NeurIPS Workshop

ELECTRICAL & COMPUTER ENGINEERING
UNIVERSITY of WASHINGTON

Microsoft

Predicting Power System Dynamics and Transients: A Frequency Domain Approach

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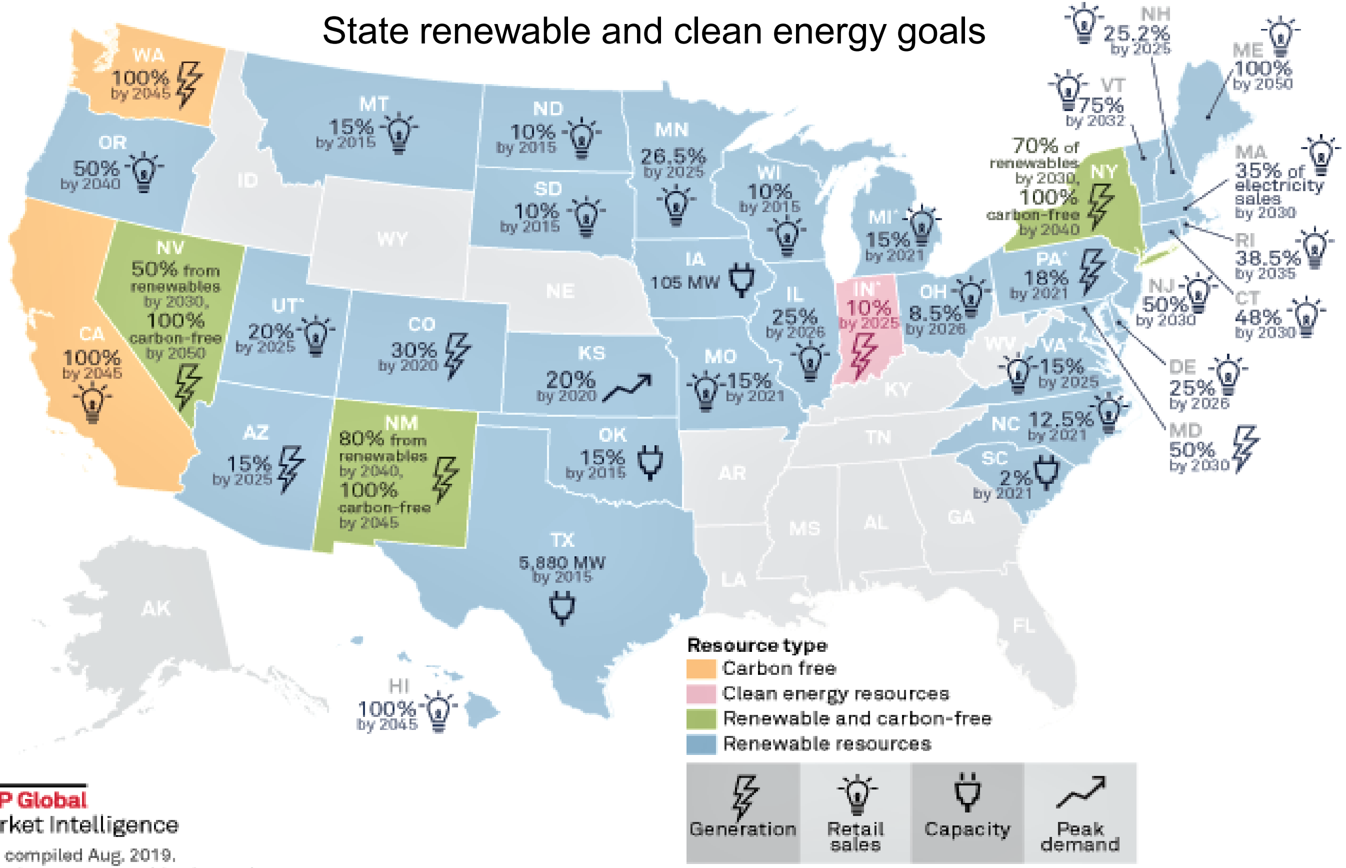
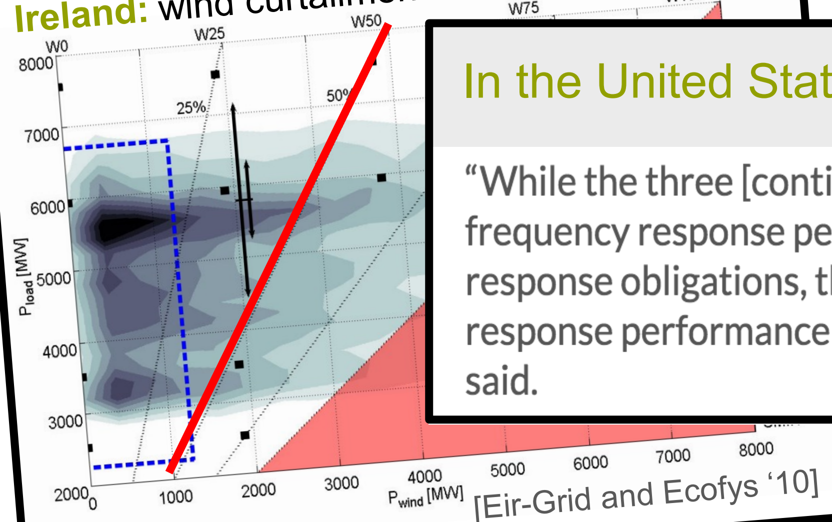
1. Background

