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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

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Project Overview

Limitations of Existing Models

Machine Learning Model Architecture
- Algorithm
- Test Results

Closed-Loop Operation

Conclusion

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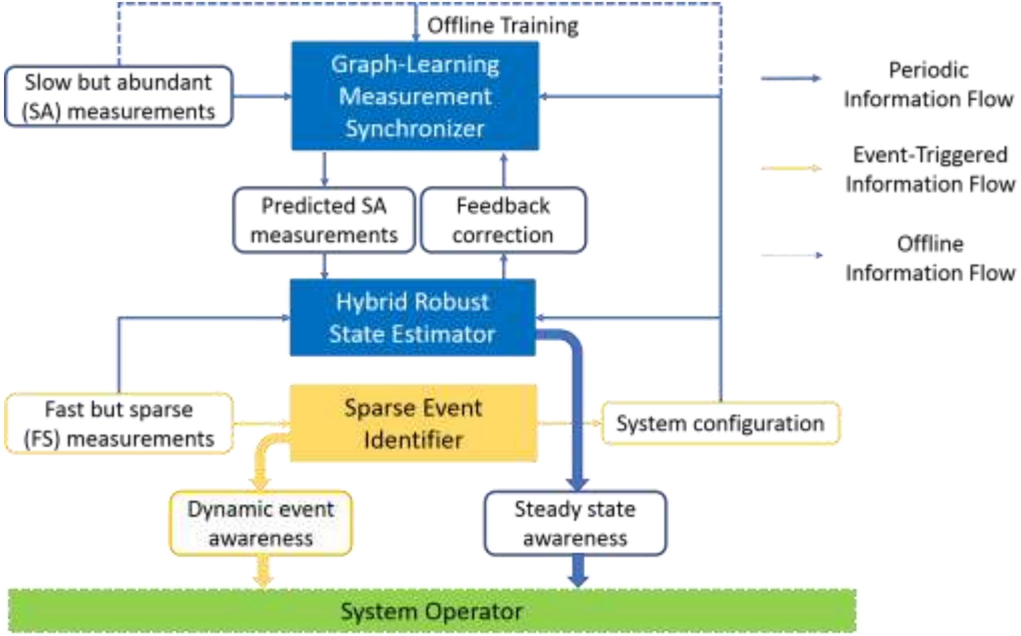
- This project aims to use of Machine Learning for **integration** and **synchronization** of diverse data sources for **distribution system** state estimation.



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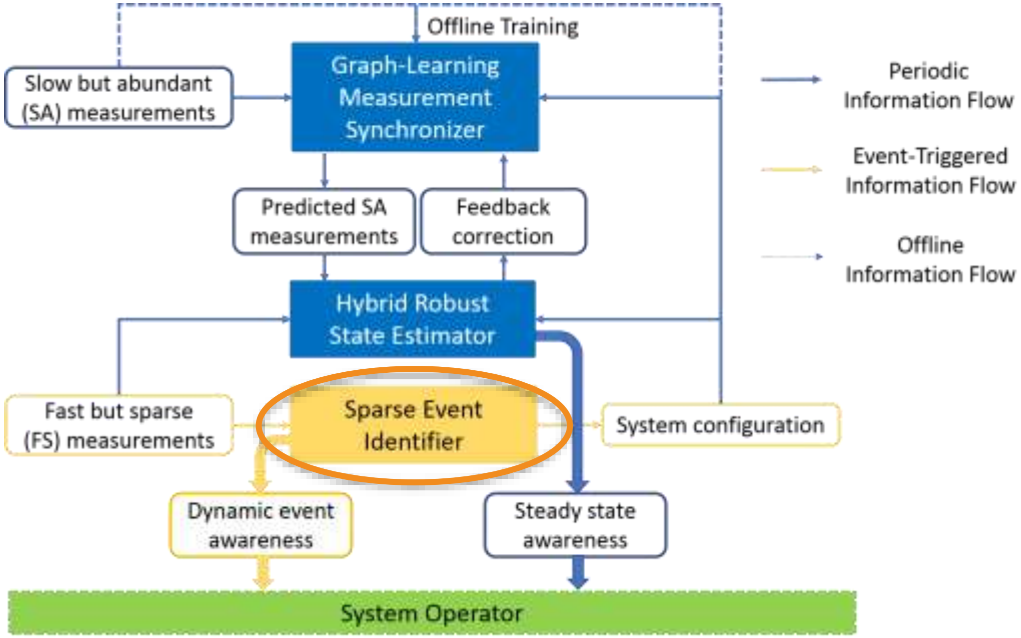

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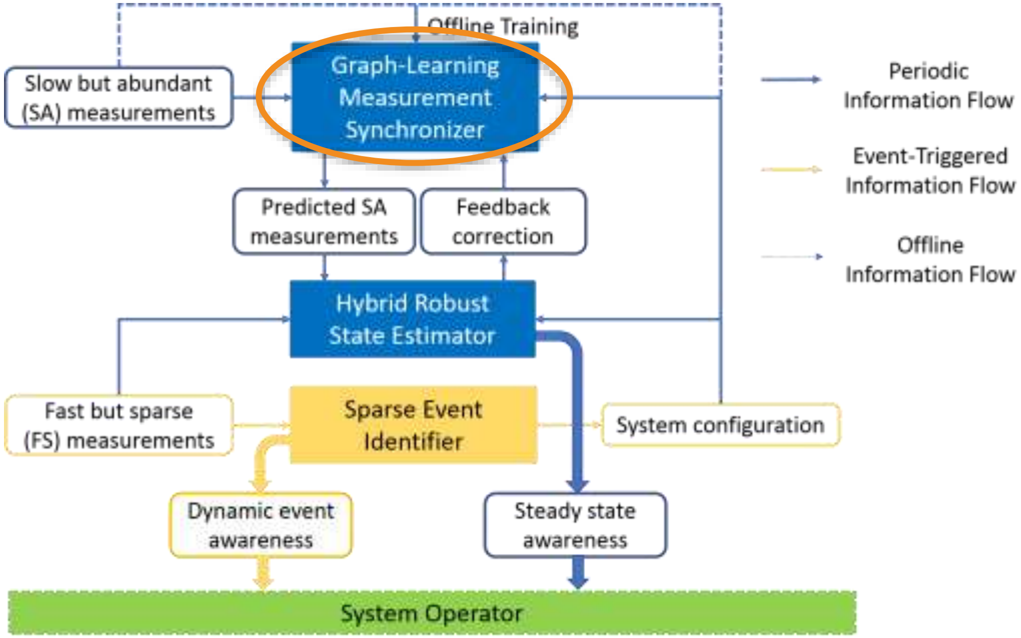

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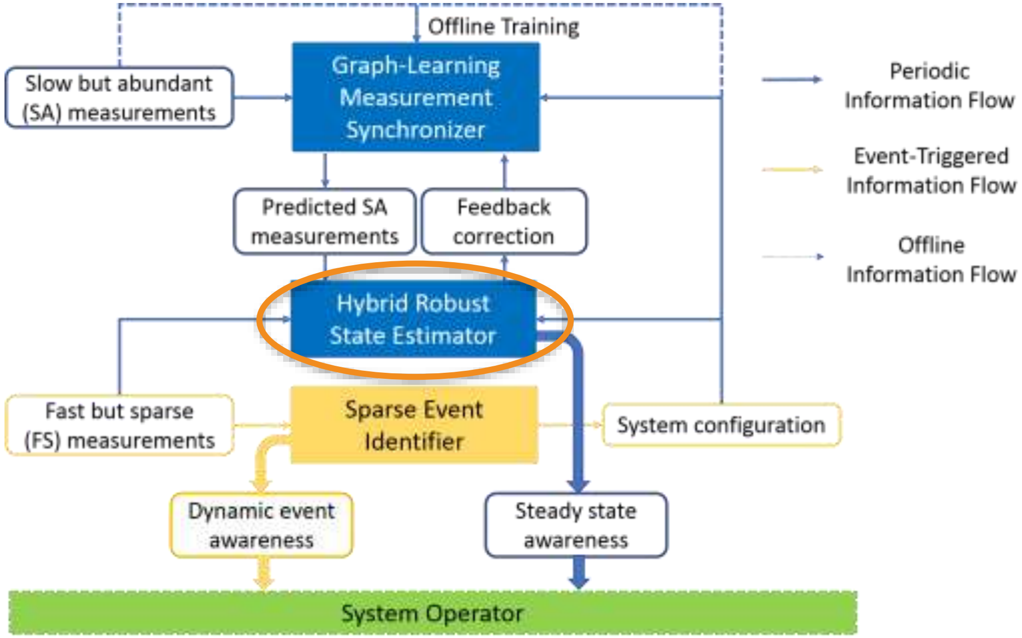

