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Stony Brook University

Solar PLUS: Physics-Aware Learning Based Scalable Modeling and Analytics for Solar Energy Integration

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Project Goal

- **Challenges**:

Massive integration of solar PV generation makes it prohibitively difficult to perform accurate transient/dynamic analyses:

  - Exhaustive physical models of all subsystems
  - Astronomical contingencies and solar generation scenarios

- **Our solution:**

Ultra-scalable modeling and analytics of both transient and dynamic behaviors of power grids with solar PVs at all grid levels by exploiting the physics-aware machine learning:

  - Accurately represent system behaviors at all levels
  - Identify security risks under infinite PV scenarios in grid operations

Solar PLUS Overview

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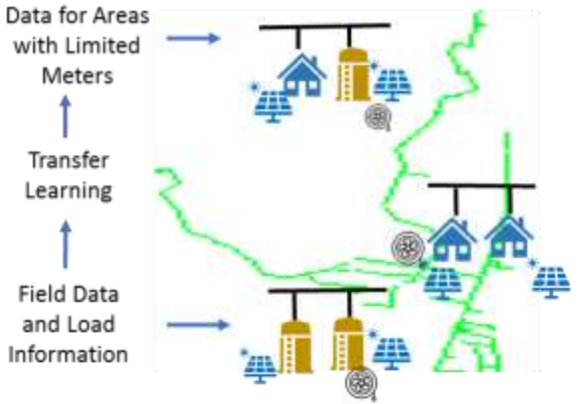
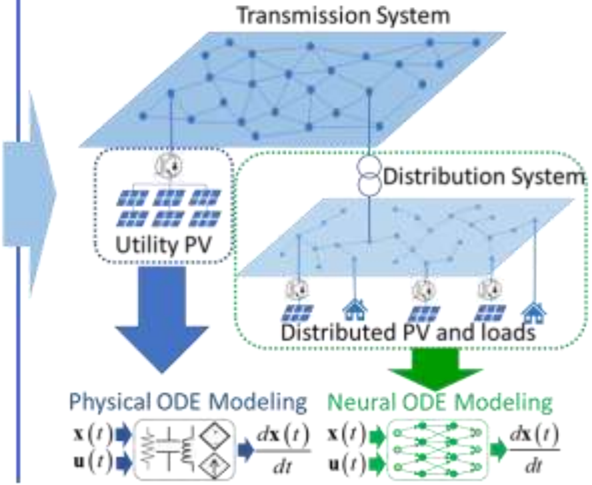
The proposed project includes three main parts:

1) Physical model library
2) AI-enabled scalable modeling
3) AI-enabled scalable analytics

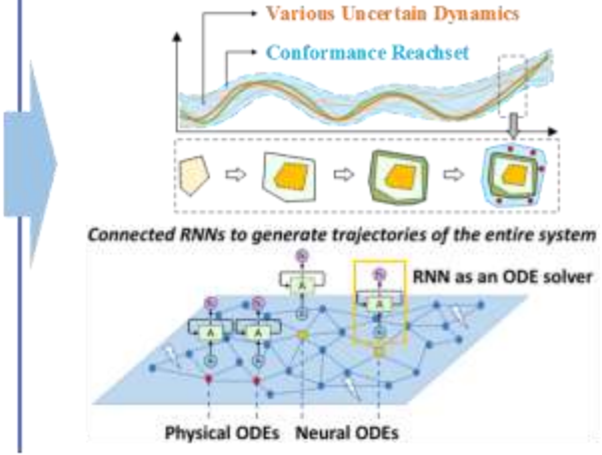
Physical Model Library: Representative BTM Load and PV Compositions



Ultra-Scalable Modeling:
Physics-Neural ODEs for Potentially Modeling 1M+ Devices



Ultra-Scalable Analytics:
Dynamic Verification for Infinite Uncertain Scenarios
Online Trans/Dynamic Analysis for Potentially Assessing 1k+ Contingencies