State renewable and clean energy goals



1. Dynamic Performance Degradation with Renewables

Ireland: wind curtailment after 50% of load



[Eir-Grid and Ecofys '10]

In the United States:

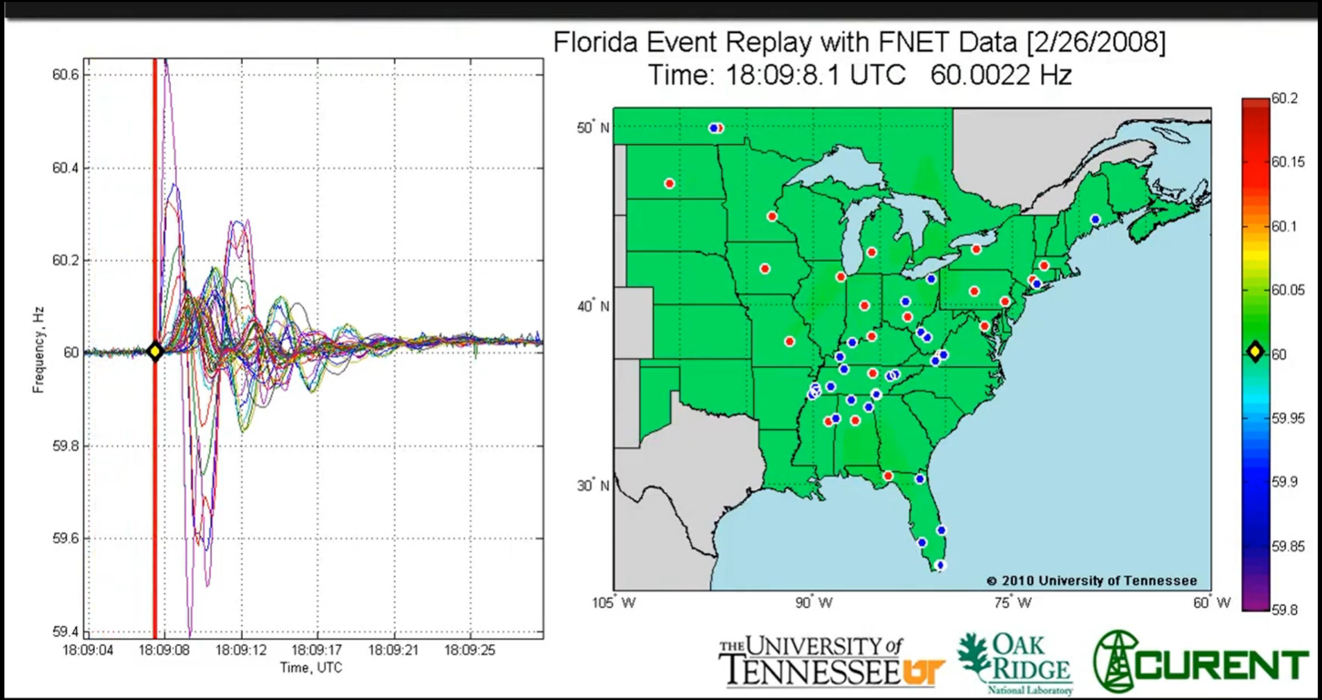
FERC Federal Energy Regulatory Commission

"While the three [contiguous] U.S. interconnections currently exhibit adequate frequency response performance above their interconnection frequency response obligations, there has been a significant decline in the frequency response performance of the Western and Eastern Interconnections," FERC said.