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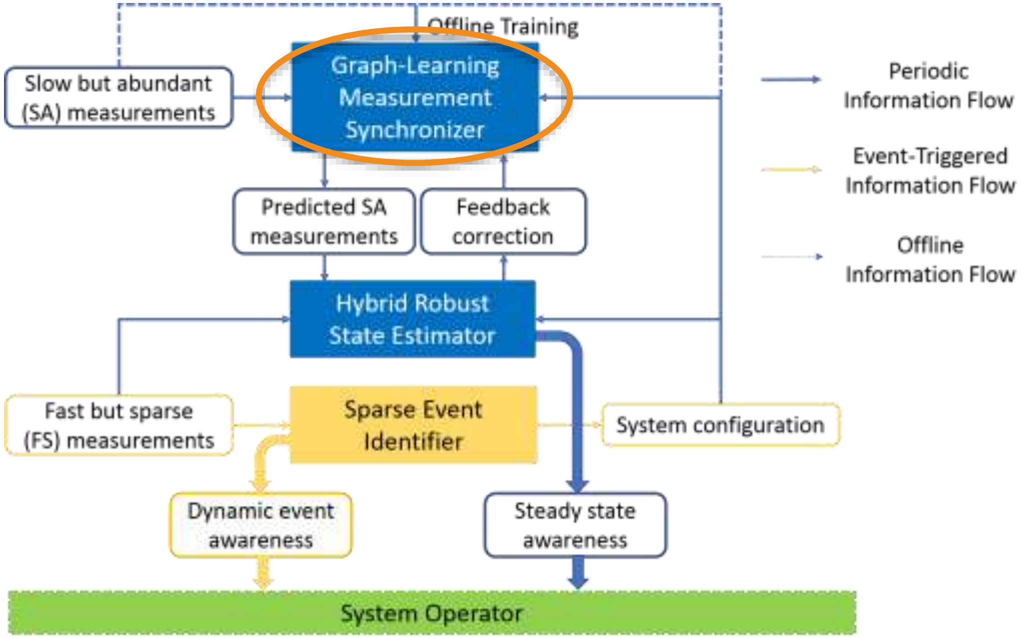

Problem Statement

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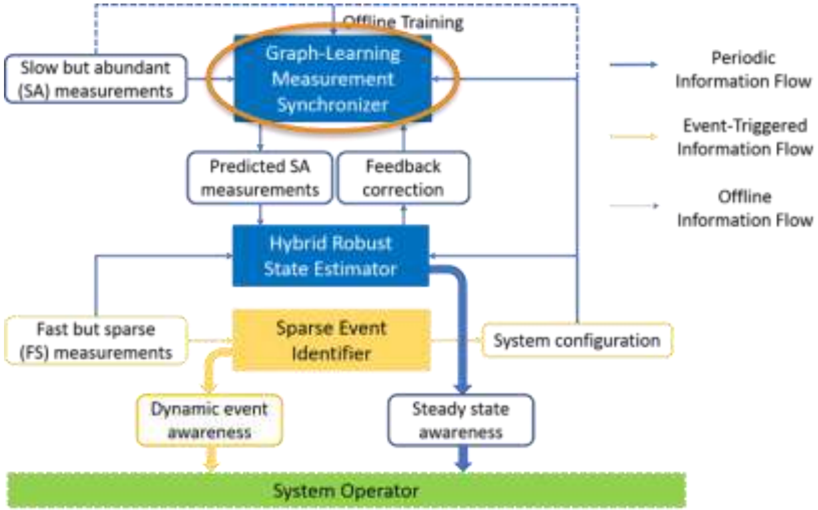
Input:

- **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

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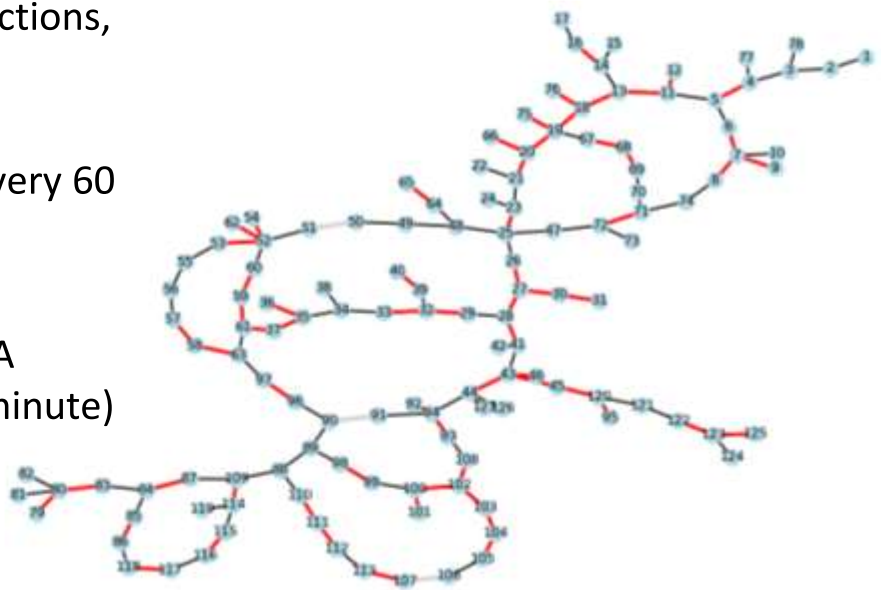
- Problem statement:
  - **Black Lines**: **observable** lines (FS measurements and derived measurements from zero injections, every 1 minute)
  - **Red Lines**: **unobservable** lines (derived measurements from SA measurements, every 60 minutes)
  - **Gray Lines**: **disconnected** lines
  - **Objective**: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



Outline

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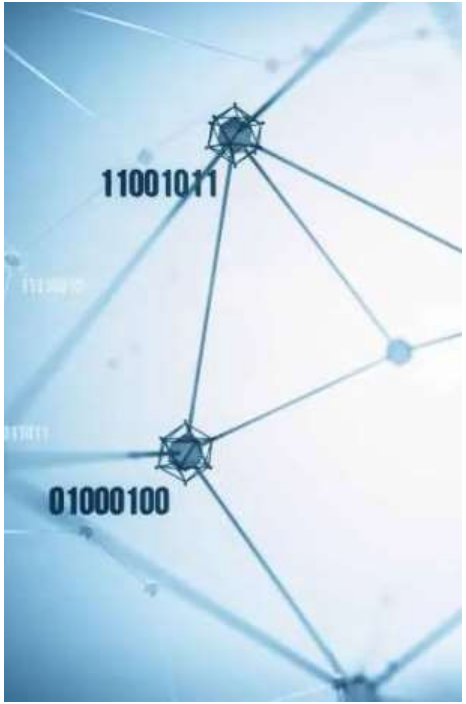

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Graph-Learning-Based SA Measurement Prediction

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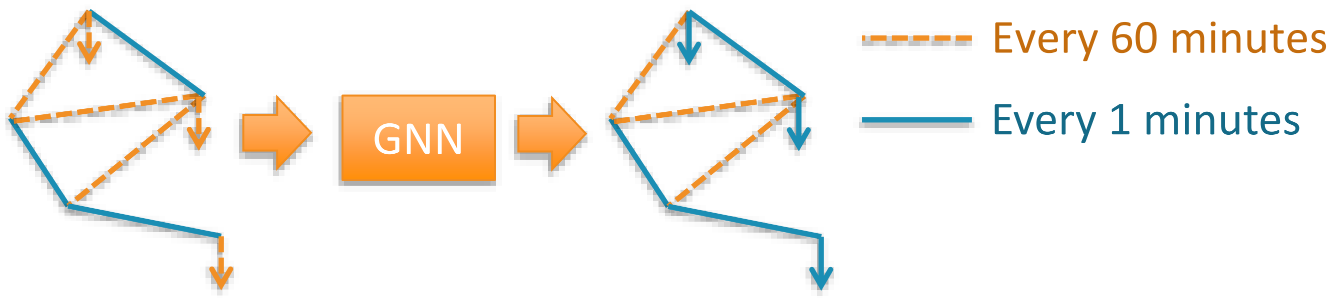
- Existing graph learning methods:
  - **Masking** the power flow features of the **unobservable lines**;
  - Use the power flow features of the **observable lines** (FA measurements) to **predict** the nodal injections (SA measurements) **directly** based on the Graph Neural Network (GNN).
- Limitations of these methods:
  - The methods have a limited performance when there are **too many unobservable lines**;



