FOA 1861 PROJECT UPDATE
BIG DATA ANALYSIS OF SYNCHROPHASOR DATA

Robust Learning of Dynamic Interactions for Enhancing Power System Resilience

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Outline

- Project Overview
- Experimental Results
- Technical Progress
- Project Challenges & Risk Mitigation
- Future Effort

Project Overview

The overall goal of the project is to leverage robust graphical learning and PMU data to learn the dynamic interactions of electrical grid components in order to improve the power system resilience. Specifically, this project incorporates four objectives:

1) Massive PMU data preparation, refining, and real-time visualization and access.
2) Identifying and cataloguing anomalous patterns.
3) Learning interaction graphs using deep graph neural networks.
4) Graph-based modeling, monitoring, and mitigation of cascading outages.

Project Overview

Project Partners

- This project is a synergistic collaborative project between Iowa State University, IBM, EPG, and Google Brain.

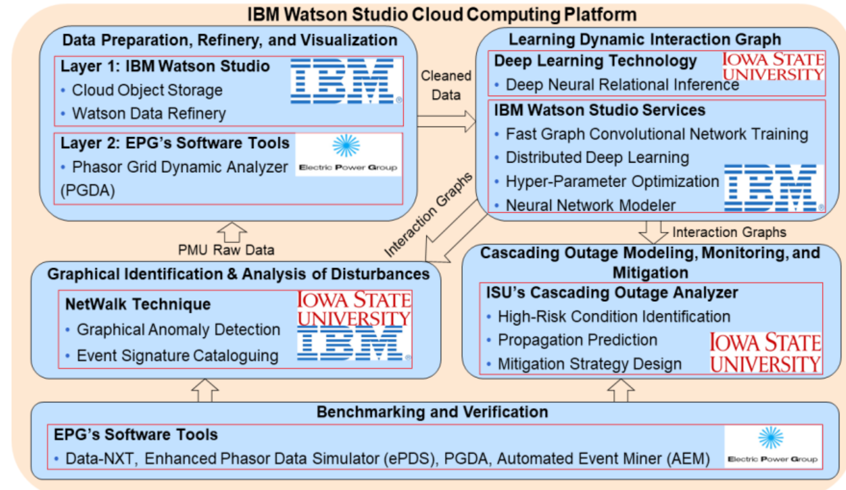

Fig. 1 Project objective overview.

Technical Approach

- Our team members will leverage the team's extensive experience and state-of-the-art algorithms in machine learning, big data analytics, and synchro-phasor data commercial tools, and cascading failure modeling.

Project Impact

- The findings of this project, including anomalous event classification, dynamic interaction graphs, and pattern signature catalogue, will be integrated on the IBM AI OpenScale platform and will be publicly accessible to the wider users and system operators for implementation in future online and offline applications.

Project Overview

Task Number	Task Title	Progress Summary	Completion Date	
			Planned	Actual
1.1	Project Management Plan (PMP)	PMP was submitted to DOE and approved by the project manager.	10/30/19	10/30/19
1.2	National Environmental Policy Act (NEPA) Compliance	The documentation was prepared and provided for NEPA.	10/30/19	10/30/19
1.3	Data Management Plan (DMP)	The Data Management Plan (DMP) was prepared and submitted to the DOE.	10/30/19	10/30/19
1.4	Non-Disclosure Agreement for PNNL and IBM	The Non-Disclosure/Data Handling Agreements have been signed with IBM and Pacific Northwest National Laboratory (PNNL) and submitted to the DOE.	10/30/19	10/30/19
2.1	PMU Data Importing and Storage	A SATA hard drive docking station and ISU server have been used for data importing and storage. 4 external hard drives have been utilized to establish local data backup.	10/31/19	10/31/19
2.2	PMU Data Real-Time Access and Visualization	A secure connection has been established between local computers and the server through PuTTY software tools to access datasets. Microsoft Power BI has been used for data visualization and statistical analysis.	11/30/19	11/30/19
2.3	PMU Data Formatting, Validation, and Conditioning	We have decomposed the available PMU dataset into training, validation, and testing sets to: 1) design robust learning-based PMU event identification method, 2) learn the interaction graphs from PMU data. EPG's software have been used to provide an assessment of PMU Data Quality for the whole dataset	12/31/19	12/31/19
3.1	Building Deep Graphical Neural Networks	We have designed an architecture of interaction graph learning model based on the guidance of IBM.	03/31/20	03/31/20
3.2	FastGCN-Based DNRI Training	The random search and k-fold cross validation strategies have been used to tune the hyperparameter of our graph learning algorithm.	05/31/20	05/31/20
3.3	Graph Visualization and Interpretation		06/30/20	

Project Overview

Task Number	Task Title	Progress Summary	Completion Date	
			Planned	Actual
3.4	Interaction Graph Validation		06/30/20	
4.1	High-Risk Operational Condition Detection		09/30/20	
4.2	Visualization and Prediction of Cascading Outage Propagation		10/31/20	
4.3	Cascading Mitigation Strategy Design		11/30/20	
4.4	Comparison of Methods		12/31/20	
5.1	Graphical Anomaly Detection	We have developed a robust learning-based two-stage event identification based on our PMU dataset. The interaction graph will be integrated with this model to further improve the classification accuracy.	10/31/20	
5.2	Event Signature Extraction		11/30/20	
5.3	Disturbance Analysis Validation		12/31/20	
6.0	Validation with Commercial Software Tools		03/12/21	
6.1	Offline Benchmarking Analysis		03/12/21	
6.2	Online Validation and Testing		03/12/21	
7.1	Module Integration		01/31/21	
7.2	Building an Open-source Platform for Project Findings		03/12/21	
8.0	Publications, Presentations, Final Briefings and Reports to DOE		03/12/21	

Experimental Results

Data Importing and Storage (Task 2)

- A ISU server, which has 256GB RAM memory, 22TB hard drive, and 2 – 10 core Xeon CPU E5-2660 v3 @ 2.6GHz, has been utilized to import and store massive PMU data.
- 4 external hard drives have been utilized to establish local data backup to protect data against server-level failures

Fig. 2 ISU server.