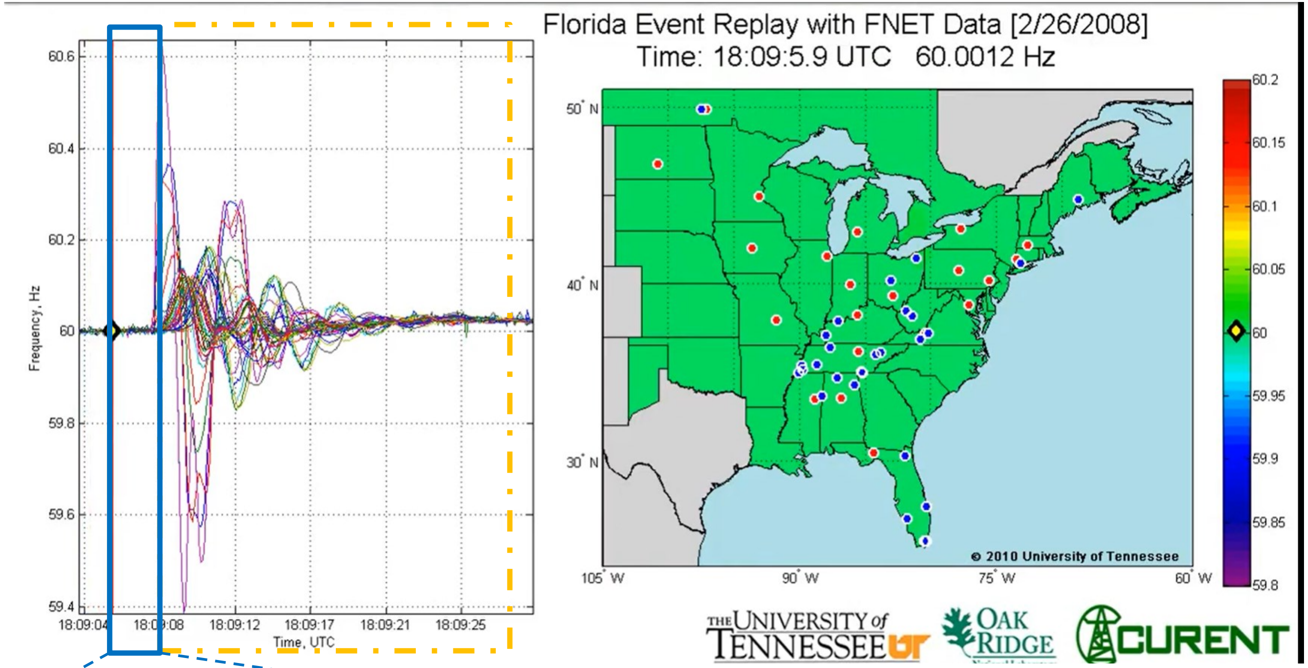
[FERC, Nov. 16]