Graph-Learning-Based SA Measurement Prediction

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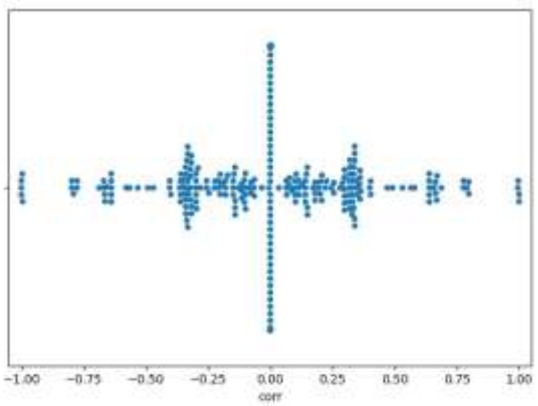
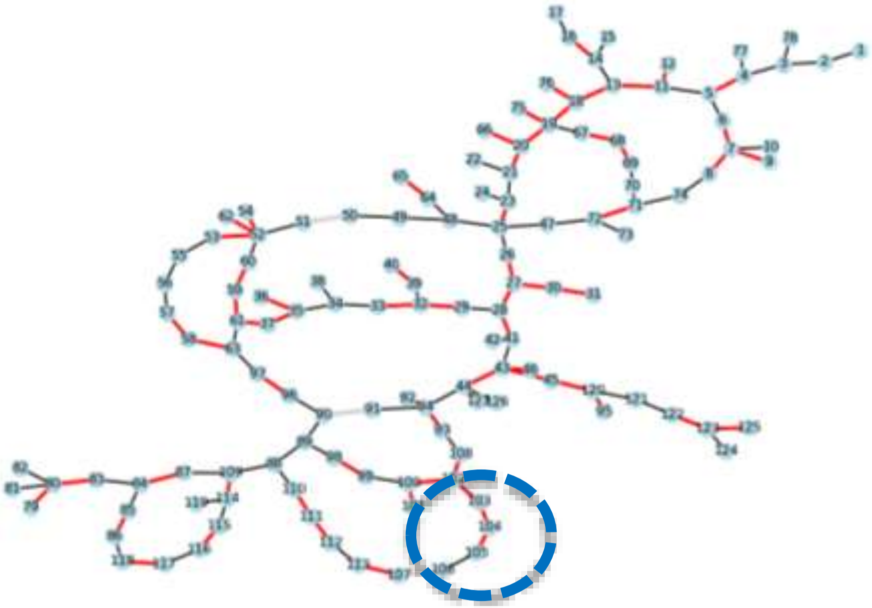
- Motivation of designing a new framework
  - Many **lines** are highly correlated to each other in terms of active/reactive power
  - Can we first predict the unobservable lines, so the GNN has a complete input for predicting the nodal injections?



Correlation Distribution
between **Line 104_105** and others



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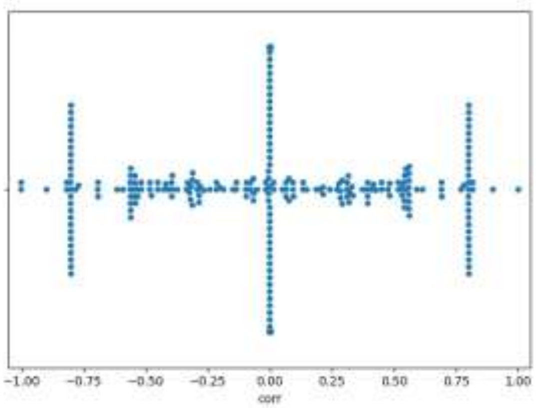
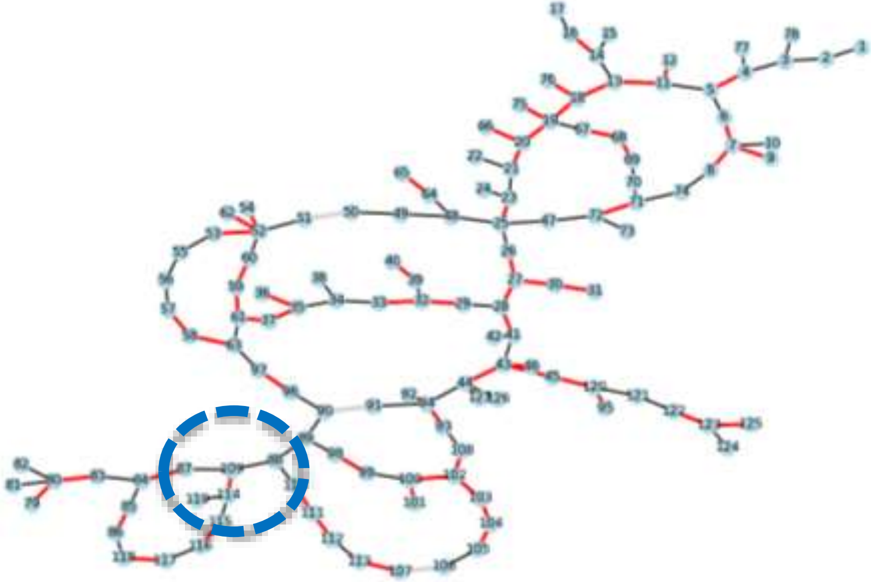


Correlation Distribution
between **Line 109_114** and others



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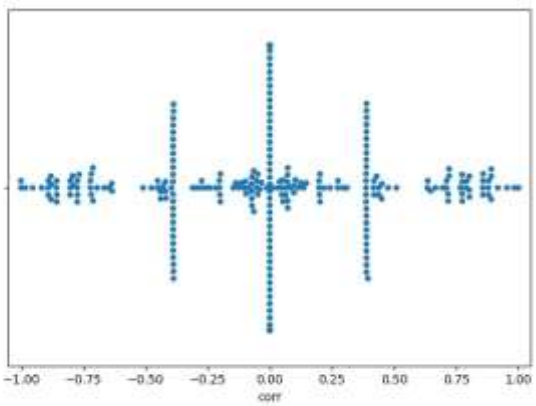
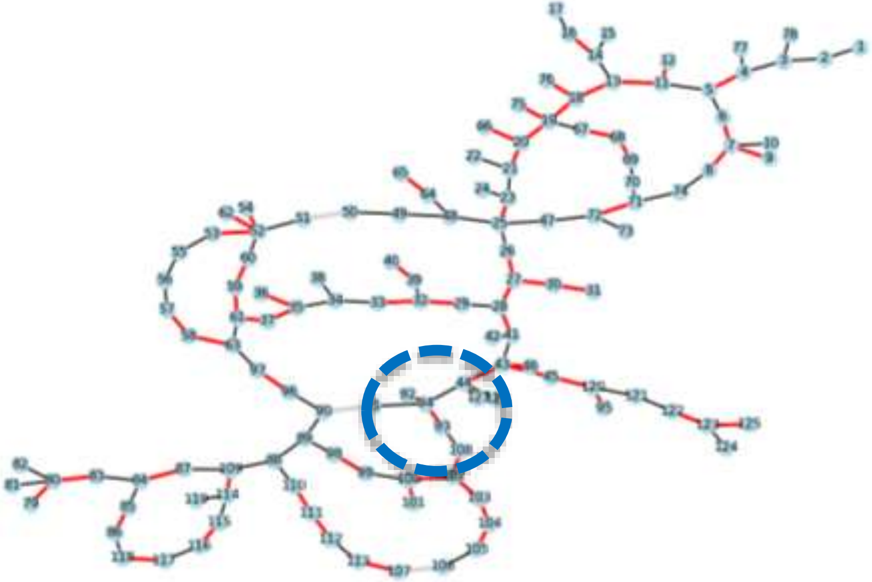


