Learning Power Grid Outages with Higher-Order Topological Neural Networks

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Contents

1 Outage detection in power distribution networks using higher-order topological neural networks (HOT-Nets)

- ❑ *Introduction* ❑ *Research Background* ❑ *Methodology* ❑ *Dataset* ❑ *Results* ❑ *Key observations*

[1] Chen, Y., Jacob, R. A., Gel, Y. R., Zhang, J., & Poor, H. V. (2023). Learning Power Grid Outages with Higher-Order Topological Neural Networks. *IEEE Transactions on Power Systems*.

2 Outage detection in power distribution networks using multi-parameter persistence

3 Outage management in power distribution networks using learning over graphs

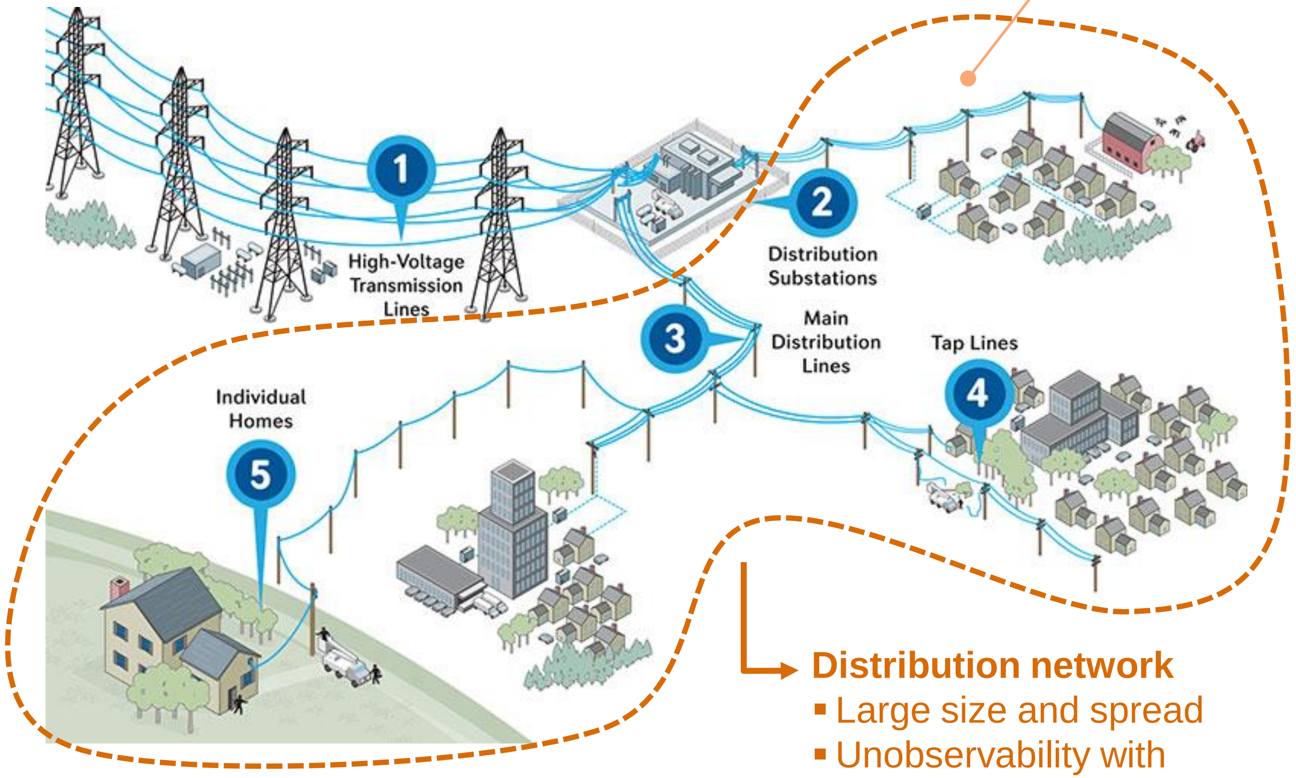
4 Conclusion and Future Works

Introduction

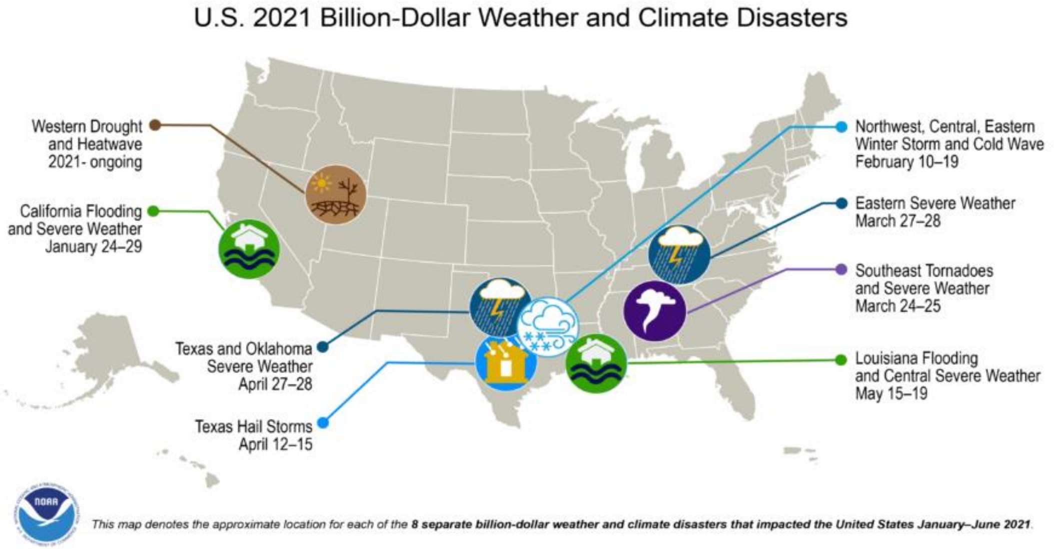
Motivation

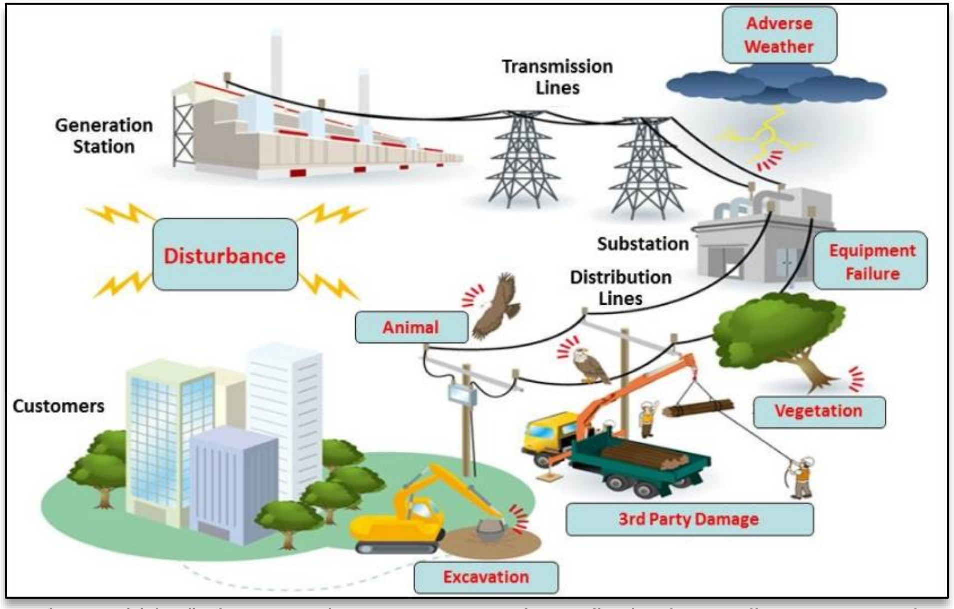
The increasing frequency of extreme weather-related outages and cyber attack threats in the power grid.

90% of power disruptions are attributed to failure in distribution network.