Data Visualization (Task 2)

- Power BI has been used to perform data visualization by developing dashboards.
- Our dashboards contains statistical information for all three systems and selected event curves.

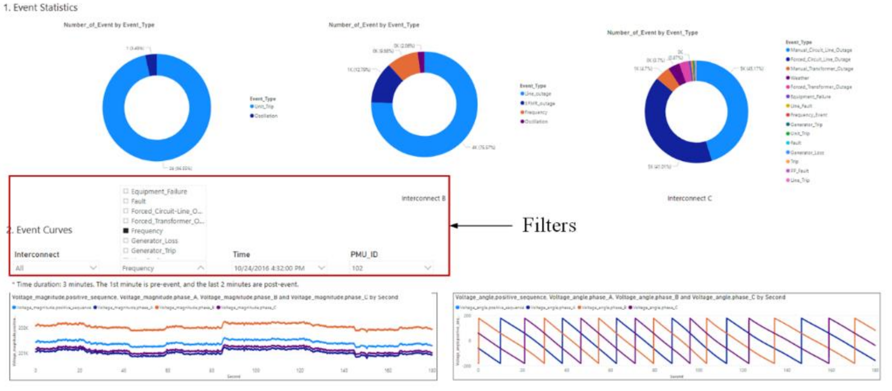

Fig. 3 Power BI dashboard.

Experimental Results

PMU Data and Event Logs Summary (Task 2)

	Interconnection A	Interconnection B	Interconnection C
Number of PMUs	212	43	188
Reporting Rate (samples/sec)	30	30, 60	30
Voltage Levels (kV)	69, 138, 345	230, 345, 500	115, 138, 161, 230, 345, 500, 765
Data Duration	2018 (July – Dec) 2019 (Jan – Aug)	2016 (Jan – Dec) 2017 (Jan – Dec)	2016 (Jan – Dec) 2017 (Jan – Dec)
No. of Data Files	2576	4365	10496
Data Size	3TB	5TB	12TB
No. of Events	29	4854	1884
No. of Unidentified Events	0	0	634

PMU Data Quality Assessment (Task 2)

- Good quality PMU data is essential in online and offline applications. We have utilized EPG commercial software (i.e., DataNXT, PGDA) to assess the data quality of the PMU dataset based on **PMU status flags**.

Experimental Results

PMU Data Quality Assessment - Overview (Task 2)

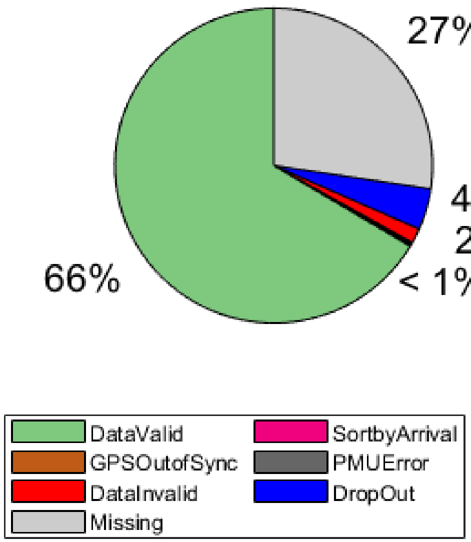

Fig. 4 System A data quality pie chart.

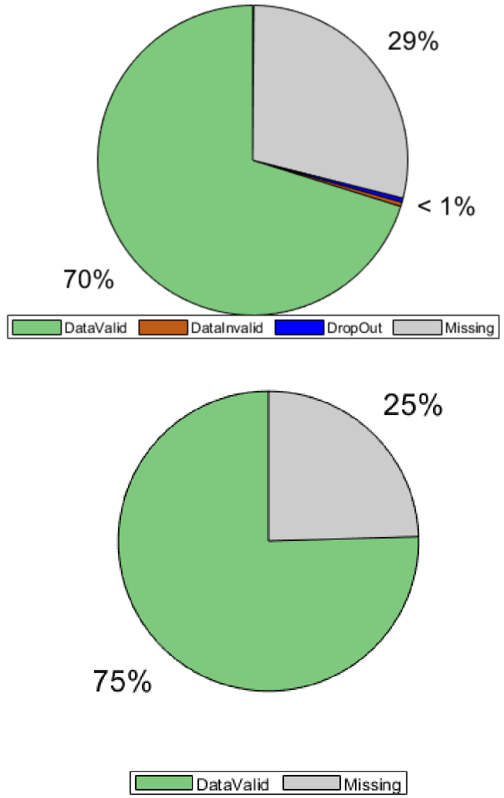

Fig. 5 System B data quality pie chart for PMUs with 30 samples/sec (above) and for PMUs with 60 samples/sec (below).

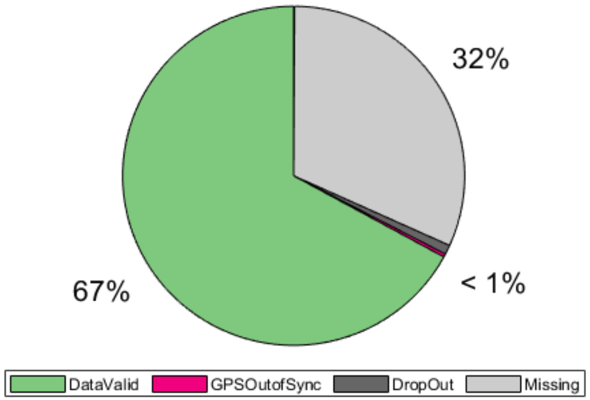

Fig. 6 System C data quality pie chart.