Correlation Distribution between **Line 93_94** and others



Graph-Learning-Based SA Measurement Prediction

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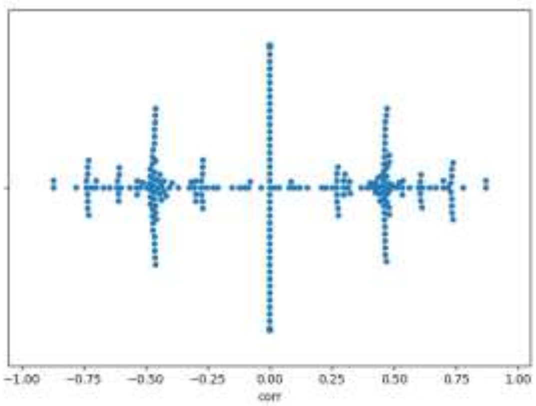
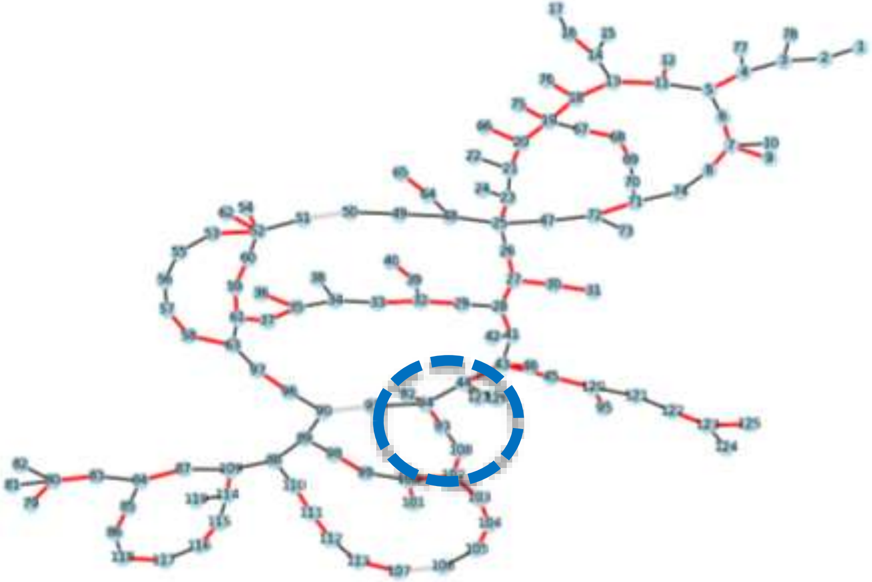


Correlation Distribution
between **Node 93** and other lines



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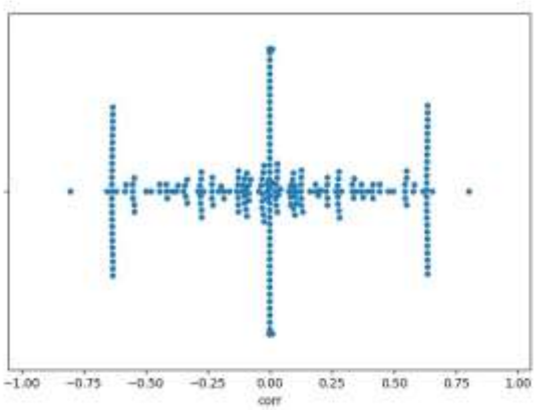
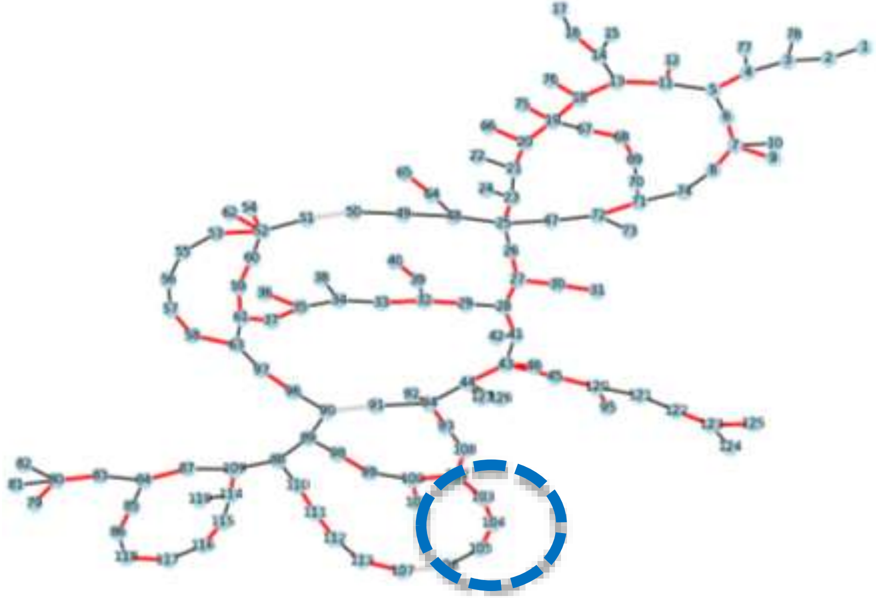


Correlation Distribution
between **Node 104** and other lines



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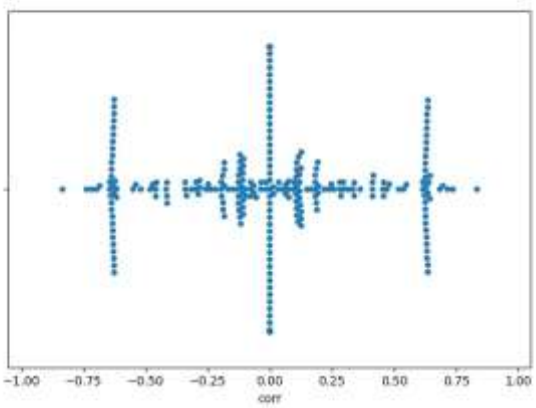
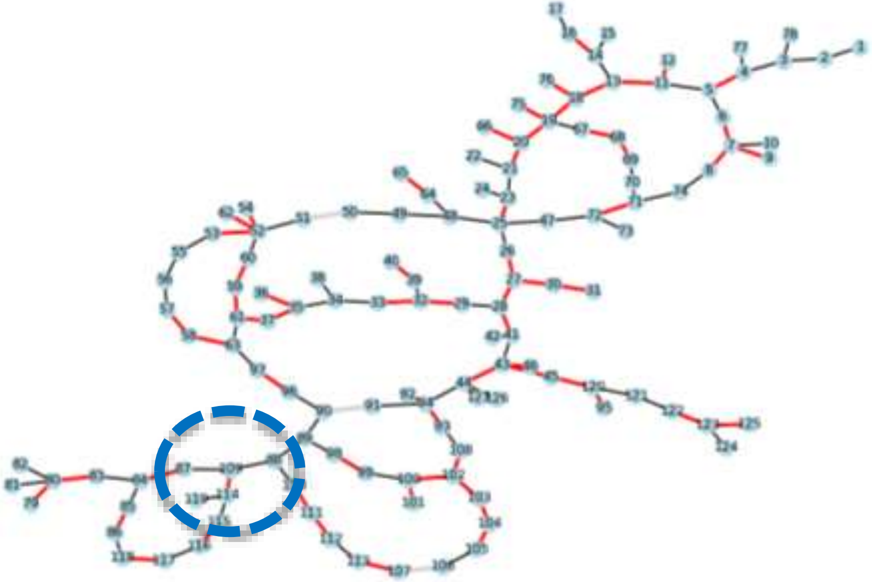


