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Powering the Future: Harnessing Neural Dynamic Equivalence for Enhanced Power System Applications

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Collaboration: ISO New England

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AI-Grid

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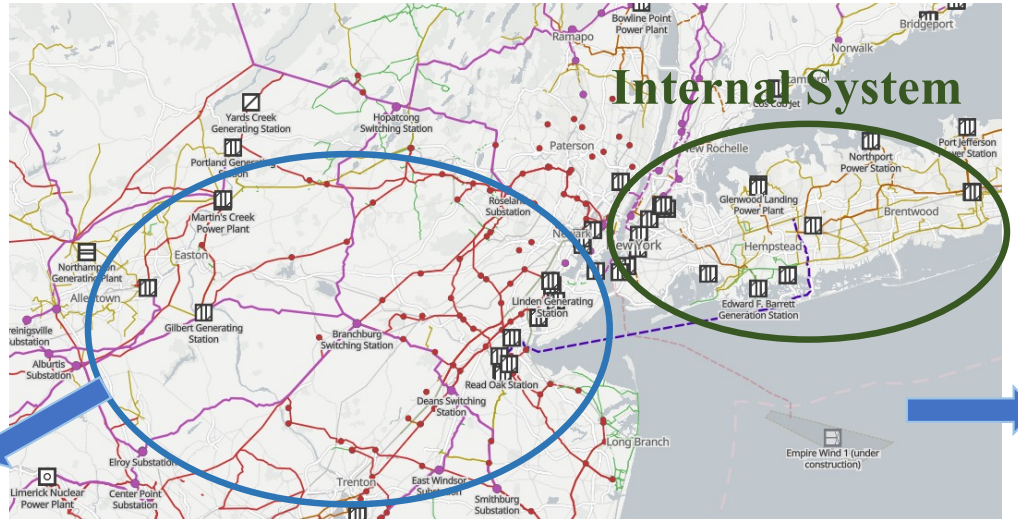
Why Neural Dynamic Equivalence?

Motivations

- ❑No access to the external system
- ❑Static equivalent model (inaccurate)
- ❑Unexploited data (SCADA and PMU)

Neural Dynamic Equivalence

- ❑ Harvest from big data
- ❑ ODE-NET: continuous differential structure
- ❑ Update in real-time via PMU measurements



External System Unidentified?

Our solution

Nonlinear Unforeseeable mode

https://openinframap.org/#8.13/40.838/-74.149

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Why is Neural Dynamic Equivalence difficult?

Curve-fitting ✗

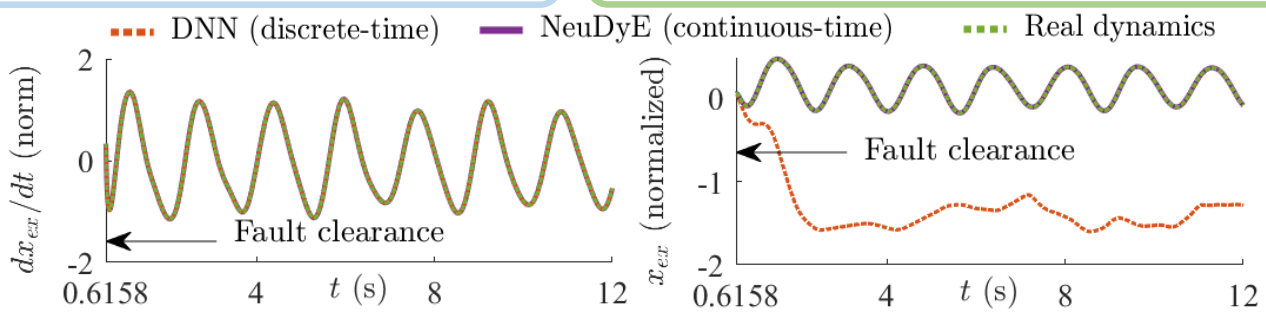
Challenges

$$\dot{x} = \mathrm{N}_{\theta}(x, u)$$

- ❑Learn from data but need to align with physics
- ❑Continuous dynamics but discrete measurements

Discretize x, then compare with the derivatives $\dot{x}$ **Discrete learning**

Continuous learning Integrate $\dot{x}$, then compare with the x



(a) Open-loop training performance (b) Closed-loop testing performance

Figure 1 Comparison of NeuDyE with conventional discrete-time DNN

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How to implement Neural Dynamic Equivalence?