Experimental Results

PMU Data Quality Assessment – System A (Task 2)

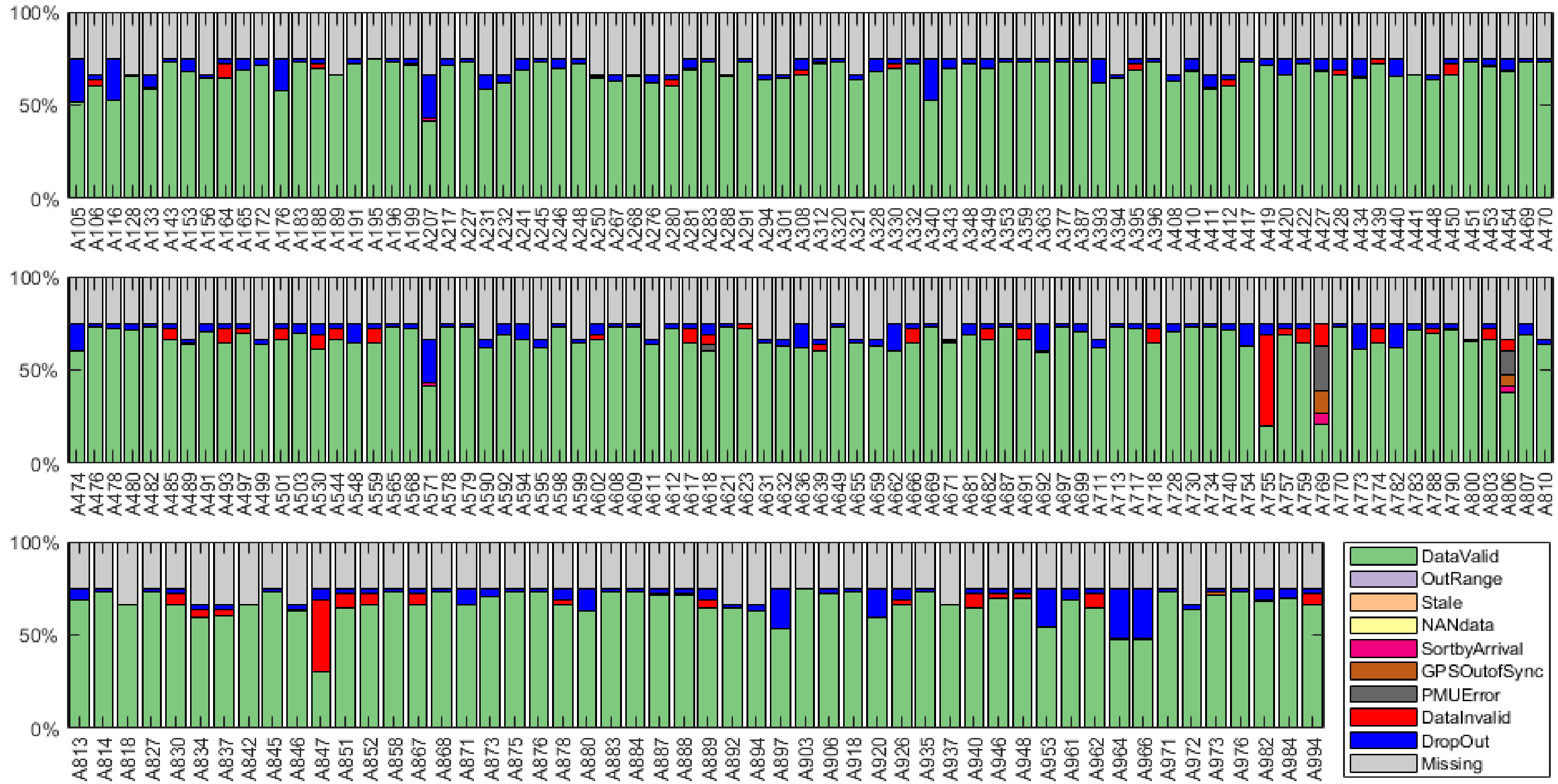

Fig. 7 Overall data quality for each PMU in system A.

Experimental Results

PMU Data Quality Assessment – System A (Task 2)