Correlation Distribution
between **Node 109** and other lines



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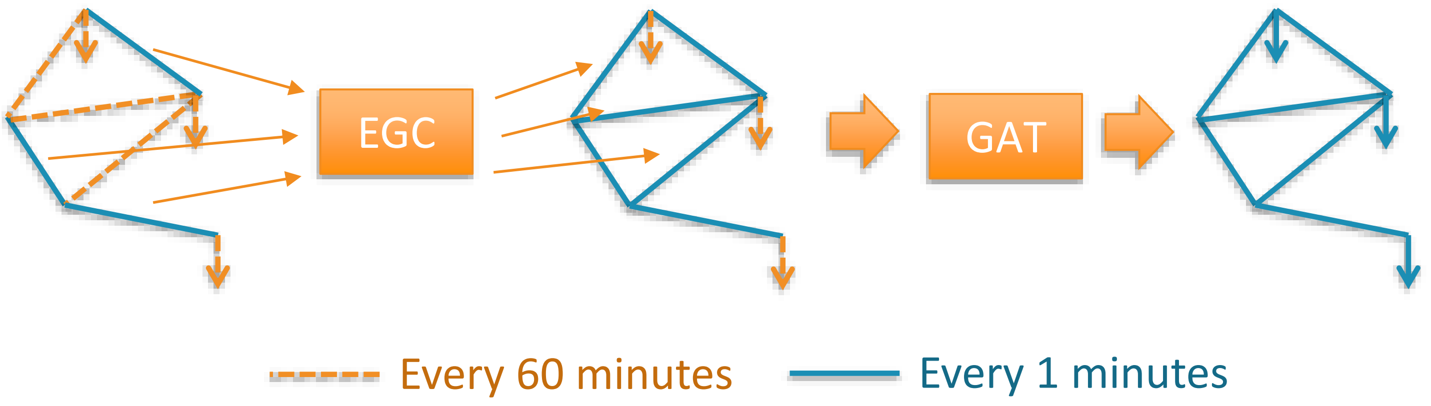
Graph-Learning-Based SA Measurement Prediction

- 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

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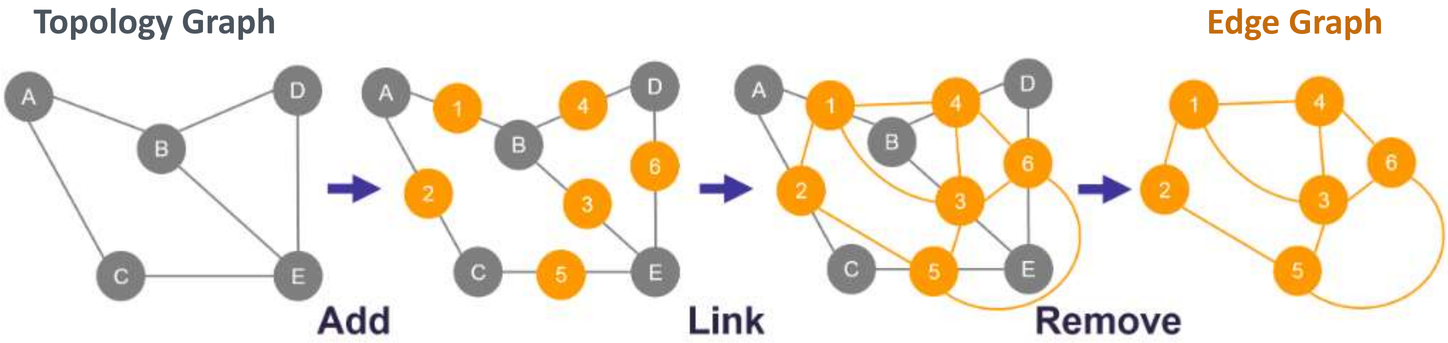
- Edge Graph Convolution (EGC)
  - Construct an **edge graph** based on the **topology graph**
    - Node in **edge graph** = Edge in **topology graph**
    - Edge in **edge graph** = two edges connected to the same node in **topology graph**



  - Adopt Graph Convolutional Network (GCN) on the edge graph

Graph-Learning-Based SA Measurement Prediction

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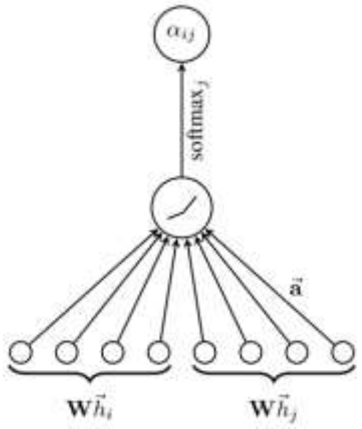
- **Traditional** Graph Attention Network (GAT)
  - *1. Apply attention coefficients to calculate relationships between nodes*
  - *2. Normalization by softmax to reweight the importance of neighbor nodes when doing graph aggregation*



attention coefficients *Combination of features of **Node i and j***

$$e_{ij} = \mathrm{LeakyReLU}\left(\vec{a}^{\top}[\mathbf{W}\vec{h}_i \,\|\, \mathbf{W}\vec{h}_j]\right)$$

Normalization

$$\alpha_{ij} = \mathrm{softmax}_j(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k\in\mathcal{N}_i}\exp(e_{ik})}$$

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Graph-Learning-Based SA Measurement Prediction

- 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*

attention coefficients

*Combination of features of **Node i, j** and **Line ij***

$$e_{ij} = \mathrm{LeakyReLU}\left(\vec{a}^{\top}[\mathbf{W}\vec{h}_i \,\|\, \mathbf{W}\vec{h}_j \,\|\, \mathbf{W}_l \vec{l}_{ij}]\right)$$

Normalization

$$\alpha_{ij} = \mathrm{softmax}_j(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(e_{ik})}$$

  - *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.

Proportions of Unobservable Lines	Node Prediction (Mean Absolute Error)		Node Prediction Error Percentage	
	Active Power	Reactive Power	Active Power	Reactive Power
10%	1.1559	0.4113	0.57%	0.91%
30%	1.7250	0.4796	0.85%	1.06%
50%	4.8650	1.0425	2.41%	2.29%

- 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%)

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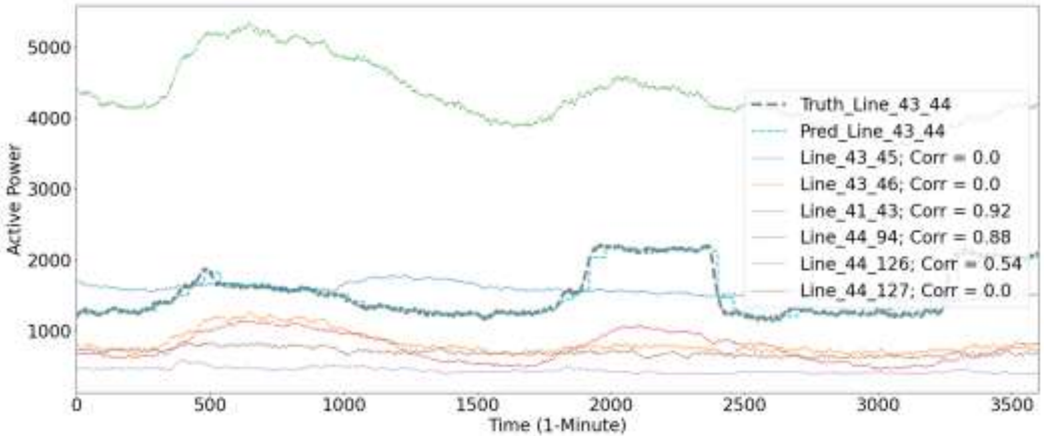
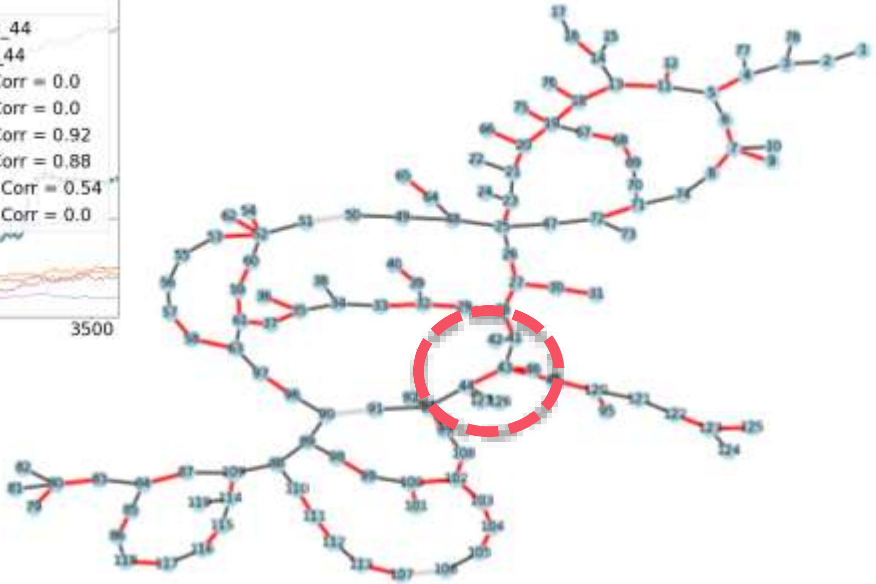
Test Results on ComEd's Bronzeville Community Microgrid