Physical Model Library

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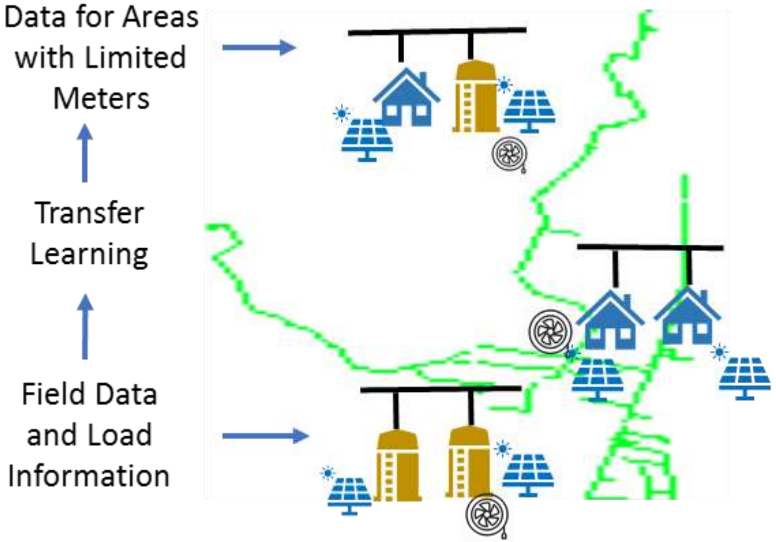
- **Goals:** a high-fidelity model library of BTM PV and loads based on real-world system information

- **Accomplishment**: Validated **library** with 10+ types of load and PV models

Benefits:

- Provide a **substantial coverage** for the dynamic models of the BTM generations and loads under different simulation scenarios
- Effectively tackle the **distribution system data-insufficiency** problem by serving as a high-fidelity training data synthesizer for data-driven modeling development.

Physical Model Library: Representative BTM Load and PV Compositions



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Scalable Subsystem Modelling via Neural ODE

- **Goal**:

Develop an advanced Neural ODE model to accurately track continuous system operational states under missing/noise data.

- **Variational Stochastic Differential Networks (VSDN) model** :
    - Generates continuous state trajectories from discrete data samples.
    - Generative model: can recurrently predict the future values of the sequence.
    - Inference model: filters out the noise and shares the ODE and drift functions.

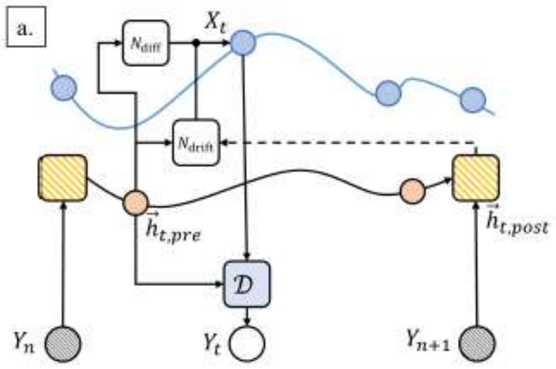

Fig 2.2: Block diagram of the filtering inference model used for experiments [1]

[1] Liu, Yingru, et al. "Continuous-time stochastic differential networks for irregular time series modeling." *Neural Information Processing: 28th International Conference, ICONIP 2021, Sanur, Bali, Indonesia, December 8–12, 2021, Proceedings, Part V 28*. Springer International Publishing, 2021.
[2] De Brouwer, Edward, et al. "GRU-ODE-Bayes: Continuous modeling of sporadically-observed time series." *Advances in neural information processing systems* 32 (2019)

Experimental Results

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Experiments were performed on SETO 1001-bus 14DG microgrid system, developed by SBU team.