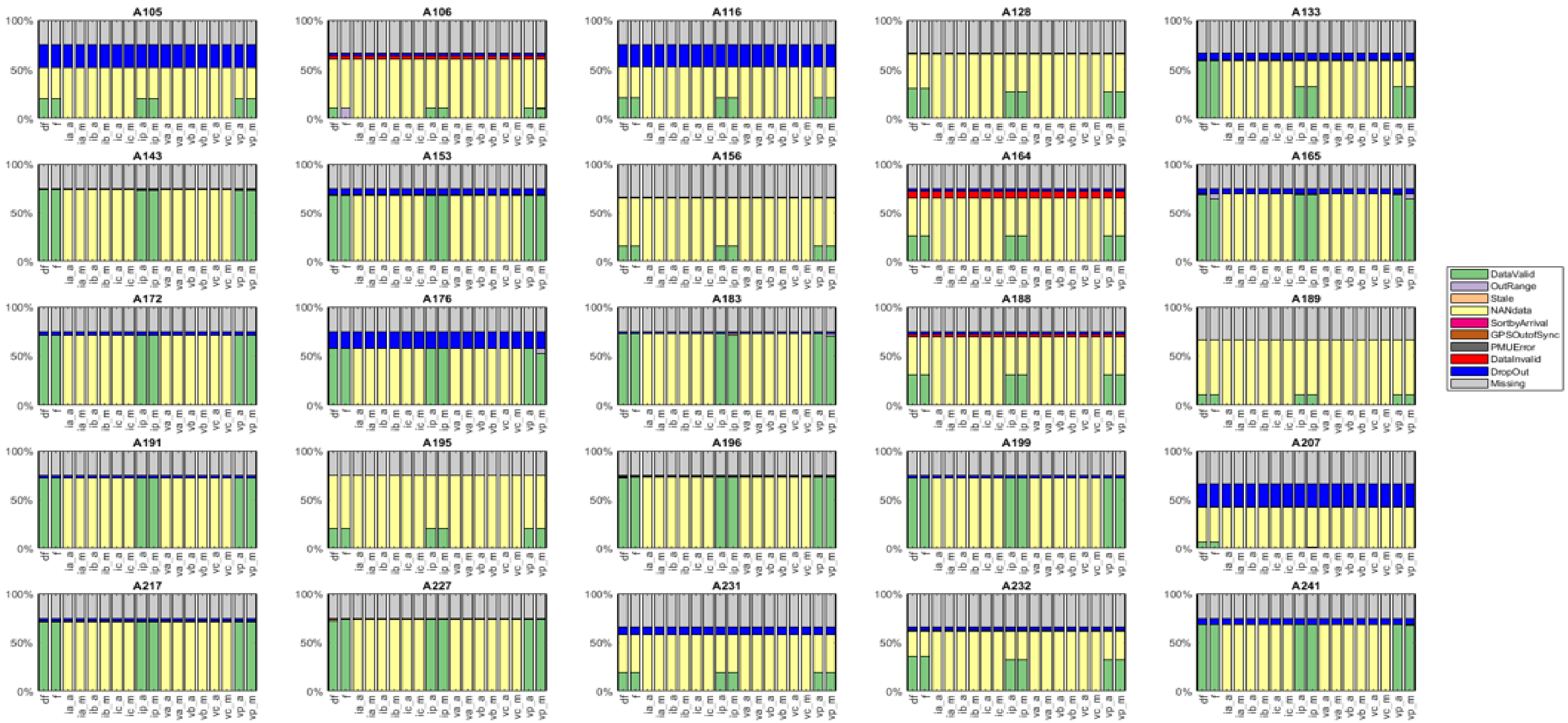

Fig. 8 Overall data quality analysis for total 18 signals of each PMUs in system A.

Experimental Results

PMU Data Quality Assessment– Statistical Analysis (Task 2)

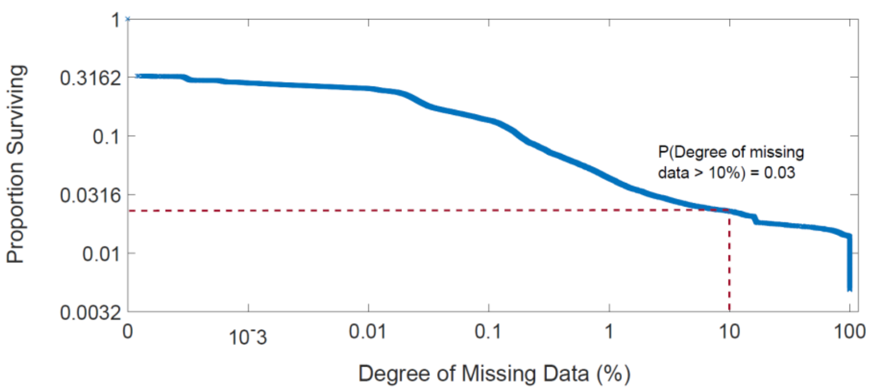

Fig. 9 Survival function $S(k)$ using PMU dataset .

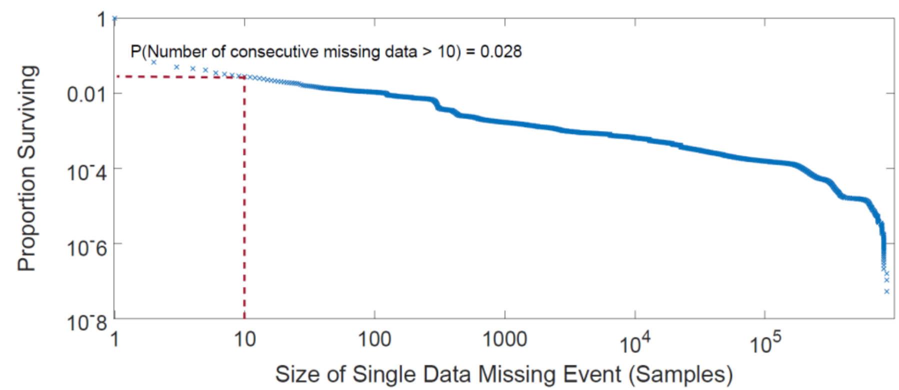

Fig. 10 Survival function $S(c)$ using PMU dataset .

To provide more details about PMU data quality, we have defined and plotted two survival functions, $S(k)$ and $S(c)$:

$$S(k) = \Pr\{\frac{\text{number of missing data per PMU per day}}{\text{total number of data per PMU per day}} > k\} \quad (1)$$

$$S(\mathrm{c}) = \Pr\{\text{number of consecutive missing data} > c\} \quad (2)$$

- Based on the left figure, PMUs show data quality issues more than 30% of time.
- Based on the right figure, around 3% of data quality issues have more than 10 consecutive bad data.

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Technical Progress

Challenges of Developing PMU-Based Event Identifiers (Task 3 & 5)

- Based on our data quality assessment, PMU data quality problems are inevitable and not rare, which can disjoint the dimensional consistency of data samples between the offline training and online testing. Poor robustness against data quality makes the PMU-based event identifiers not sufficiently convincing [1].

- Machine learning-based methods typically suffer from event data scarcity, resulting in a data imbalance problem [2].

- Most of the signal processing-based methods require massive computations due to the complicated mathematical transformation and optimization, which might challenge the practical deployment of the methods [3].

Technical Progress

Robust Two-Stage Learning-Based Real-Time Event Identification

- The first stage is Markov-based time-series feature reconstruction to capture the time-varying statistical characteristics of PMU data.
- The second stage is spatial pyramid pooling (SPP)-aided convolutional neural network (CNN)-based mode to identify event types.

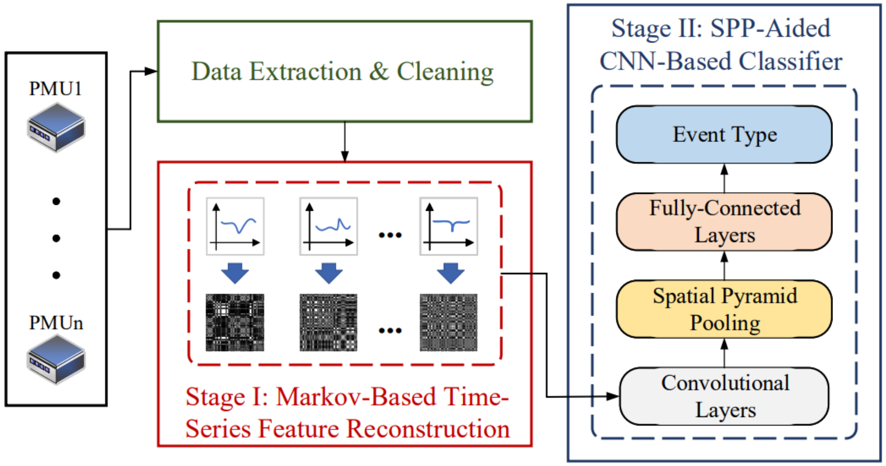


Fig. 11 Illustration of two-stage event identification.

