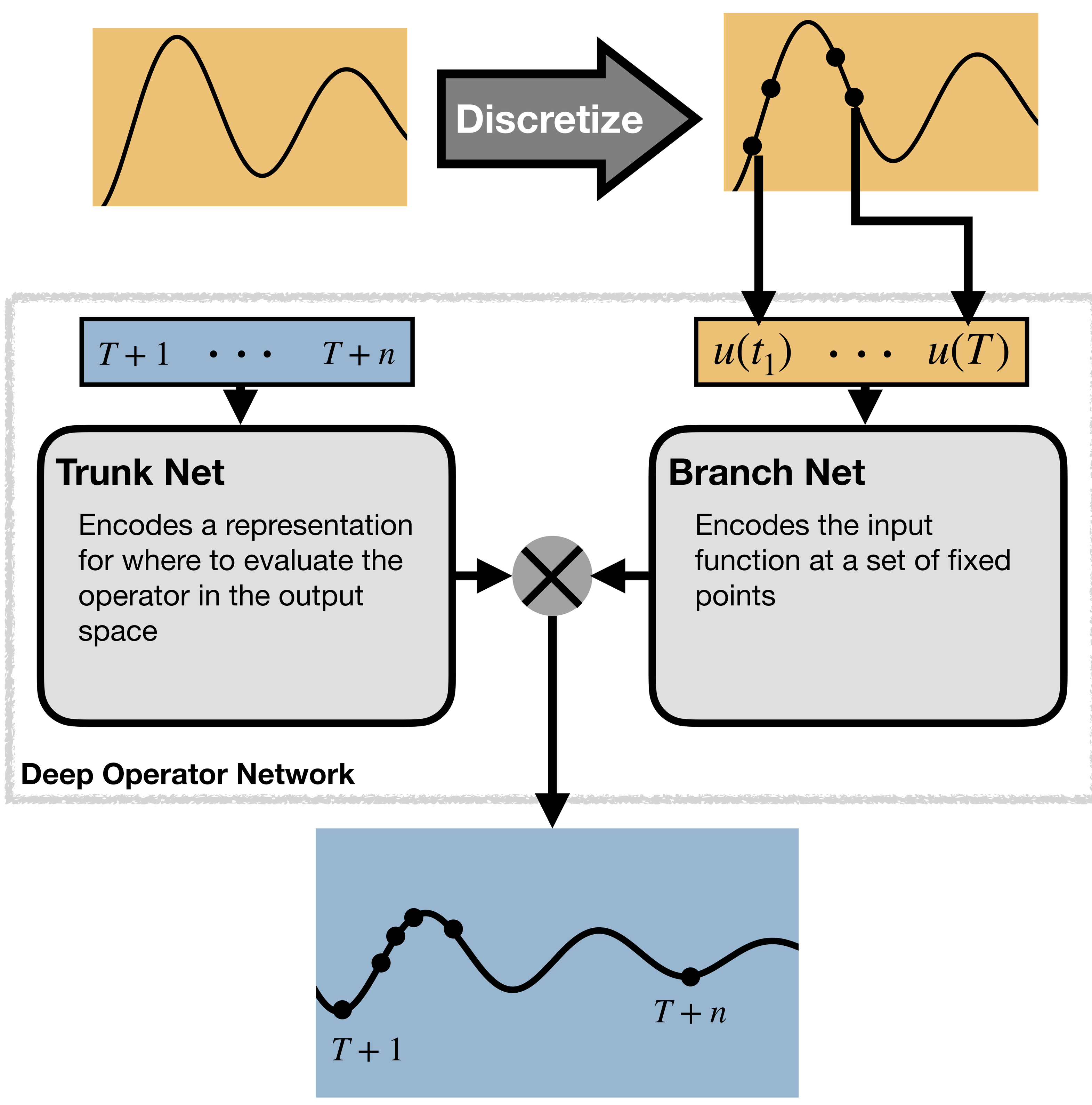
**Single-Machine Infinite-Bus**

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

A well-known disturbance creating oscillatory dynamics is used to benchmark operator learning for resolution-invariant time-domain simulation.