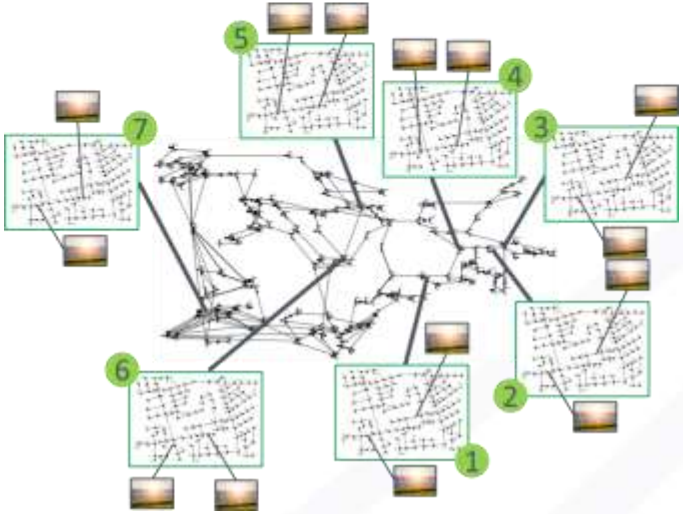


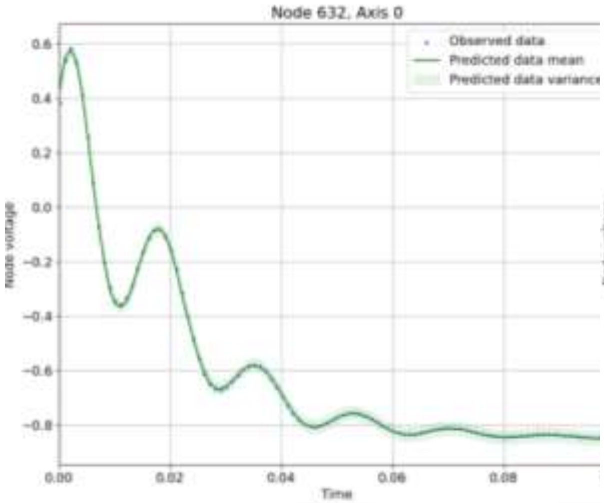
Fig 2.2: Topology of the SETO 1001-bus 14-DG system

% noise	% missing data	RMSE	MAE	MAPE
0%	0%	0.0097	0.0042	0.0201
	30%	0.0414	0.0124	0.0610
	50%	0.0586	0.0168	0.0973
1%	0%	0.0122	0.0074	0.0271
	30%	0.0421	0.0152	0.0669
	50%	0.059	0.0192	0.1021
5%	0%	0.0381	0.0270	0.0848
	30%	0.0575	0.0344	0.1313
	50%	0.0695	0.0361	0.1523

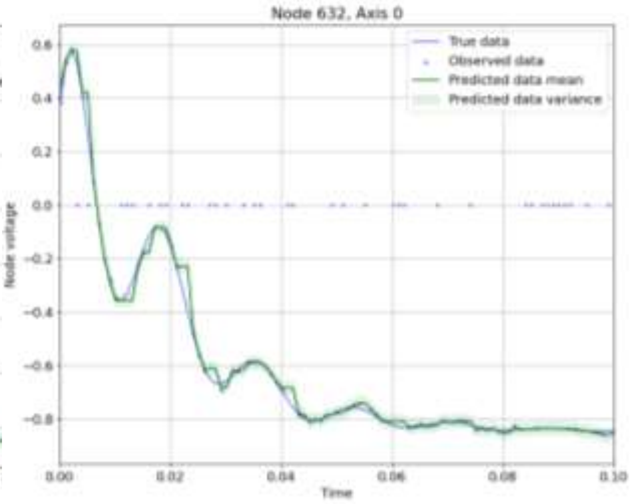
Table 2.1: Error performance metrics of VSDN model on 1001-bus data

Experimental Results

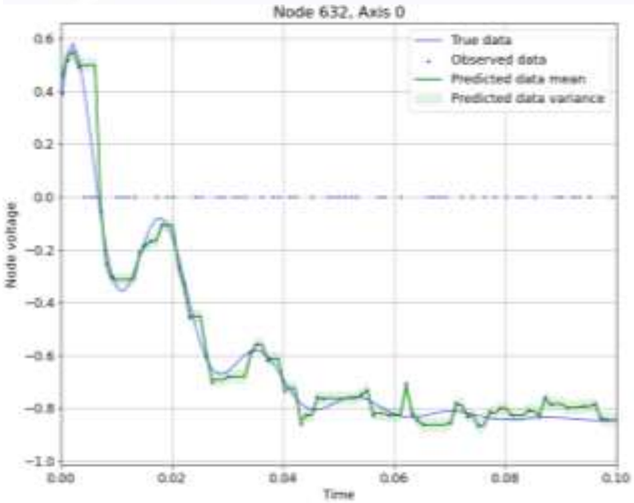
- Predicted mean of node voltage trajectories of node 632 of 1001-bus data for different scenarios