- Line Prediction Results: Line 43-44





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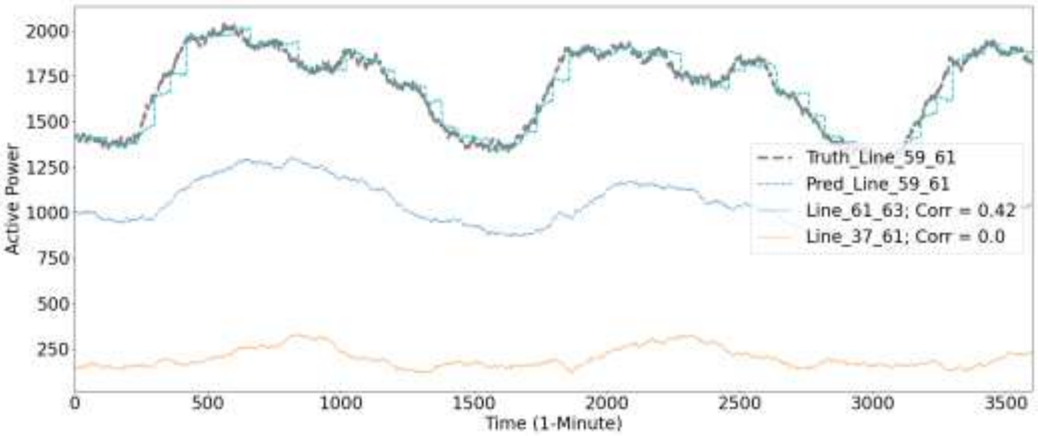
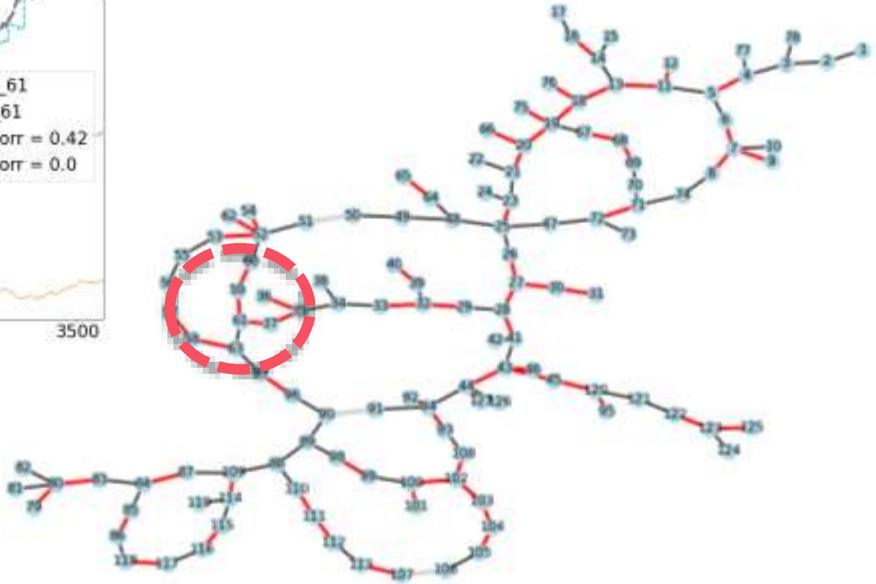
Test Results on ComEd’s Bronzeville Community Microgrid