Our solution: Neural ODE-Net

- ❑Continuous-time space model
- ❑Physics-informed training
- ❑Guaranteed closed-loop accuracy

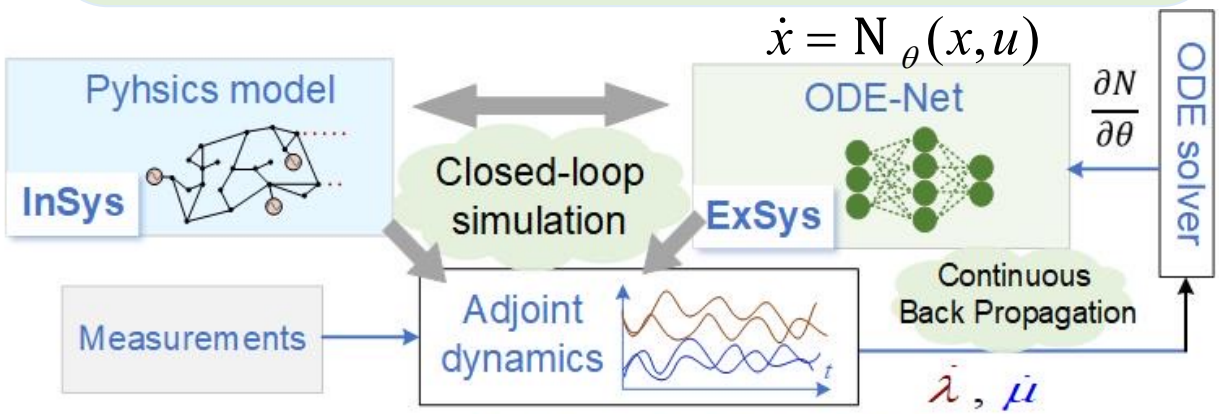

Figure 2 PI-NeuDyE continuous learning

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Result of Physics-Informed Dynamic Equivalence