- One unique advantage of the proposed method can allow the signals of **arbitrary dimensions** during online testing, thus introducing **robustness against online data quality issues**.

Technical Progress

PMU Data Extraction & Cleaning

- To apply PMU-based event identifiers in real-time, a 2-second analysis-window is selected to extract the event data based on the event logs.
- We use the voltage magnitude and frequency variation data from each PMU to train our learning model.
- For each PMU, the event data is re-sorted based on time stamps.
- Following our data quality assessment, when the consecutive missing/bad data occurs, the data is excluded from our study.
- The rest of the missing/bad data are filled and corrected by taking an average of the two preceding samples.

Technical Progress

Stage I: Markov-Based Time-Series Feature Reconstruction

- A Markov matrix-based method known as Markov Transition Filed (MTF) is adopted to encode the temporal dependency and transition statistics of PMU data in a compact metric [4].
- The goal of the stage I is to **improve the event classification accuracy** by performing feature reconstruction.
- MTF is applied to the event dataset including voltage magnitudes and frequency variations to obtain the MTF-based graph set, which are used for training a learning model in the stage II.

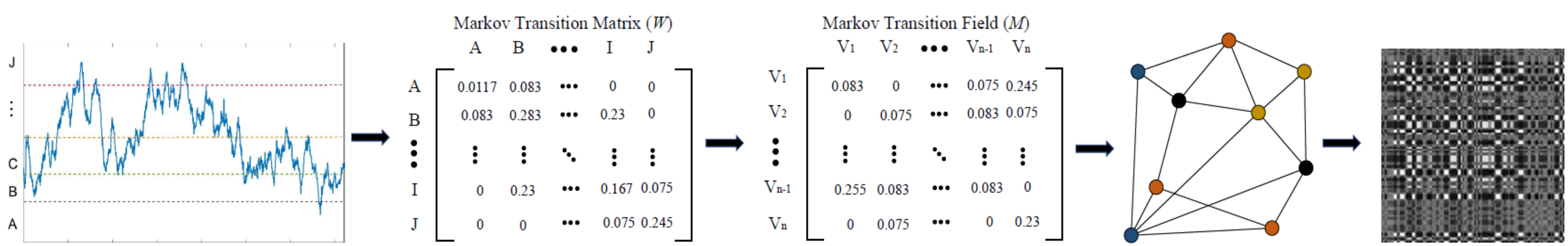


Fig. 12 Illustration of the proposed encoding map of MTF.

Technical Progress

Stage II: SPP-Aided CNN-Based Event Identifier

- Constructing an end-to-end **mapping relationship** between **MTF-based graphs** and the **event types**.
- Including multiple convolutional, batch normalization, max-pooling. SPP, and the fully-connected layers.
- Introducing robustness to data quality problems during online testing by eliminating the fixed-size input requirement of CNNs [5].

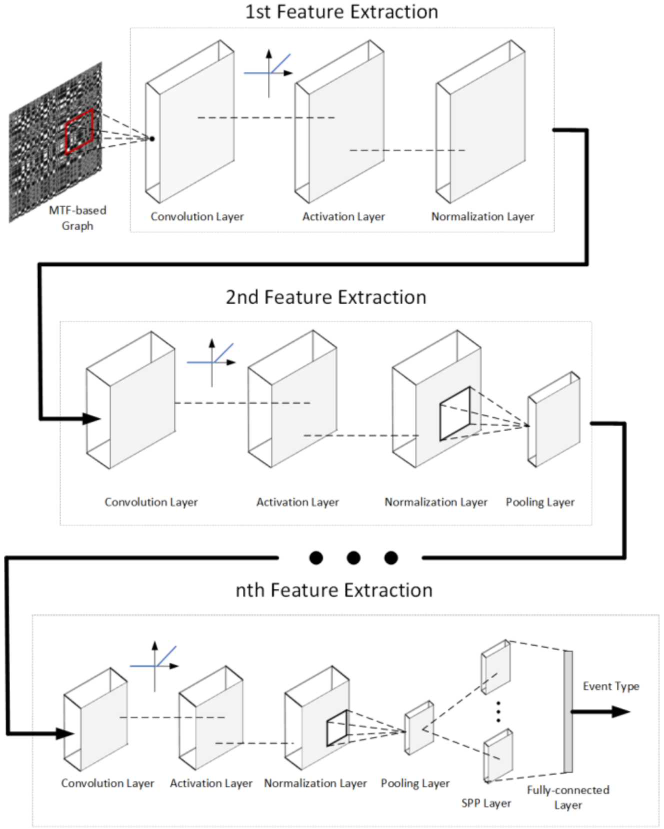


Fig. 13 Proposed SPP-aided CNN-based event classifier.

Technical Progress

Numerical Results Using the Data of System B

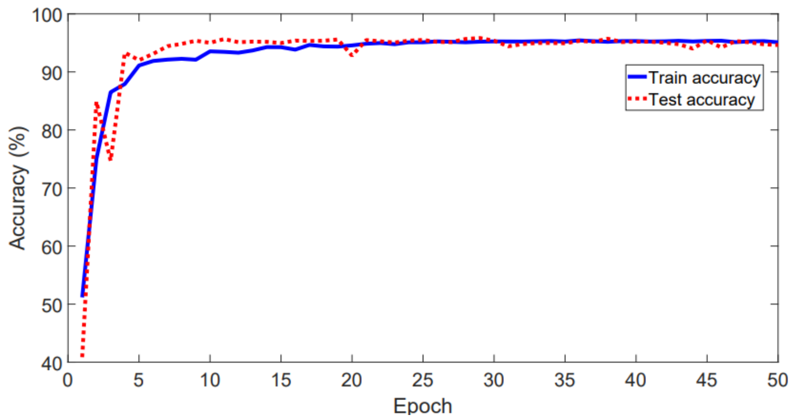


Fig. 14 Training/testing results for the proposed model.