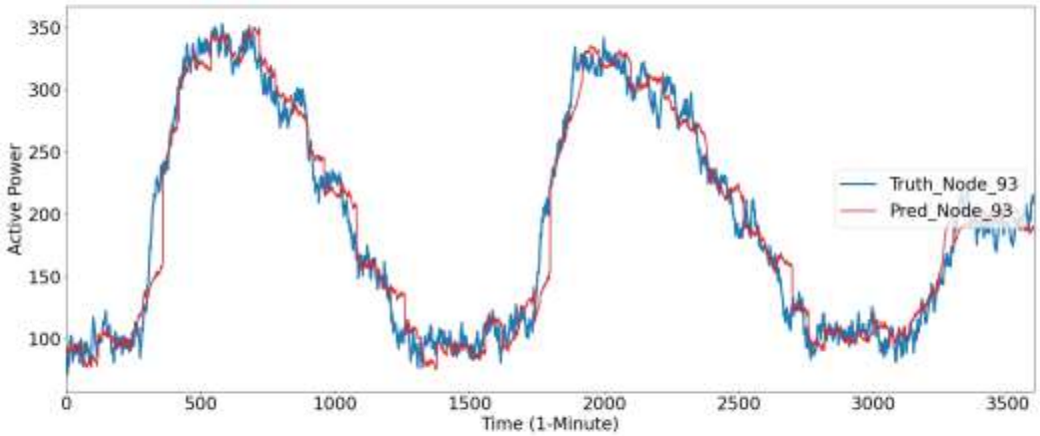
- Line Prediction Results: Line 59-61

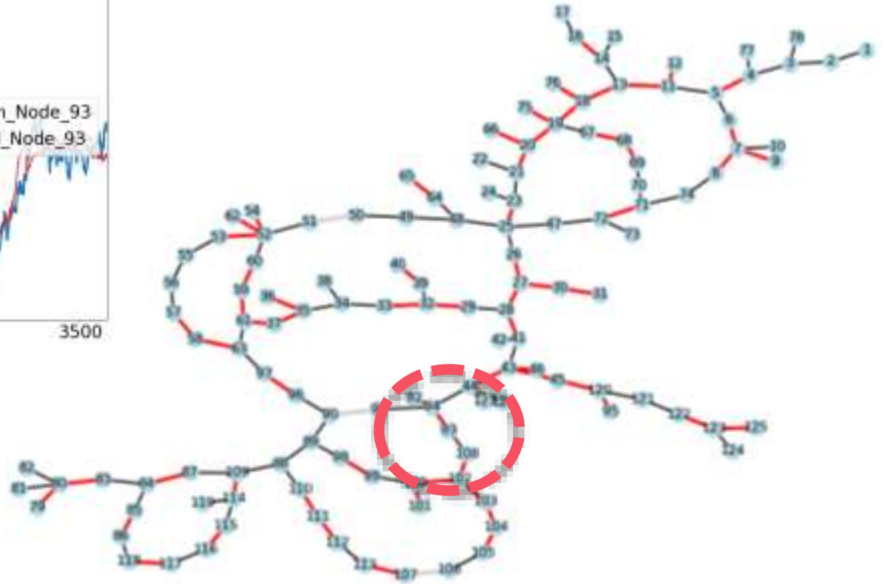




Test Results on ComEd's Bronzeville Community Microgrid

- Node Prediction Results: Node 93





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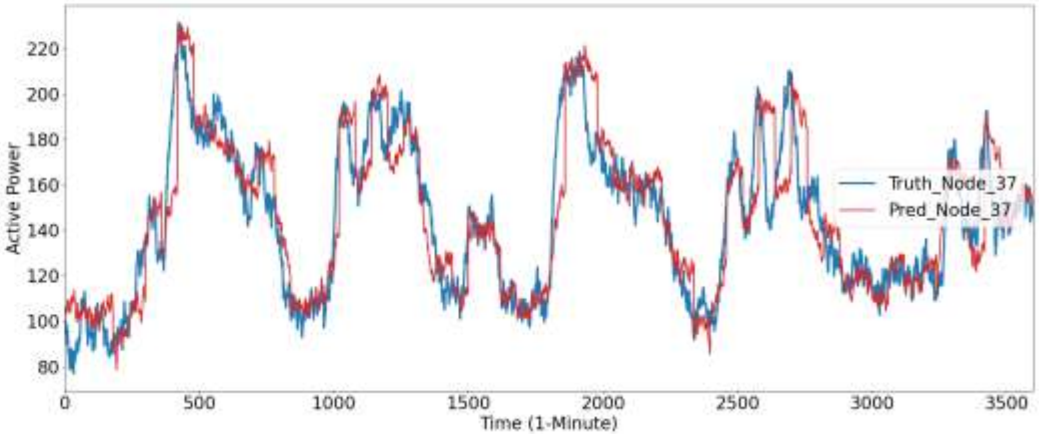
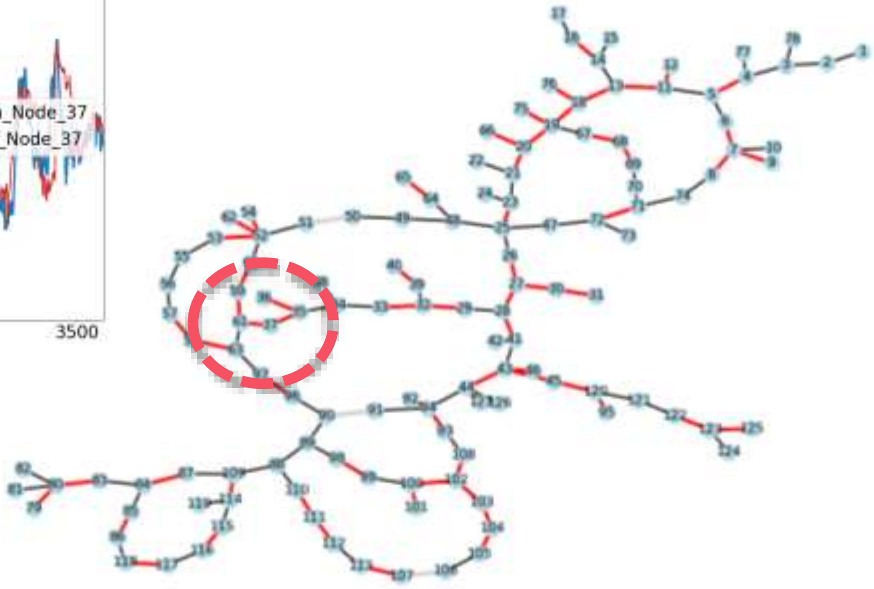
Test Results on ComEd’s Bronzeville Community Microgrid

- Node Prediction Results: Node 37





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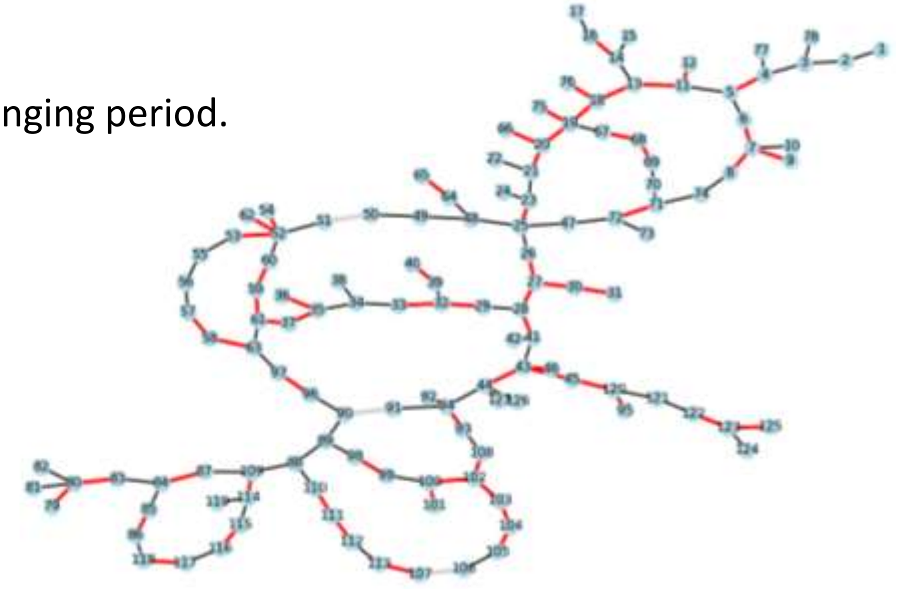
Future Work

- Next Steps:
  - Incorporate time series information;
  - Test the performance during topology changing period.



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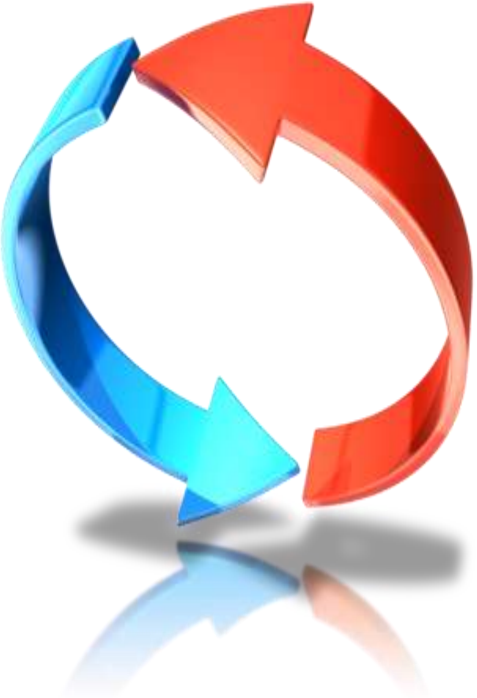

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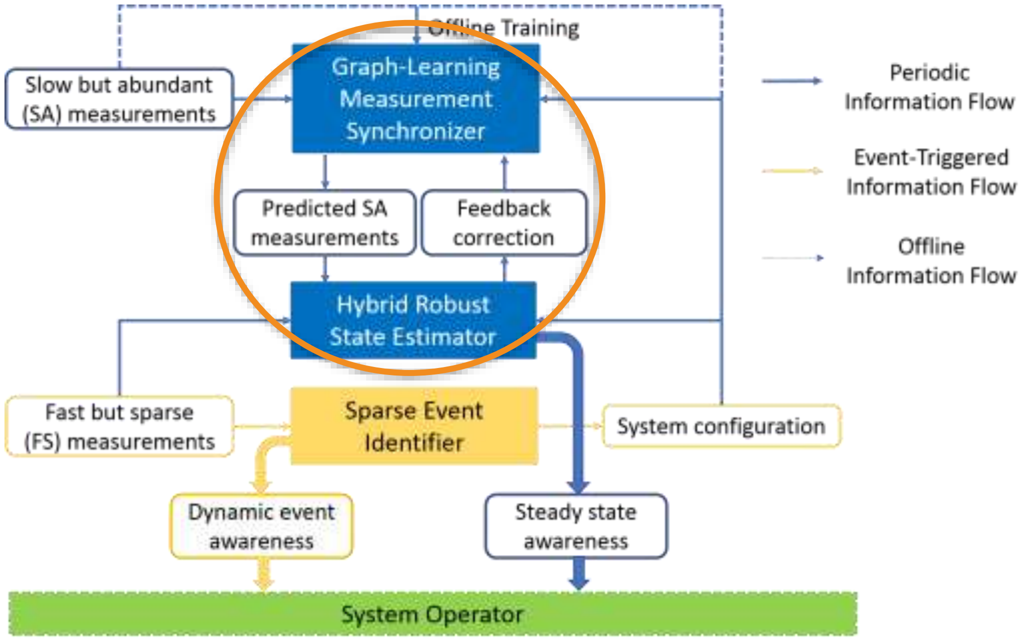

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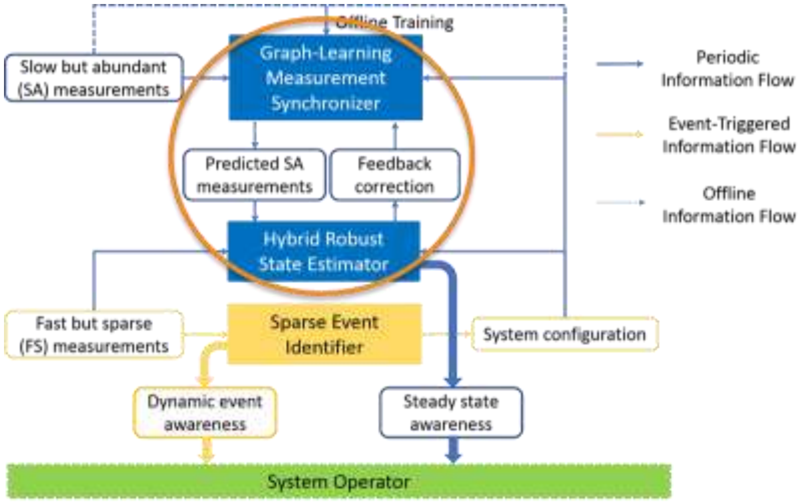
Closed-Loop Operation