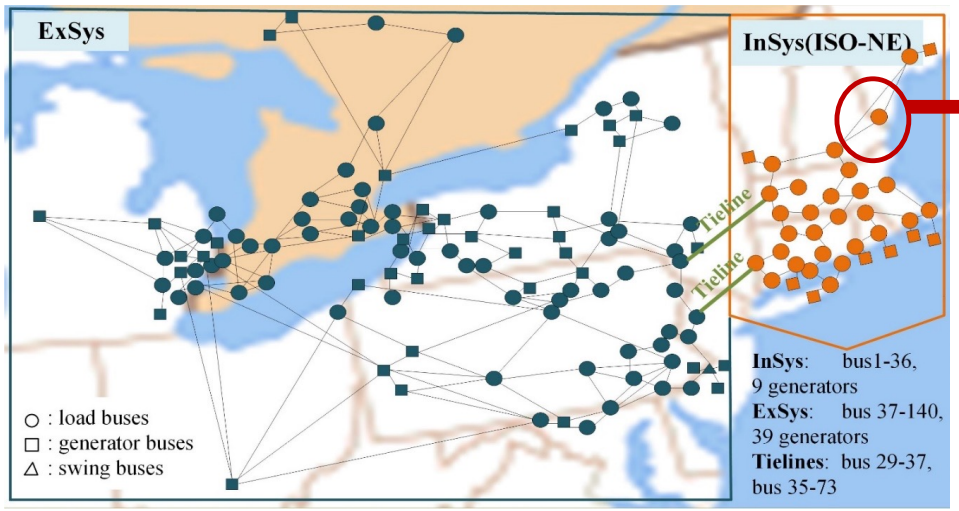

Figure 2 Topology of the NPCC system

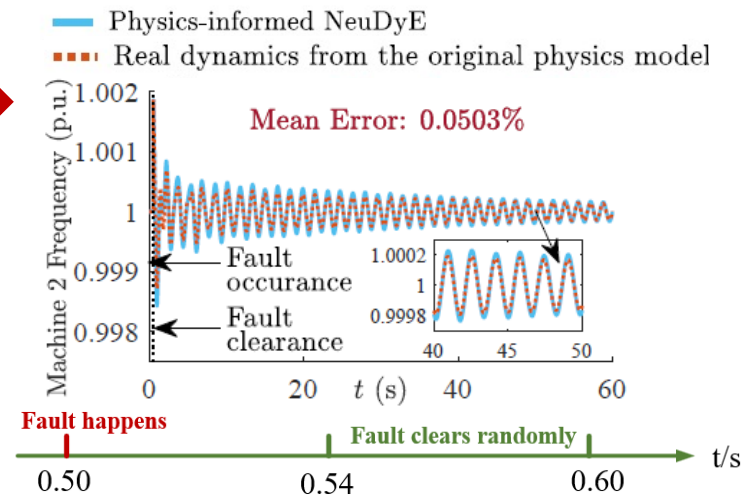

Figure 4 Closed-loop tests with fault clears at 0.56s at bus 19

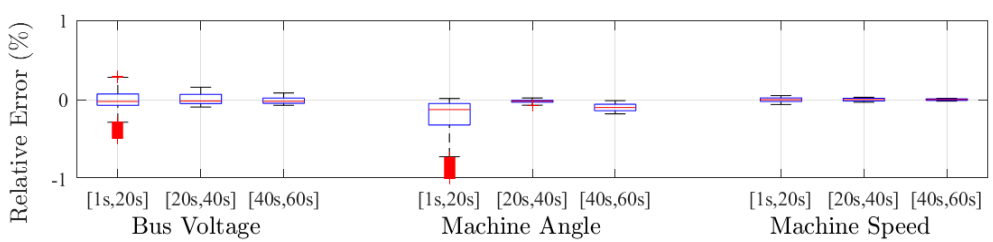

Figure 3 Accuracy of PI-NeuDyE under 108 cases

- ❑ High accuracy: <1% overall relative error
- ❑ High adaptability: various fault scenarios
- ❑ High generalization ability: new case

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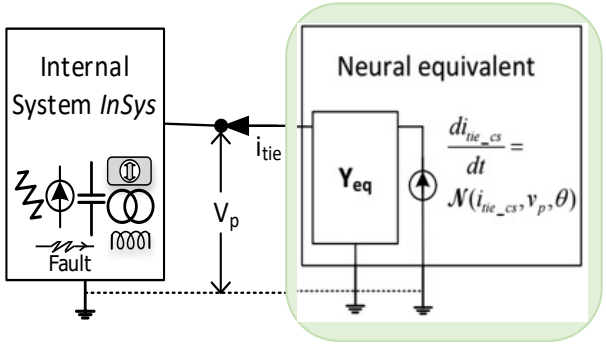
Practical application of Dynamic Equivalence

Challenges

- ❑ Suffer from heavy training
- ❑ Less inputs? Only boundary?

Driving Port Dynamic Equivalence

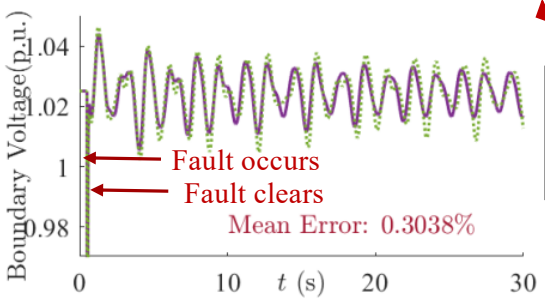
- ❑ Norton equivalent theory (boundary voltages)
- ❑ Algebraic component separation
- ❑ Strengthening ODE-NET via Recurrent Neural Network



Neural network equivalent

Figure 5 Driving Port-ODE-NET

Utilize only **6% of inputs**
Comparable **high accuracy**



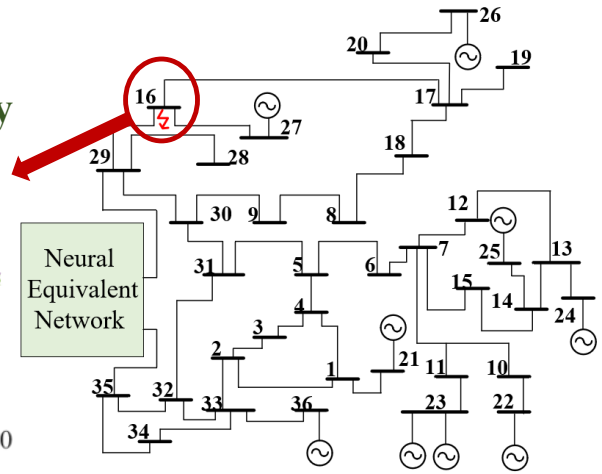


Figure 6 DP-NeuDyE closed-loop simulation

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Conclusion and Promising Future

Achievements

- ❑ Only need boundary measurements
- ❑ Accurately capture the dynamics of the external system
- ❑ Predict in real-time

Industrial Applications

- ❑ Update external equivalent model in real time
- ❑ Online transient analysis
- ❑ Stability analysis…

Future Steps:

- More complicated system with diversified testing cases
- More efficient and scalable in larger systems
- Integrated with other AI components

Neuro-Reachability of Networked Microgrids, Y. Zhou, P. Zhang
Physics-Informed, Safety and Stability Certified Neural Control for Uncertain Networked Microgrids, L Wang, S Zhang, Y Zhou

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Questions?

Acknowledgment:

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