1. Power System Dynamics

Florida blackout : Two-thirds of the state of Florida experienced a loss of load



1. Prediction for Power System Dynamics



Initial state trajectory shortly after fault

Predict

Transient dynamics

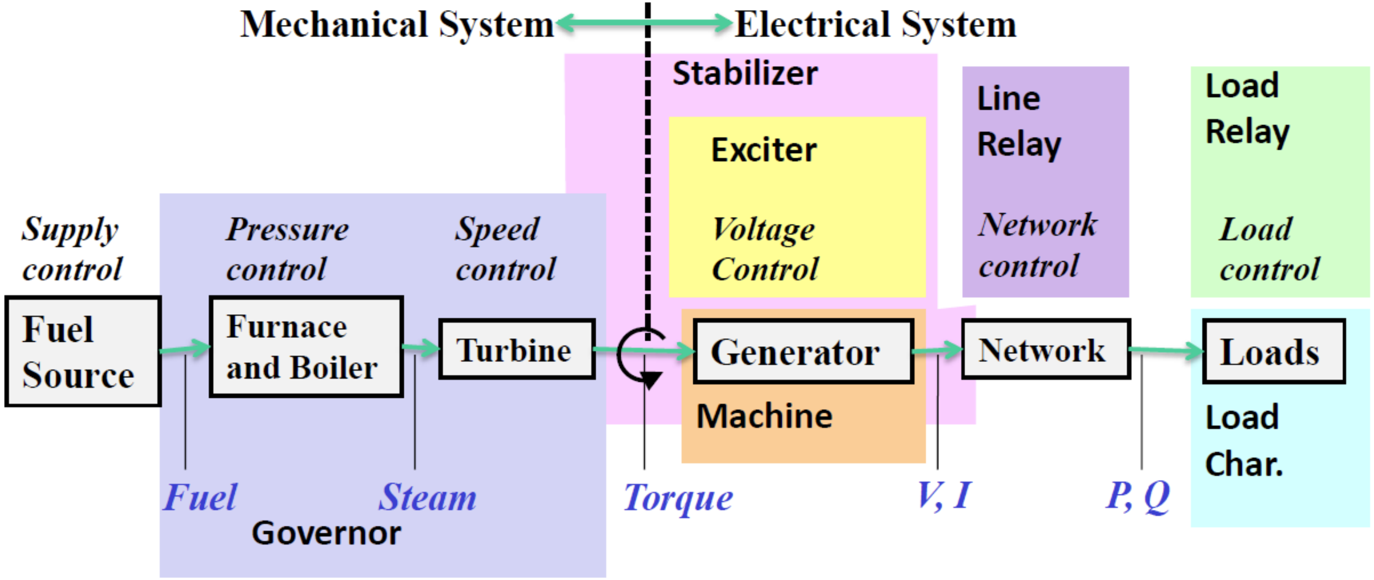
Numerical simulation

Application goals:

- Faster real time prediction, take interim actions to minimize impact
- Better planning, so single line faults don't lead to load shedding

2. Solving ODEs for Power System Dynamics

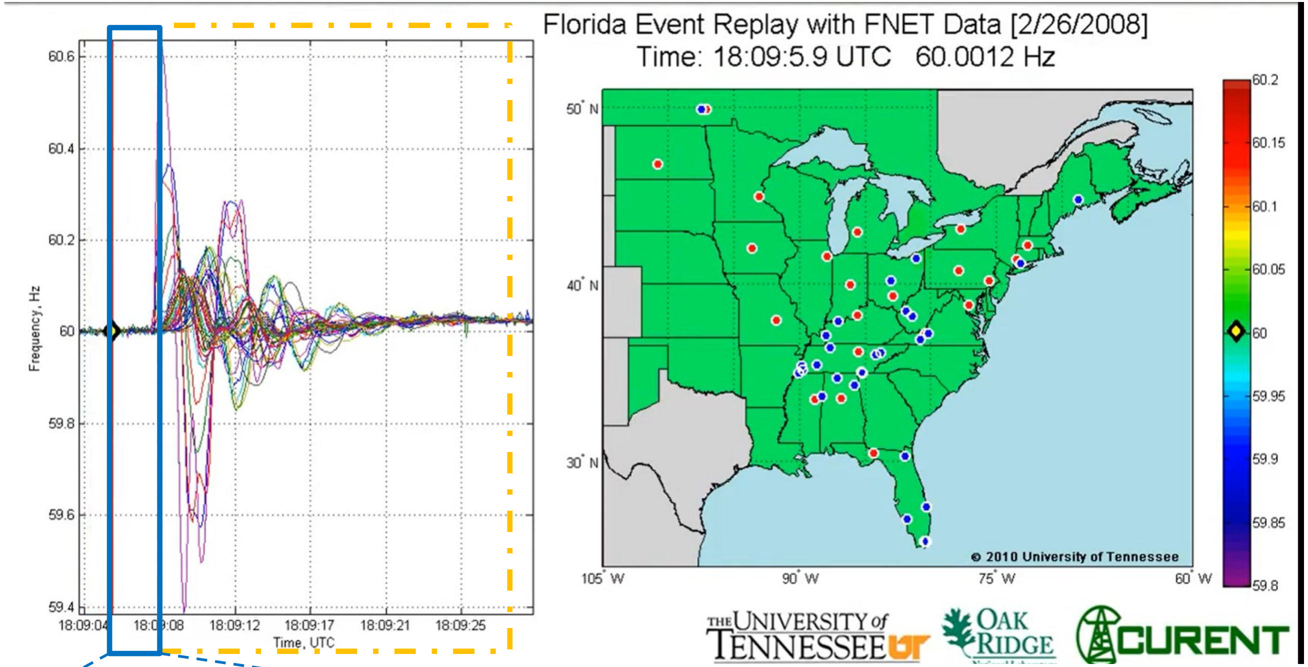
Solving high-dimensional non-linear ODEs for Power system transient dynamics



More than 1000 ODEs to be solved for a moderate sized power grid

hing, 2006.

