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
The proposed project includes three main parts:

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

- **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.
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.


Experimental Results

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

![Topology of the SETO 1001-bus 14-DG system](image)

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

<table>
<thead>
<tr>
<th>% noise</th>
<th>% missing data</th>
<th>RMSE</th>
<th>MAE</th>
<th>MAPE</th>
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<tbody>
<tr>
<td>0%</td>
<td>0%</td>
<td>0.0097</td>
<td>0.0042</td>
<td>0.0201</td>
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<tr>
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<td>50%</td>
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<td>0.0168</td>
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<tr>
<td>1%</td>
<td>0%</td>
<td>0.0122</td>
<td>0.0074</td>
<td>0.0271</td>
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<tr>
<td></td>
<td>30%</td>
<td>0.0421</td>
<td>0.0152</td>
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<tr>
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<td>50%</td>
<td>0.0695</td>
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**Fig 2.2:** Topology of the SETO 1001-bus 14-DG system
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

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

Neuro-Reachability: conformance-empowered reachable dynamics

State

Real dynamics (Measurements)

Learned dynamics (ODE-Net model)

Reachset

$[t - \Delta t, t]

Data-Driven Formal Verification

$t - \Delta t$

Linearization error $R_{\text{linear}}$

Real trajectory measurements

Neural error $R_{\text{NN}}$

Data-driven formal verification

Real trajectory measurements $[t - \Delta t, t]$

Linearization error $R_{\text{err}}$

Real trajectory $R(t)$

Neural error $R_{\text{NN}}$

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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.**

### System Frequency

- Without fault
- Under the short-circuit fault

### PV Output Voltage

- Without fault
- Under the short-circuit fault

### PV Output Power

- Without fault
- Under the short-circuit fault

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
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

- **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.

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

State trajectories of current control signal under different noise levels

(a) High noise  
(b) Low noise
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.

TABLE I: Performance Comparison of Training Strategies

<table>
<thead>
<tr>
<th>Training Strategy</th>
<th>Avg. RMSE</th>
<th>Avg. Relative RMSE</th>
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<tr>
<td>Joint</td>
<td>3.631 x 10^{-3}</td>
<td>4.056 x 10^{-2}</td>
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<tr>
<td>Local</td>
<td>5.372 x 10^{-3}</td>
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<tr>
<td>Singular</td>
<td>8.720 x 10^{-3}</td>
<td>8.861 x 10^{-2}</td>
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TABLE II: Computational Efficiency

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<tr>
<td>Numerical</td>
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