No missing samples, no noise



30% missing samples, 1% noise



50% missing samples, 5% noise

AI-enabled scalable analytics: Neuro-Reachability

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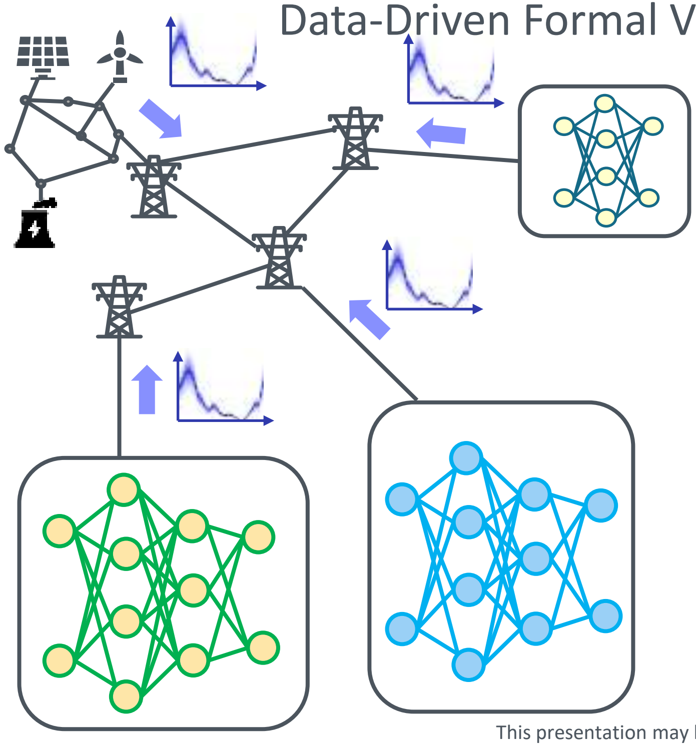
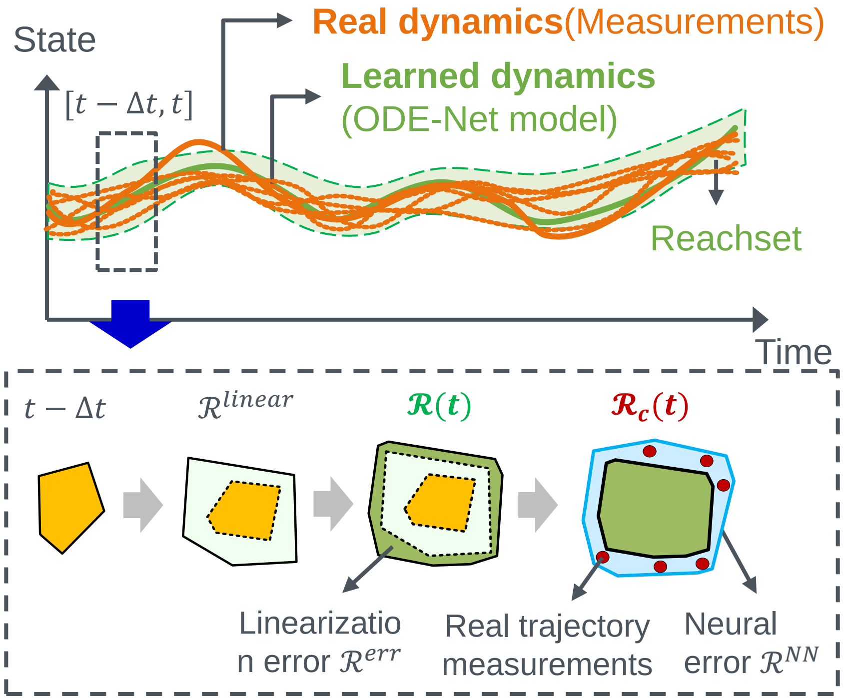
How to verify uncertain dynamics with data-driven system models?