2. Challenges in Dynamic Prediction



Initial state trajectory shortly after fault

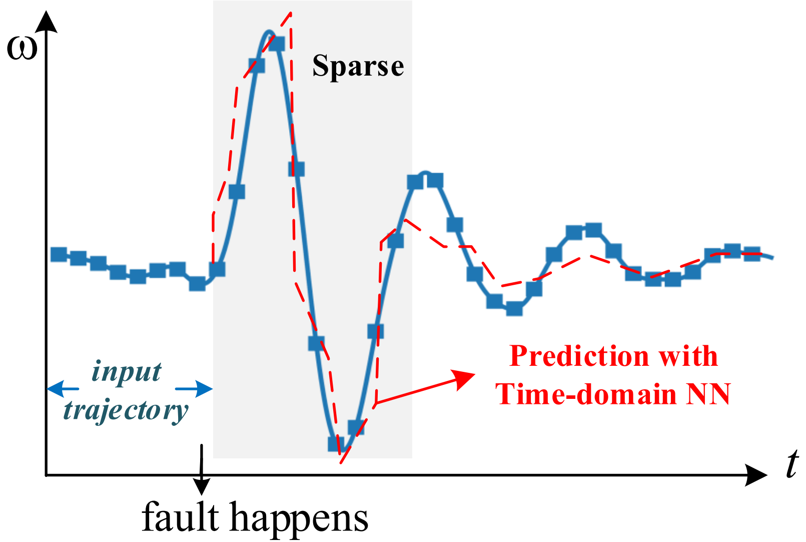
Neural network →

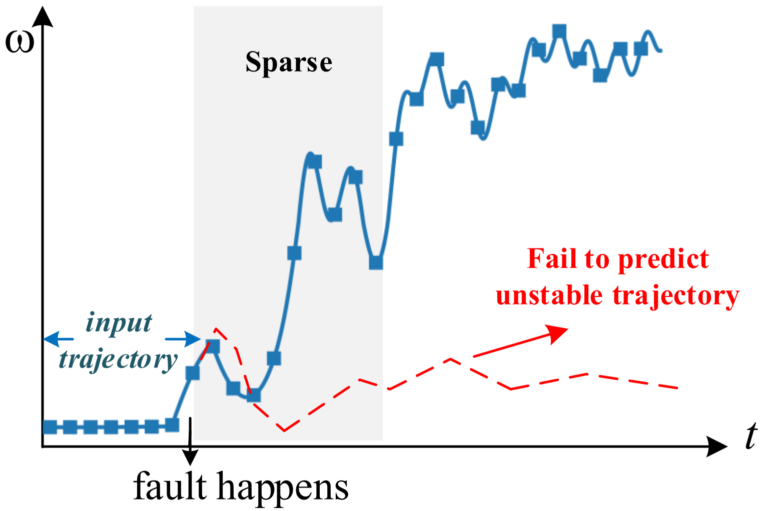
Future trajectory

2. Challenges in Dynamic Prediction

Generic machine learning approach purely learn the mapping in time-domain

- Easy to overfit in training set with majority to be stable trajectory
- Difficult to learn a smooth curvature
- Failing to capture unstable trajectory will lead to catastrophic consequences





