Graph-Learning-Based Measurement Synchronization for Distribution System State Estimation

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Motivation

• Distribution systems historically **lack enough sensor measurements**

• Available measurements **fail to provide a universal solution** involving a wide variety of sources
  • **Fast but sparse (FS)** measurements: PMUs, SCADA
  • **Slow but abundant (SA)** measurements: smart meters

• Distribution systems not fully observable
  • Hosting capacity for solar generation cannot be accurately estimated
  • Unnecessary solar curtailments
Outline

Project Overview

Limitations of Existing Models

Machine Learning Model Architecture
Algorithm
Test Results

Closed-Loop Operation

Conclusion

This presentation may have proprietary information and is protected from public release.
Project Overview

- This project aims to use of Machine Learning for integration and synchronization of diverse data sources for distribution system state estimation.
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Project Overview

• This project aims to use of Machine Learning for **integration** and **synchronization** of diverse data sources for **distribution system** state estimation.
Input:
- **FS** measurements (node voltage, FS line active power, FS line reactive power) each 1 minute;
- **SA** measurements (node active power, node reactive power, derived active power of unmeasured lines, derived reactive power of unmeasured lines) each 60 minutes;
- network **topology** as a graph.

Output:
- predicted SA measurements each 1 minute
Problem Statement

• Problem statement:
  • **Black Lines**: observable lines (FS measurements and derived measurements from zero injections, every 1 minute)
  • **Red Lines**: unobservable lines (derived measurements from SA measurements, every 60 minutes)
  • **Gray Lines**: disconnected lines
  • **Objective**: predict the power injections (SA measurements) at all the nodes (every 1 minute)
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Graph-Learning-Based SA Measurement Prediction

- **Existing graph learning methods:**
  - **Masking** the power flow features of the **unobservable lines**;
  - Use the power flow features of the **observable lines** (FA measurements) to **predict** the nodal injections (SA measurements) **directly** based on the Graph Neural Network (GNN).

- **Limitations of these methods:**
  - The methods have a limited performance when there are **too many unobservable lines**;

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Graph-Learning-Based SA Measurement Prediction

- Motivation of designing a new framework
  - Many **lines** are **highly correlated** to each other in terms of active/reactive power
  - Can we first predict the unobservable lines, so the GNN has a complete input for predicting the nodal injections?

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Graph-Learning-Based SA Measurement Prediction

• Motivation of designing a new framework
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![Correlation Distribution between Line 109_114 and others](image)

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Motivation of designing a new framework

- Many lines are highly correlated to each other in terms of active/reactive power.
- Can we first predict the unobservable lines, so the GNN has a complete input for predicting the nodal injections?

Correlation Distribution between Line 93_94 and others
Motivation of designing a new framework
- Many **lines** are **highly correlated** to each other in terms of active/reactive power
- Can we first predict the unobservable lines, so the GNN has a complete input for predicting the nodal injections?

Correlation Distribution between **Node 93** and other lines
Motivation of designing a new framework

- Many **lines** are **highly correlated** to each other in terms of active/reactive power
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Correlation Distribution between **Node 104** and other lines
Graph-Learning-Based SA Measurement Prediction

• Motivation of designing a new framework
  • Many **lines** are *highly correlated* to each other in terms of active/reactive power
  • Can we first predict the unobservable lines, so the GNN has a complete input for predicting the nodal injections?

Correlation Distribution between **Node 109** and other lines
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Graph-Learning-Based SA Measurement Prediction

• Framework Overview
  • A basic version of the line prediction model has been built. An Edge Graph Convolution (EGC) is used to predict active/reactive power of unobservable lines, and a Graph Attention Network (GAT) is used to capture the power grid topology information for node injection prediction.
**Graph-Learning-Based SA Measurement Prediction**

• **Edge Graph Convolution (EGC)**
  • Construct an *edge graph* based on the *topology graph*
    • Node in *edge graph* = Edge in *topology graph*
    • Edge in *edge graph* = two edges connected to the same node in *topology graph*

• Adopt Graph Convolutional Network (GCN) on the edge graph
Graph-Learning-Based SA Measurement Prediction

- **Traditional** Graph Attention Network (GAT)
  1. Apply *attention coefficients* to calculate relationships between nodes
  2. *Normalization* by softmax to reweight the importance of neighbor nodes when doing graph aggregation

\[
e_{ij} = \text{LeakyReLU} \left( \tilde{d}^T [\mathbf{W} \overrightarrow{h}_i \parallel \mathbf{W} \overrightarrow{h}_j] \right)
\]

\[
\alpha_{ij} = \text{softmax}_j (e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k \in N_i} \exp(e_{ik})}
\]
Our **Modified GAT**