Neuro-Reachability: conformance-empowered reachable dynamics

Data-Driven Formal Verification





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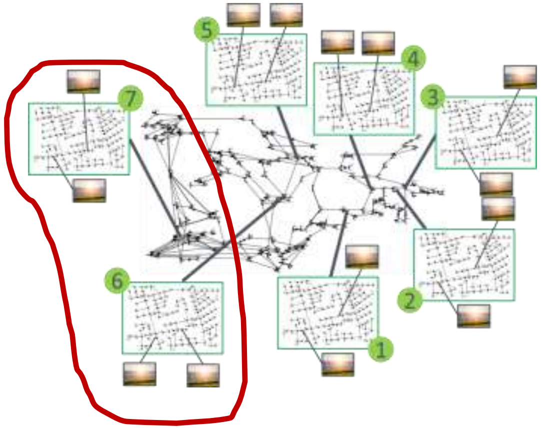
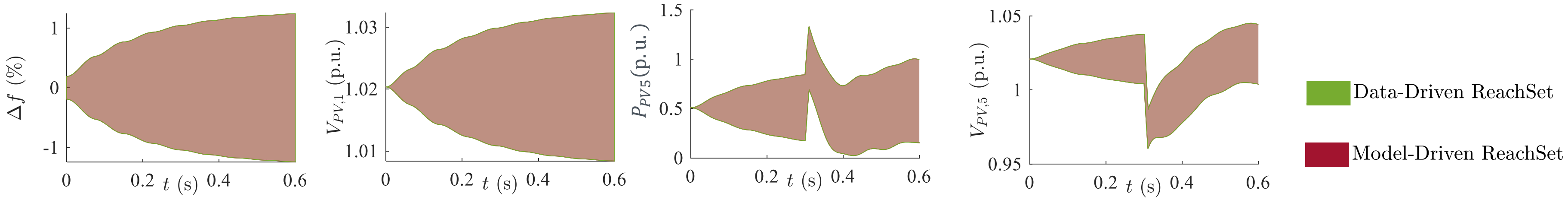
Experiments and Validation

- Test system: 1001-bus transmission-distribution system
  - 7 distribution grids and 14 IBRs
  - Each IBR has a double-loop droop controller
  - Grid 6 and 7 are modeled by ODE-Net
- Reachable set under 10% uncertainty from each PV.



Without fault

Under the short-circuit fault



System frequency

PV output voltage

PV output power

PV output voltage

ODE-Net-enabled neuro-reachability conforms with the model-driven reachable sets ➔ A data-driven tool for verifying power grid dynamics with both renewable uncertainties and unidentified subsystem models

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AI-enabled scalable analytics: Neuro-Awareness

How to track dynamics of the system with unidentified subsystems?

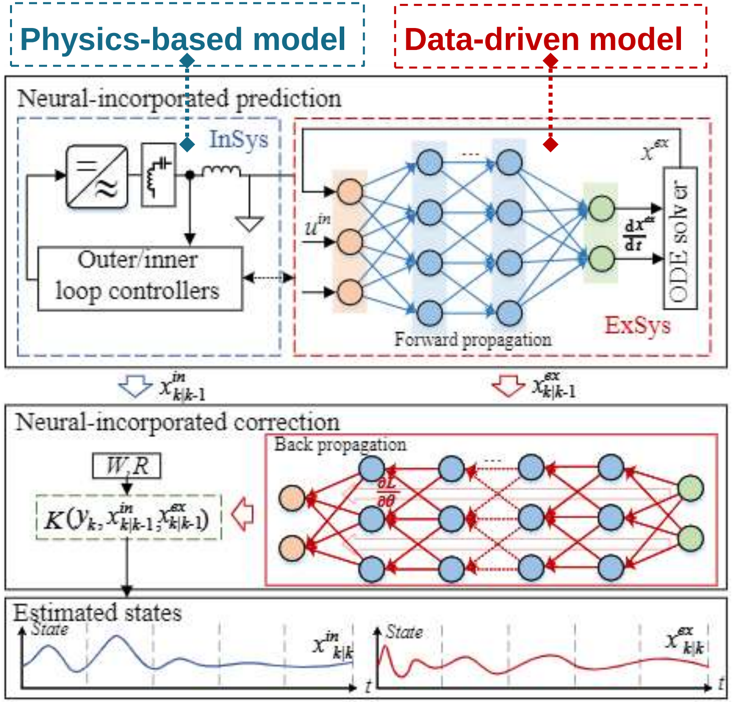
Neuro-Awareness: Data-driven dynamic state estimation(DSE)

Challenges:

- Complete physics model of the whole systems may not always be attainable

Contributions:

- Neural dynamic state estimation (Neuro-DSE) for Networked Microgrids with partially unidentified subsystems by integrating ODE-Net into Kalman filters.