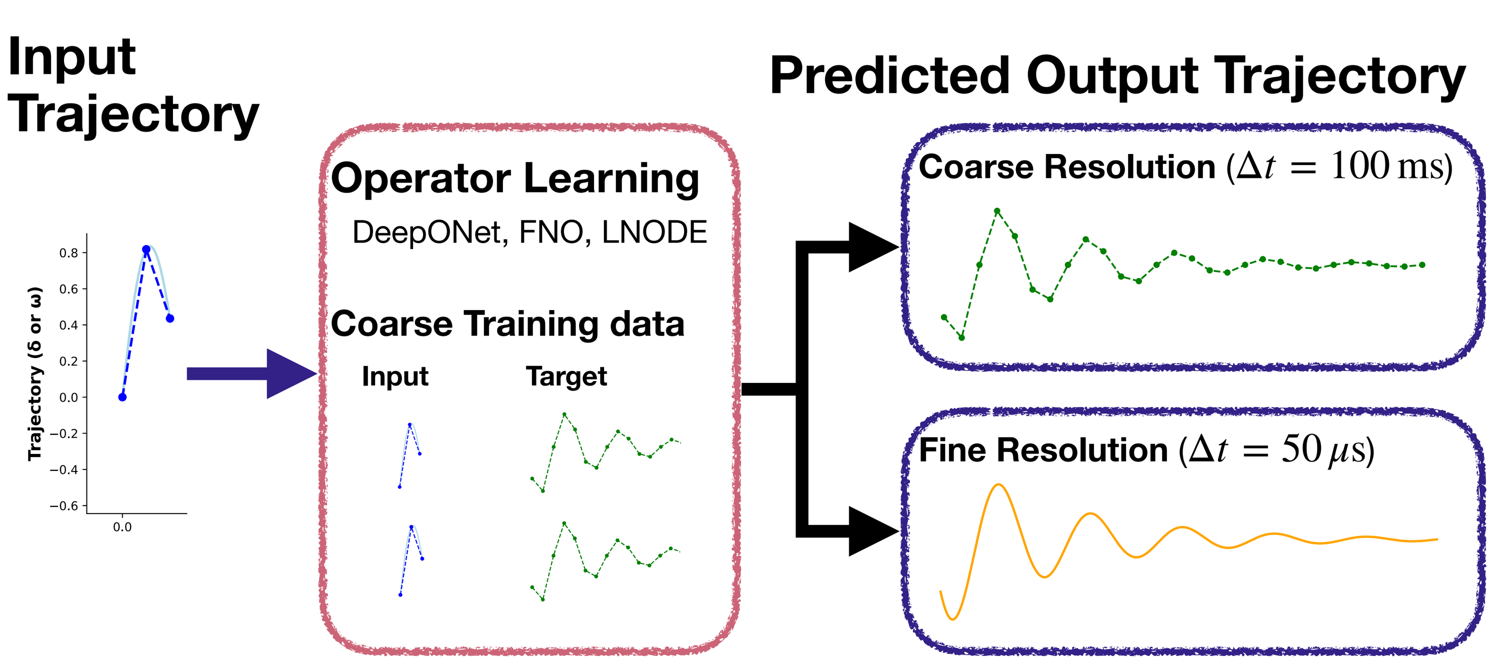



## Operator Learning

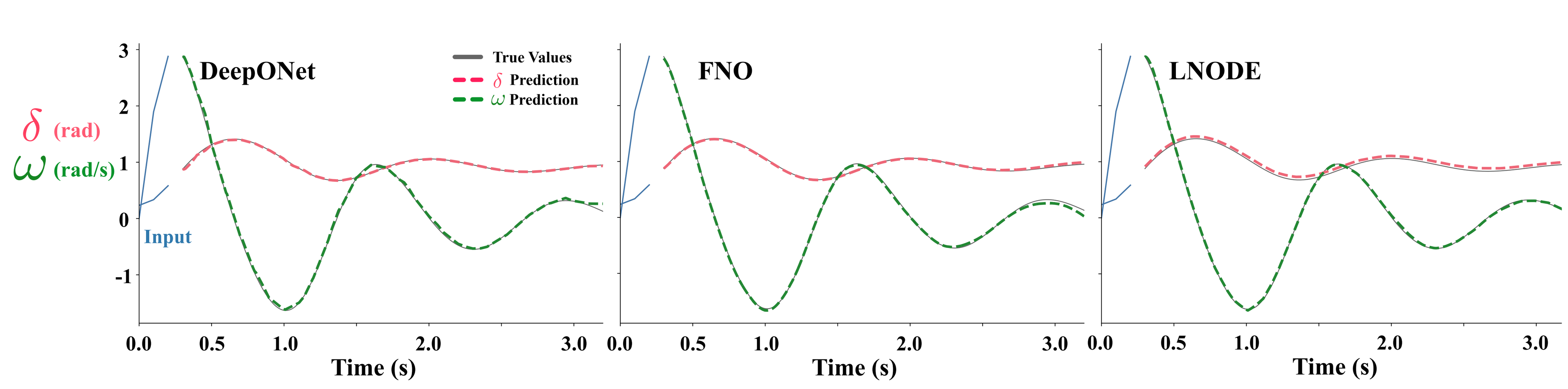



## Zero-shot super-resolution (resolution-invariant inference)

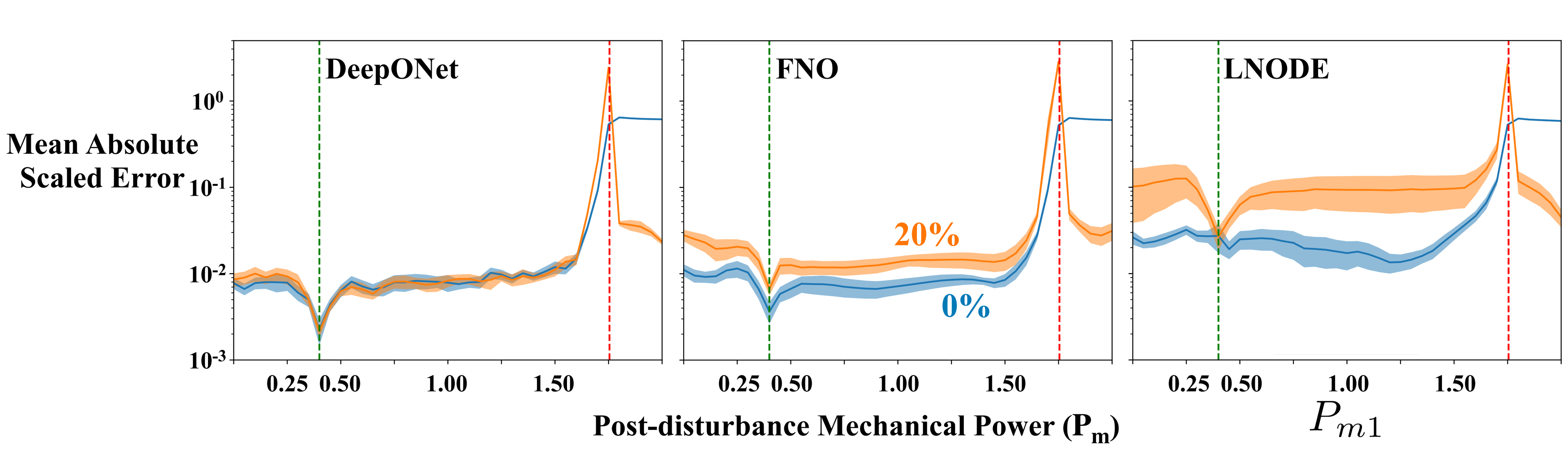
FNOs get the lowest RMSE, but LNODEs maintain accuracy between resolutions




| Model Name | Δt = 100 ms (RMSE) | Δt = 50 μs (RMSE) | %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 stable and unstable regimes




- **0% unstable training data:** all methods perform well in the stable regime and poorly in unstable regime
- **20% unstable training data:** DeepONets perform best across both regimes