- 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

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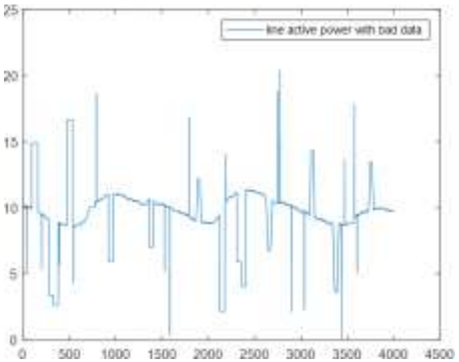
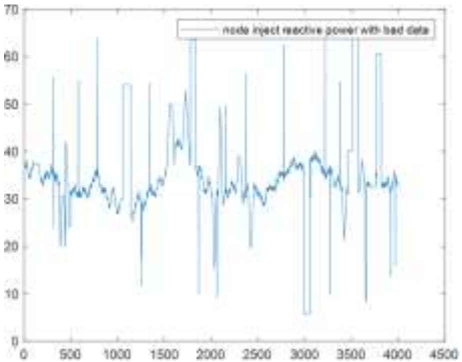
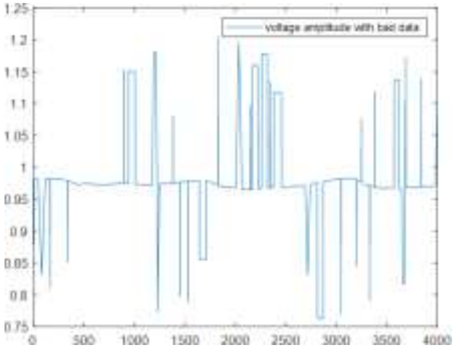
- Generation of bad data



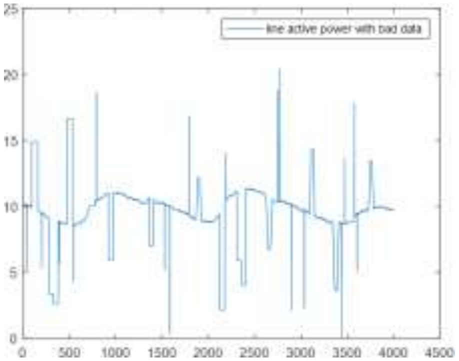
Corrupted line active power



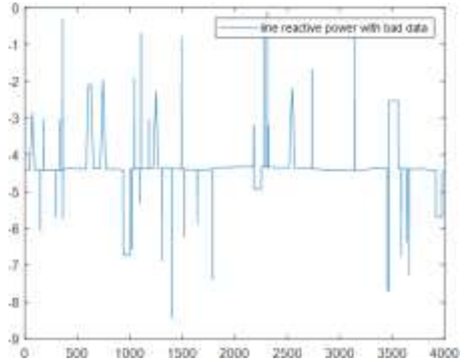
Corrupted line reactive power



Corrupted Node voltage magnitude



Corrupted node active power



Corrupted line reactive power

Test Results on ComEd's Bronzeville Community Microgrid

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

Measurement Prediction accuracy of the DL model under different measurement corruption conditions

Data	Active Power	Reactive Power
Clean	11.9233	5.7904
Corrupted	29.1641	9.7516
Residual-Corrected	13.9248	6.2632

- The feedback mechanism significantly enhances the prediction accuracy of the deep learning model.

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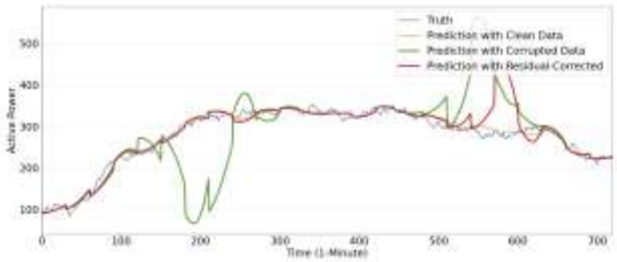
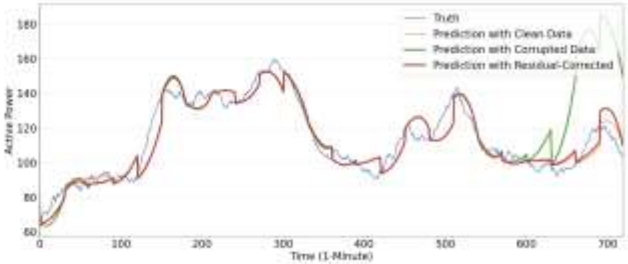
Test Results on ComEd's Bronzeville Community Microgrid

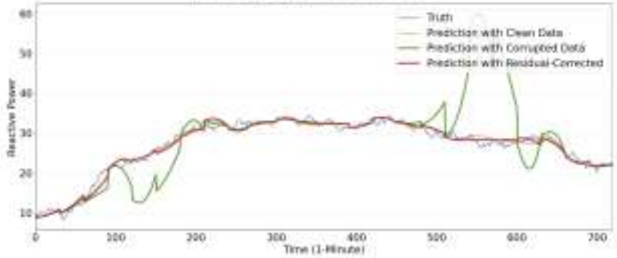
- Results show that the feedback of the robust WLAV estimator can significantly enhance the prediction performance of the deep learning model.



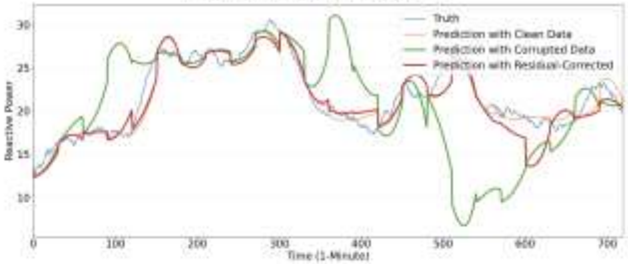
(a) Active power prediction for Node 93



(a) Active power prediction for Node 104



(b) Reactive power prediction for Site 93



(b) Reactive power prediction for Node 104

Outline

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Project Overview

Limitations of Existing Models

Machine Learning Model Architecture
- Algorithm
- Test Results

Closed-Loop Operation

Conclusion

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Conclusion

- 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

Funded by: SOLAR ENERGY TECHNOLOGIES OFFICE U.S. Department Of Energy

- 1. U. C. Yilmaz and A. Abur, "A Robust Parallel Distributed State Estimation for Large Scale Distribution Systems," IEEE Transactions on Power Systems, doi: 10.1109/TPWRS.2023.3292552.
- 2. G. Cheng, Y. Lin, A. Abur, A. Gómez-Expósito and W. Wu, "A Survey of Power System State Estimation Using Multiple Data Sources: PMUs, SCADA, AMI, and Beyond," IEEE Transactions on Smart Grid, doi: 10.1109/TSG.2023.3286401.
- 3. T. Yildiz and A. Abur, "Computationally Robust Line Outage Detection and Identification in Three-Phase Networks," Proceedings of IEEE PES GT&D, Istanbul, Turkey, May 23-25,2023,
- 4. T. Yildiz and A. Abur, "Improved line outage detection in transmission systems with few PMUs," 2022 North American Power Symposium (NAPS), 2022, pp. 1–5.
- 5. U. C. Yilmaz and A. Abur, "A general state estimation formulation for three-phase unbalanced power systems," 2022 North American Power Symposium (NAPS), 2022, pp. 1–5.
- 6. H. Yue, W. Zhang, U. C. Yilmaz, T. Yildiz, H. Huang, H. Liu, Y. Lin, A. Abur, "Graph-Learning-Assisted State Estimation Using Sparse Heterogeneous Measurements," 2024 Power Systems Computation Conference (PSCC), under review.

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