Fig. 16 Sensitivity of event identification accuracy to the size of missing data.

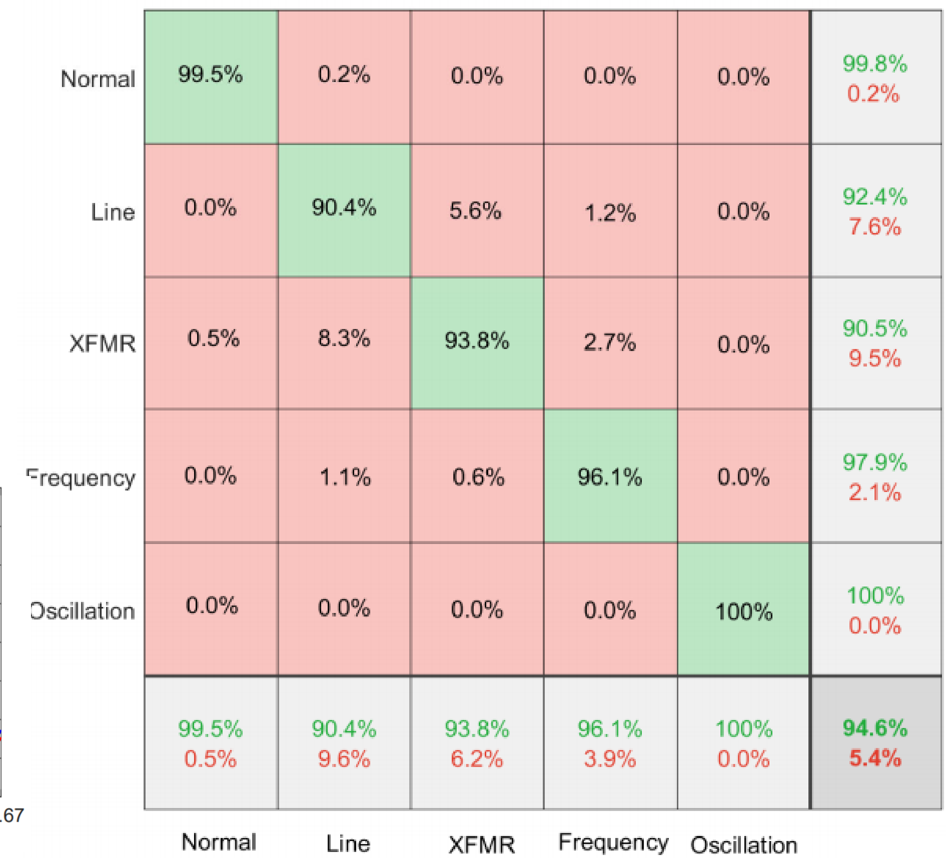
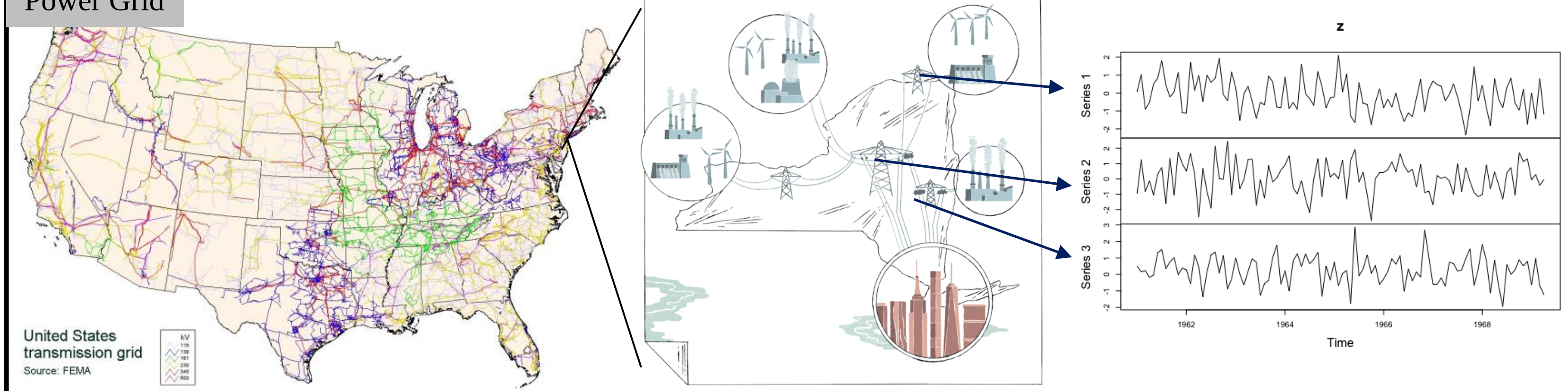


Fig. 15 Confusion matrix using the proposed model.

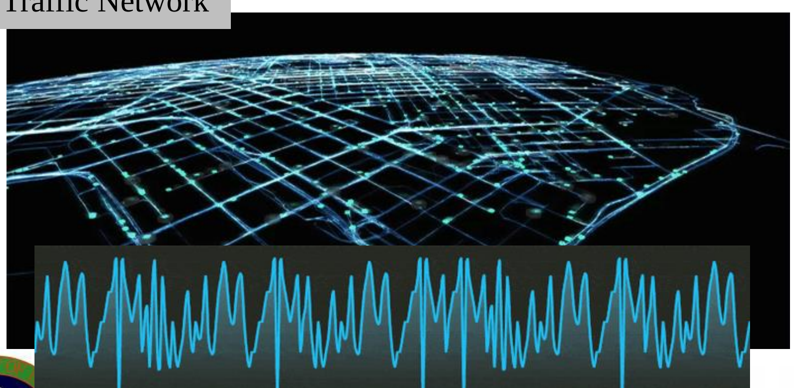
Technical Progress

Similar to traffic network and stocks, power systems are complex networks of interdependent components with interactions. (Task 3 & 5)