1. Apply **attention coefficients** to calculate relationships between nodes **based on both node features and line features**
2. **Normalization** by softmax to reweight the importance of neighbor nodes when doing graph aggregation

**Combination of features of Node \( i, j \) and Line \( ij \)**

\[
e_{ij} = \text{LeakyReLU} \left( \frac{1}{M} \left[ W \overset{\rightarrow}{h}_i \| W \overset{\rightarrow}{h}_j \| W_l \overset{\rightarrow}{l}_{ij} \right] \right)
\]

**Normalization**

\[
\alpha_{ij} = \text{softmax}_j(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k \in N_i} \exp(e_{ik})}
\]

3. **Only in-degree lines** are involved in graph aggregation
4. **Aggregated line features** are also **concatenated** to node features after node aggregation
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Test Results on ComEd’s Bronzeville Community Microgrid

- Three scenarios with different percentages of unobservable lines are simulated.

<table>
<thead>
<tr>
<th>Proportions of Unobservable Lines</th>
<th>Node Prediction (Mean Absolute Error)</th>
<th>Node Prediction Error Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Active Power</td>
<td>Reactive Power</td>
</tr>
<tr>
<td>10%</td>
<td>1.1559</td>
<td>0.4113</td>
</tr>
<tr>
<td>30%</td>
<td>1.7250</td>
<td>0.4796</td>
</tr>
<tr>
<td>50%</td>
<td>4.8650</td>
<td>1.0425</td>
</tr>
</tbody>
</table>

- Even with some of the line flows are unobservable and cannot be derived based on the physical distribution system model (i.e., unobservable system), the model can still achieve a relatively low error (much less than 10%)
Test Results on ComEd’s Bronzeville Community Microgrid

- Line Prediction Results: Line 43-44
Test Results on ComEd’s Bronzeville Community Microgrid

- Line Prediction Results: Line 59-61
Test Results on ComEd’s Bronzeville Community Microgrid

• Node Prediction Results: Node 93
Test Results on ComEd’s Bronzeville Community Microgrid

- Node Prediction Results: Node 37
Future Work

• Next Steps:
  • Incorporate time series information;
  • Test the performance during topology changing period.
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This project aims to use ML for integration and synchronization of diverse data sources for distribution system state estimation.
Closed-Loop Operation

• Mutually-assisted measurement predictor and state estimator:
  • The ML-based measurement predictor enhances the system observability and measurement redundancy for the robust SE;
  • The robust SE checks the predicted measurements against the physical grid model, rejects those with plausible errors, and estimates the errors as residuals. This information will be fed back to the ML-based predictor to enhance the prediction accuracy.
Test Results on ComEd’s Bronzeville Community Microgrid

- Generation of bad data

- Spike-shape bad data.
- Triangular-shape bad data.
- Square-shape bad data.
- Trapezoidal-shape bad data.

- Corrupted line active power
- Corrupted line reactive power
- Corrupted node active power
- Corrupted line reactive power

Corrupted Node voltage magnitude

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Test Results on ComEd’s Bronzeville Community Microgrid

- The deep learning model uses the measurement residuals of the WLAV state estimator to retrain the model and refine the prediction of SA measurements.

<table>
<thead>
<tr>
<th>Data</th>
<th>Active Power</th>
<th>Reactive Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clean</td>
<td>11.9233</td>
<td>5.7904</td>
</tr>
<tr>
<td>Corrupted</td>
<td>29.1641</td>
<td>9.7516</td>
</tr>
<tr>
<td>Residual-Corrected</td>
<td>13.9248</td>
<td>6.2632</td>
</tr>
</tbody>
</table>

- The feedback mechanism significantly enhances the prediction accuracy of the deep learning model.
Test Results on ComEd’s Bronzeville Community Microgrid

- Results show that the feedback of the robust WLAV estimator can significantly enhance the prediction performance of the deep learning model.
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• We propose a graph-learning-based measurement predictor to **synchronize measurements with different reporting rates** in distribution systems.

• The EGC-GAT measurement predictor can **infer unobservable** line flows and nodal injections by capturing variable correlations.

• The robust WLAV state estimation can **check the consistency** between predicted measurements and grid models and **provide useful information** for enhancing the learning-based prediction.
## Publications


Acknowledgement