Experiments and Validation

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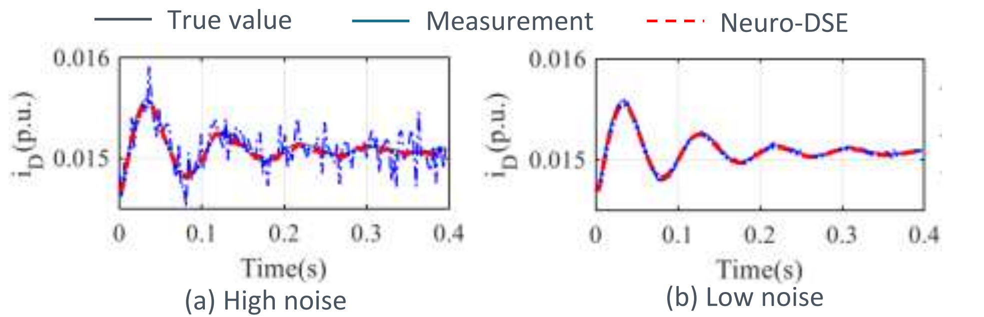
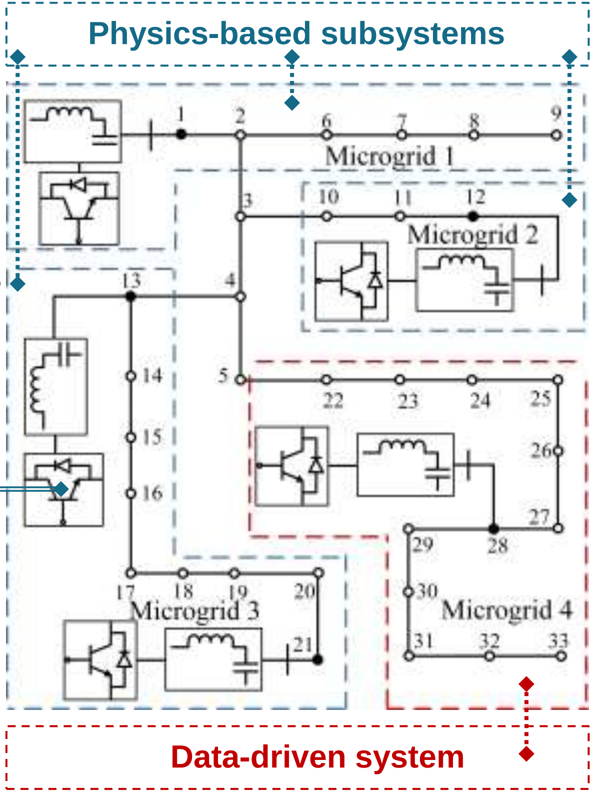
- Test system: 33-bus microgrid system
  - 5 grid forming based IBRs
  - Each IBR has a double-loop droop controller
  - Microgrid 4 is modeled by ODE-Net
- ODE-Net under 20% uncertainties of DER power input.



State trajectories of current control signal under different noise levels



Simulation validates the effectiveness of Neuro-DSE under different noise levels

Integrating Learning and Physics based Computation for Fast Online Transient Analysis

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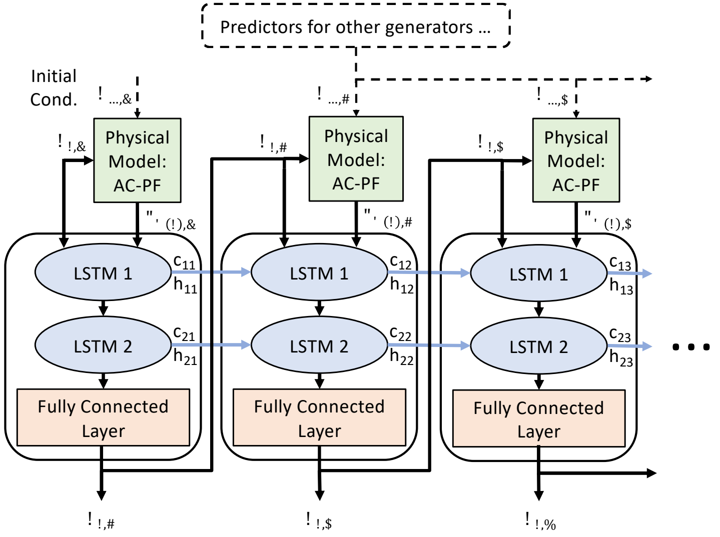
- **Goal: to accelerate the simulation of full power system transient trajectories.**
  - Key: One predictor is trained for each generator.