2. Contribution: Learning in Frequency Domain

Time domain trajectory

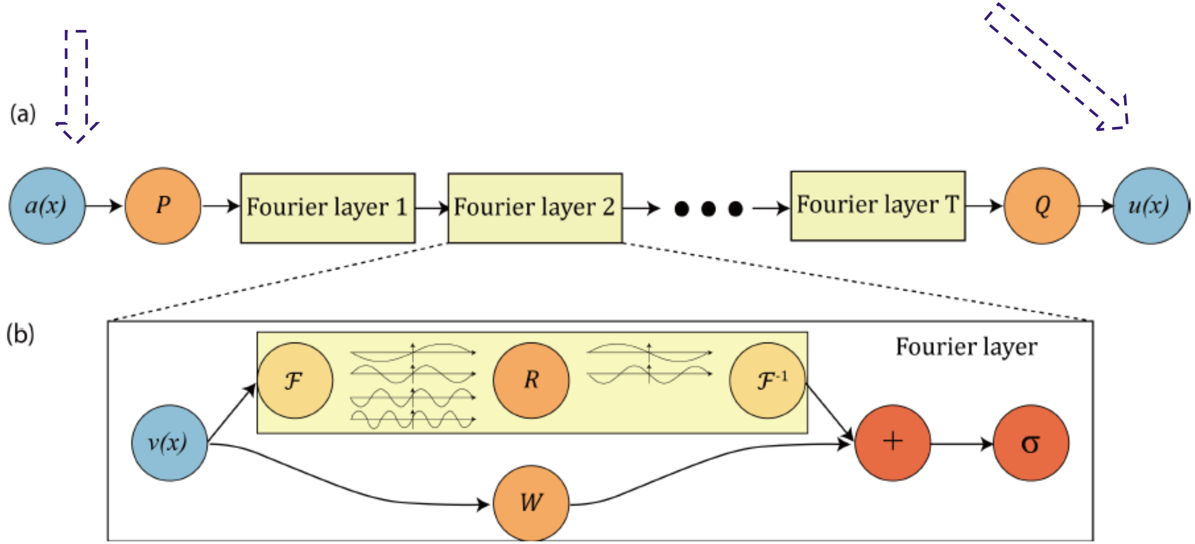
↓ Fourier Transform

Learning in the Frequency domain
: Filtering & Equivalent convolution

↓ Inverse Fourier Transform

Prediction

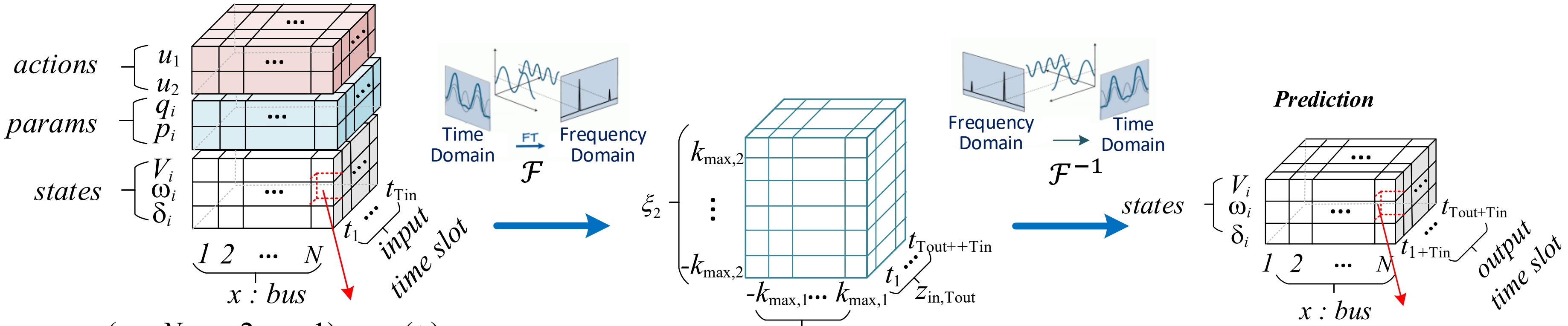
Initial state trajectory → **Fourier Neural Operator** → Future trajectory



Li, Zongyi, et al. "Fourier neural operator for parametric partial differential equations." *arXiv preprint arXiv:2010.08895* (2020).