Distribution network
- Large size and spread
- Unobservability with limited sensors





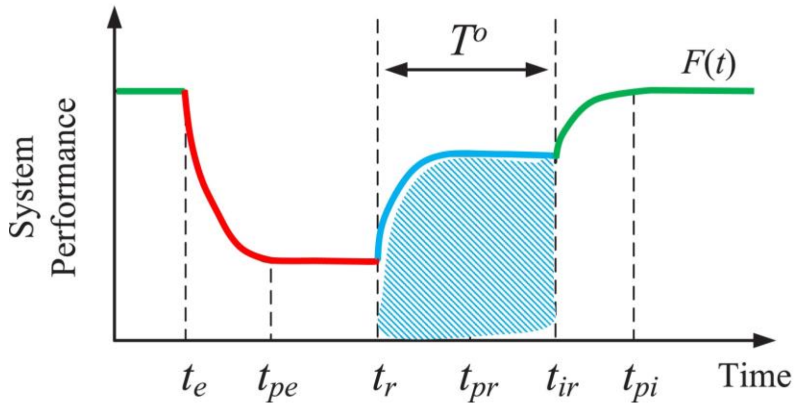
https://www.clp.com.hk/en/help-support/power-outages-voltage-dips/understanding-outages-voltage-dips

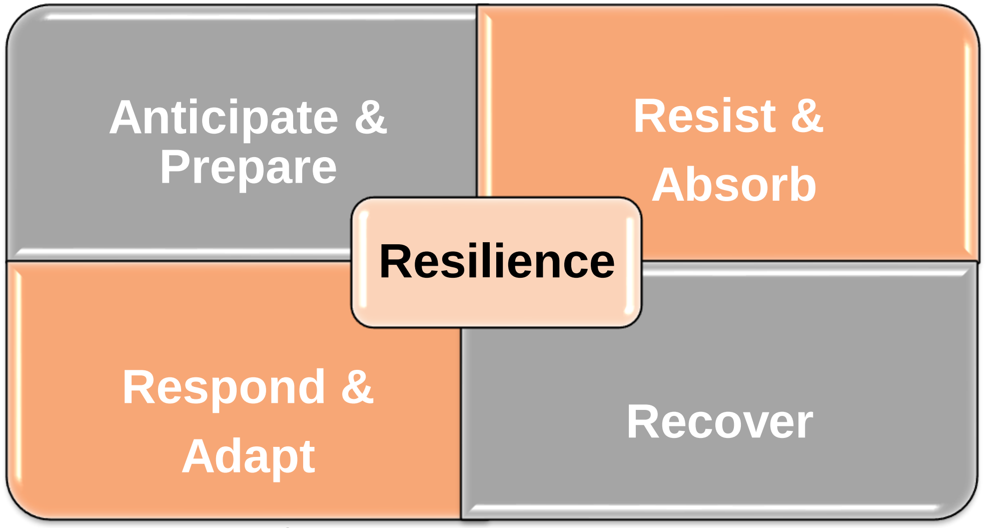
Introduction

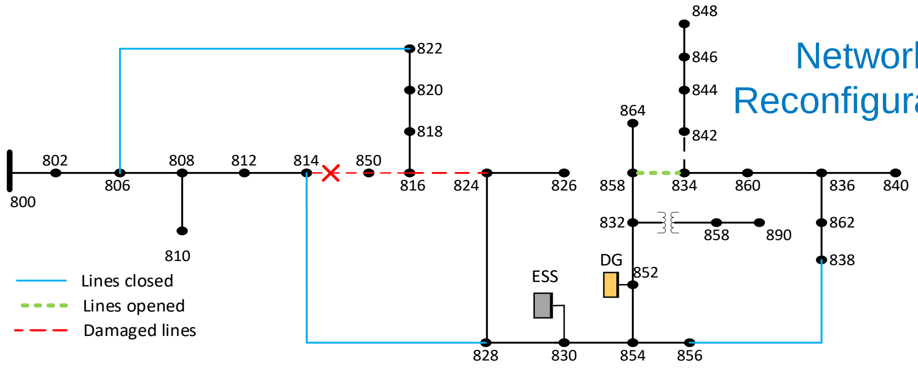
Goal

Improve the resilience of power distribution network using tools that are adaptable, online, and time sensitive.