Power Grid



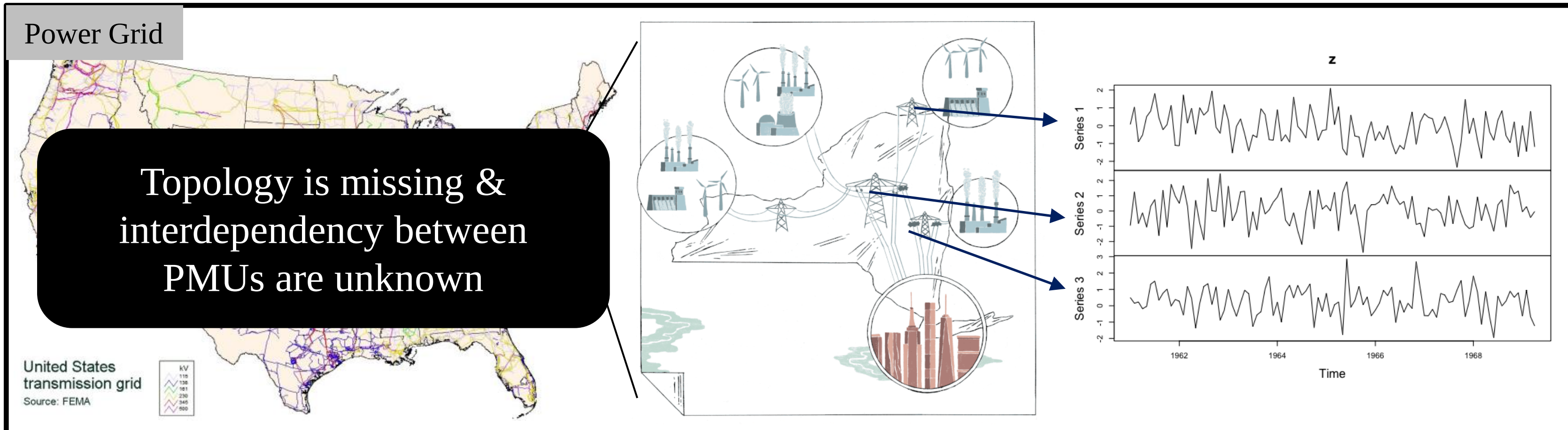
Traffic Network

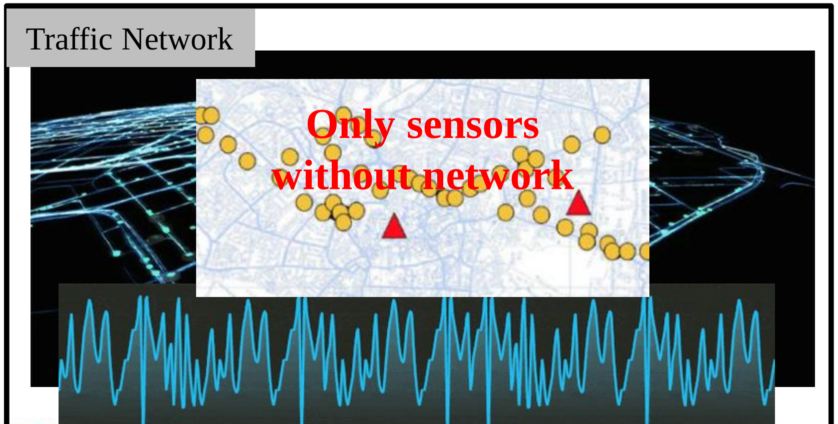


Stocks

Technical Progress

Missing Relations (Task 3 & 5)

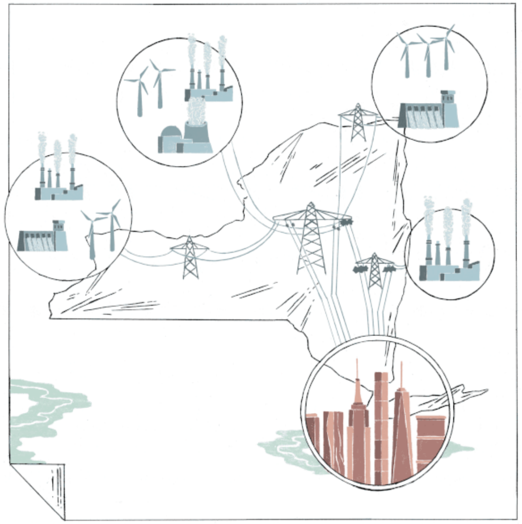




Technical Progress

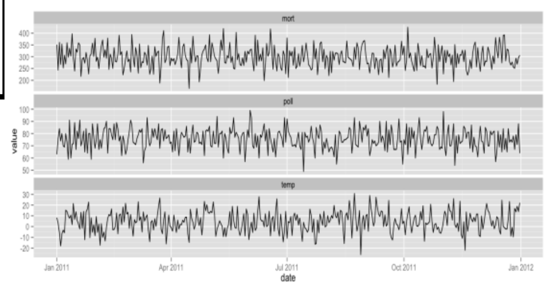
Learning Interaction Graphs using GNNs (Task 3 & 5)

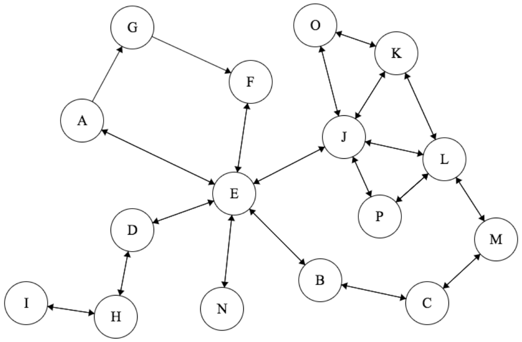
Power Grid is an interdependent network.



Goal:

- Explicitly learn the **pairwise interactions** in the form of a **graph** based on PMU data and use it to further improve event classification accuracy.
- Simultaneously optimize the graph learning and event classification tasks.