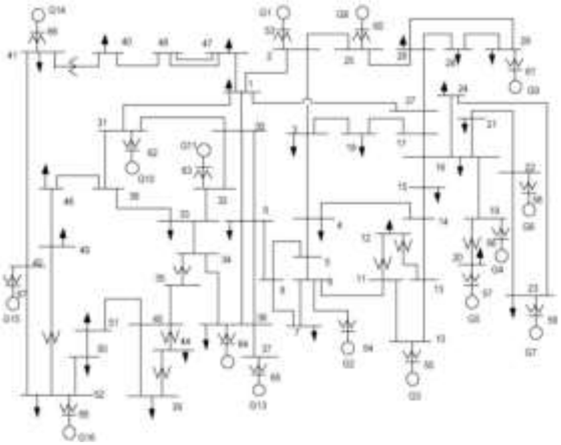
  Replace the time-consuming dynamic computation of the generators with trained predictors
  - Retain the time-efficient algebraic computation of solving AC-PF
- **Key Advantages**
  - **Scalability** : independent complexity
  - **No re-training**: agnostic to changes
  - **Flexible training strategies**:– joint, local, and singular – allowing different trade-offs between offline training complexity and online testing accuracy.



Iteratively alternates between calling all the trained predictors, solve AC-PFs and update inputs collectively.

Performance Evaluation

- We simulated 2,460 N – 2 contingencies in a 68 bus system, collected the simulated trajectories.
- Excellent performance in both accuracy and computation speed is demonstrated.



68-bus 16-generator system.

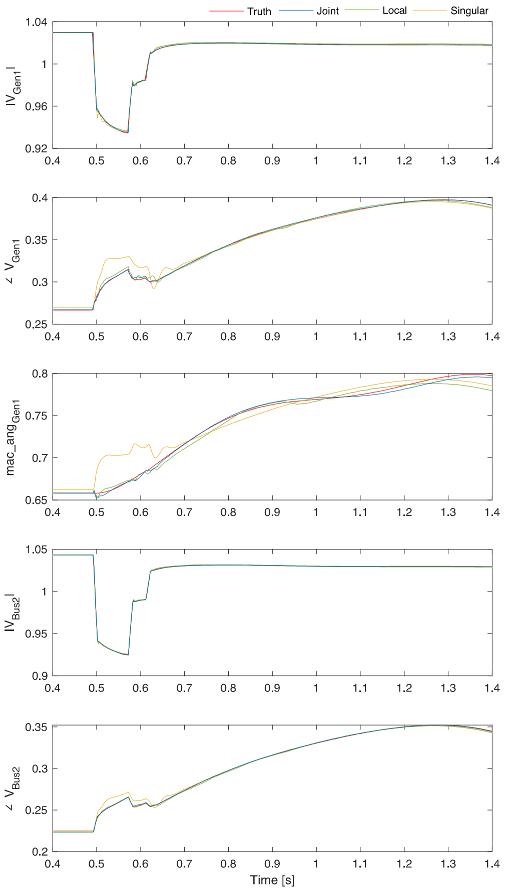


TABLE I: Performance Comparison of Training Strategies

Training Strategy	Avg. RMSE	Avg. Relative RMSE
Joint	$\mathbf{3.631 \cdot 10^{-3}}$	$\mathbf{4.056 \cdot 10^{-2}}$
Local	$5.372 \cdot 10^{-3}$	$5.684 \cdot 10^{-2}$
Singular	$8.720 \cdot 10^{-3}$	$8.861 \cdot 10^{-2}$

TABLE II: Computational Efficiency

Model	Offline Training time [min]	Offline Compute Memory [MB]	Online Compute Time [s]	Online Compute Memory [MB]
Singular	229	2245	2.16	1545
Local	767	2247	2.16	1545
Joint	2609	2941	2.16	1545
Numerical	-	-	19.9	269

J. Li, Y. Zhao, and M. Yue, "Integrating learning and physics based computation for fast online transient analysis," Proc. IEEE Conference on Innovative Smart Grid Technologies (ISGT), 2023.