3. Incorporating Parameter Variations and Outages

Input Tensor Encoding with Params and Actions



$g\,(x = N, y = 2, z = 1) = \omega_N(t_1)$

$\hat{g}(x = N, y = 2, z = 1) = \omega_N(t_{1+T_{in}})$

Fault-Clear Action Encoder

$u_1(t)$: line outage at t

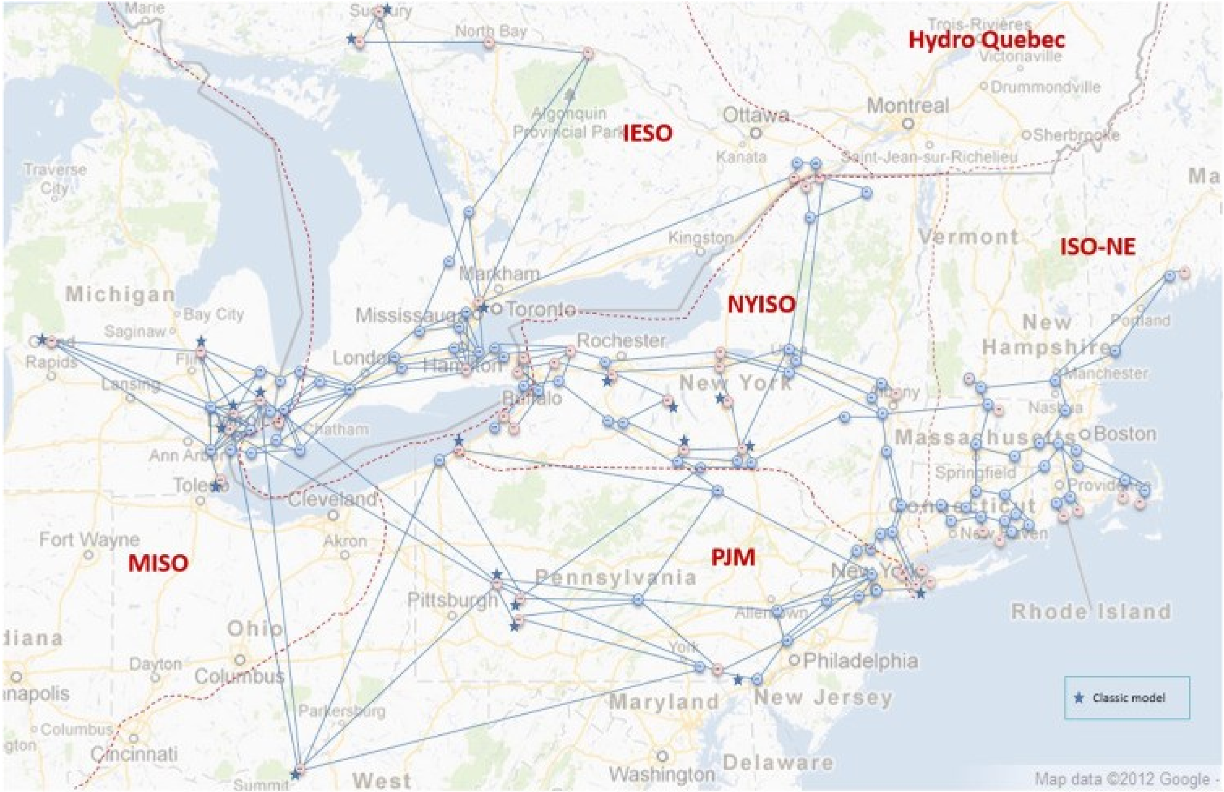
$u_2(t)$: type of outage at t
- *single-phase-to-ground*
- *two-phase-to-ground*
- *line-to-line*
- *three-phase-fault*
- …

$\times W_\phi$

Equivalent convolution in Frequency domain

4. Case studies

Northeastern Power Coordinating Council (NPCC) 48-machine,140-bus power system



4. Metrics

- Type 1: percentage of unstable predicted to be stable
- Type 2: : percentage of stable predicted to be unstable

TABLE I
PERFORMANCE - ON FAULT

Metric	Relative mse			Error-Type1			Error-Type2		
Cycle after fault	0	2	4	0	2	4	0	2	4
FNO	**0.0546**	**0.0084**	**0.0056**	**0.22**	**0**	**0**	0.022	0.011	0.011
DNN	0.0712	0.0696	0.0663	1	0.714	0.714	0	0	0.011

TABLE II
PERFORMANCE - POST FAULT

Metric	Relative mse			Error-Type1			Error-Type2		
Cycle after fault	10	20	30	10	20	30	10	20	30
FNO	**0.0035**	**0.0026**	**0.0016**	**0**	**0**	**0**	0.011	0.011	0
DNN	0.0710	0.0324	0.0193	0.429	0	0.143	0.022	0.022	0.011

One cycle is 1/60=0.017 seconds

Thank you!

- Online version of this work can be found in https://arxiv.org/abs/2111.01103
- Feel free to contact me at wenqicui@uw.edu