Technical Progress

Proposed Spatial GNN-Based Event Identifier (Task 3 & 5)

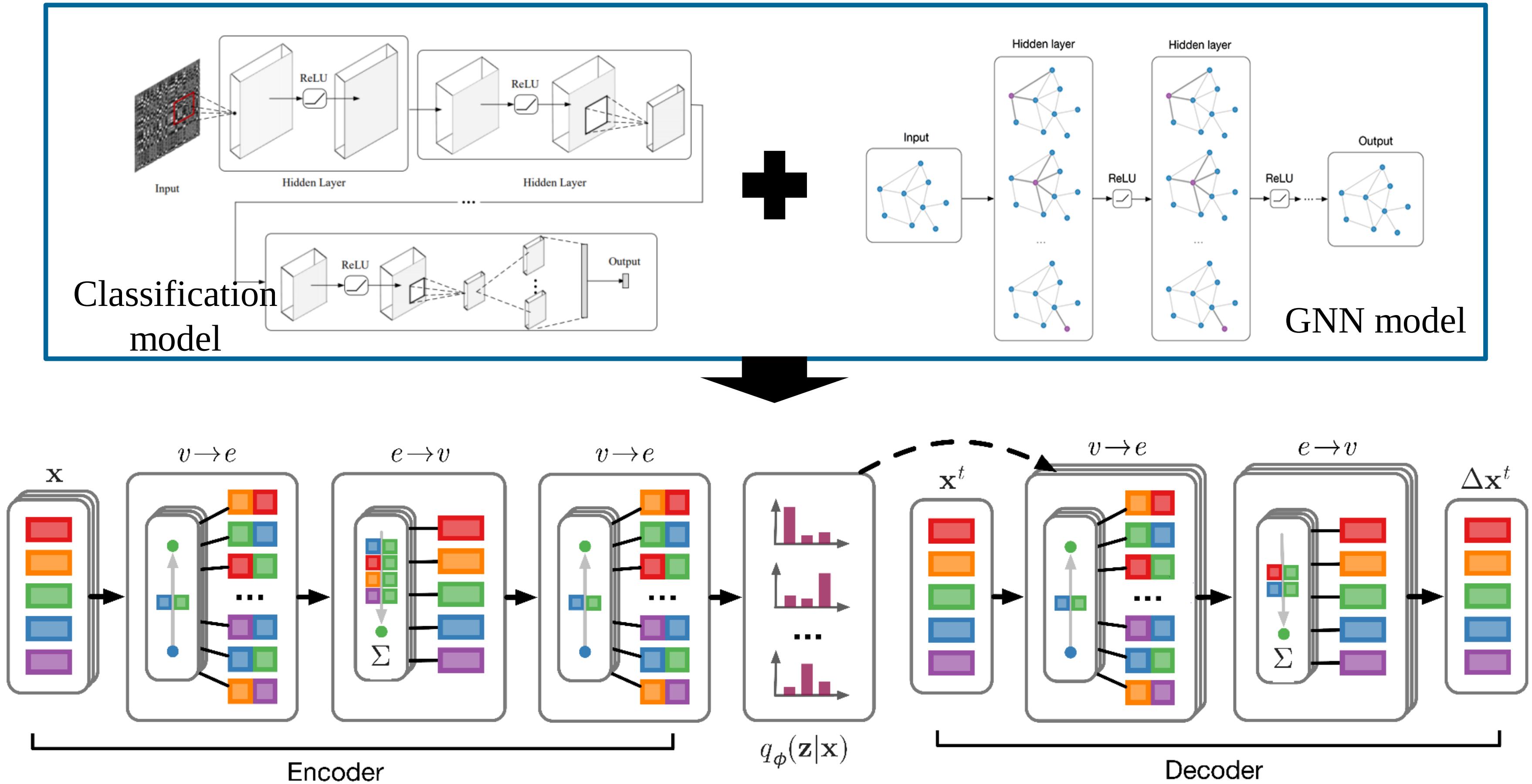


Fig. 17 Spatial GNN-based event identifier.

Future Effort

Remaining Tasks and Schedule

- **Graphical Cascading Failure Modeling, Monitoring, and Mitigation (Task 4):** The possible cascading failure data will be extracted to develop a PMU-based influence graph for monitoring and mitigating cascading outages.

- **Interaction Graph-based Event Identifier (Task 5)**: The proposed spatial GNN-based event identifier will be validated using our PMU dataset.

- **Unidentified Event Extraction (Task 5)**: We will utilized a unsupervised graphical data clustering method to extract and catalogue unidentified events.

Future Effort

Remaining Tasks and Schedule

- **Event Identification using Poor Event Logs (Task 5):** We will developed a novel event identification model to mitigate the challenge of event data scarcity using recent semi-supervised machine learning technique.

- **Offline Benchmarking Analysis (Task 6)**: EPG's commercial software such as PGDA or AEM will be used to compare with the proposed learning-based method in identifying anomalous events.

- **Integration with Open Source Platform (Task 7)**: The resulted deep learning models will be deployed as a service on big data platform such as IBM AI OpenScale

Reference

[1] J. Zhao, J. Tan, L. Wu, L. Zhan, W. Yao, and Y. Liu, "Impact of the measurement errors on synchrophasor-based wams applications," IEEE Access, vol. 7, pp. 143 960–143 972, 2019.

[2] H. Li, Y. Weng, E. Farantatos, and M. Patel, "An unsupervised learning framework for event detection, type identification and localization using pmus without any historical labels," 2019 IEEE Power Energy Society General Meeting (PESGM), pp. 1–5, 2019.

[3] S. Liu, Y. Zhao, Z. Lin, Y. Liu, Y. Ding, L. Yang, and S. Yi, "Data-driven event detection of power systems based on unequal-interval reduction of pmu data and local outlier factor," IEEE Trans. Smart Grid, vol. 11, no. 2, pp. 1630–1643, 2020.

[4] Z. Wang and T. Oates, "Encoding time series as images for visual inspection and classification using tiled convolutional neural networks," Association for the Advancement of Artificial Intelligence, pp. 40–46, 2015.

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Spatial pyramid pooling in deep convolutional networks for visual recognition," IEEE Trans. on Pattern Analysis and Machine Intell., vol. 37, no. 9, pp. 1904–1916, 2015.

Q&A

THANKS