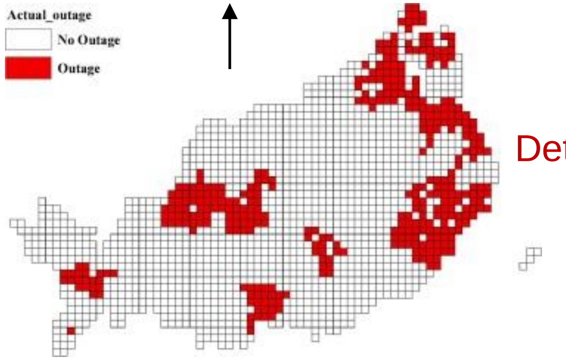
The “Resiliency Curve”







Network Reconfiguration

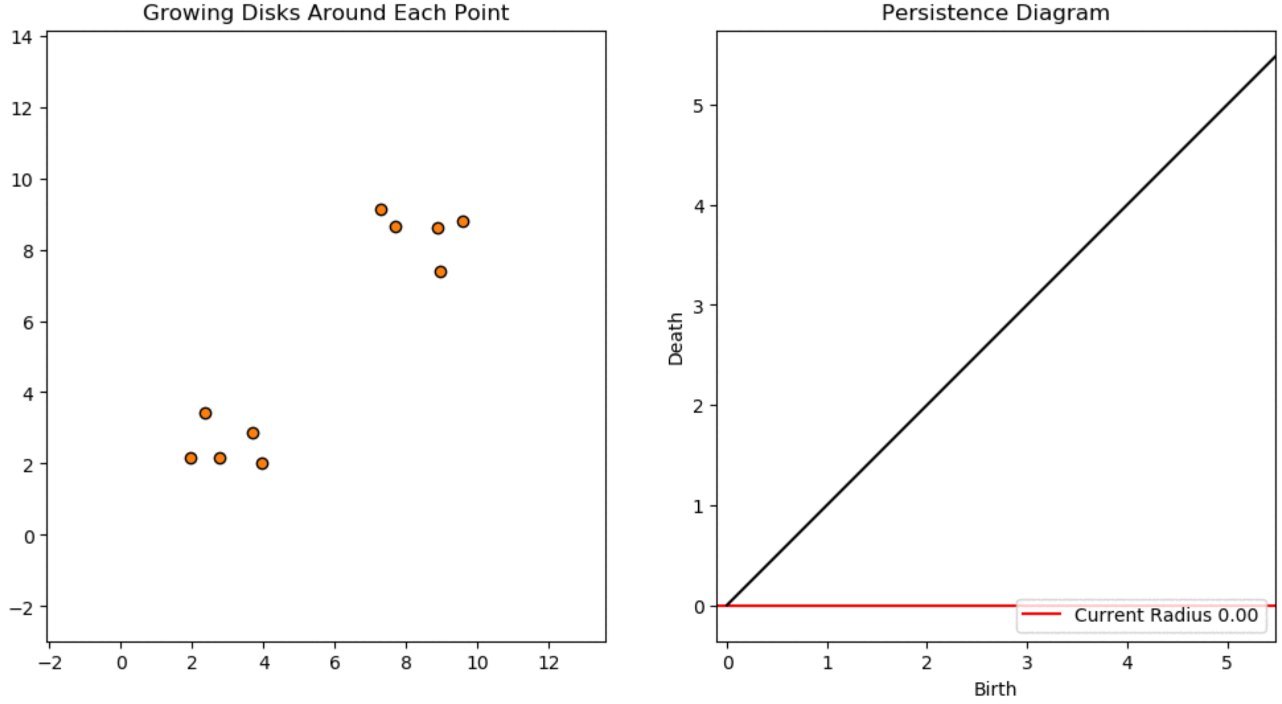


Detection of outages

Research Background

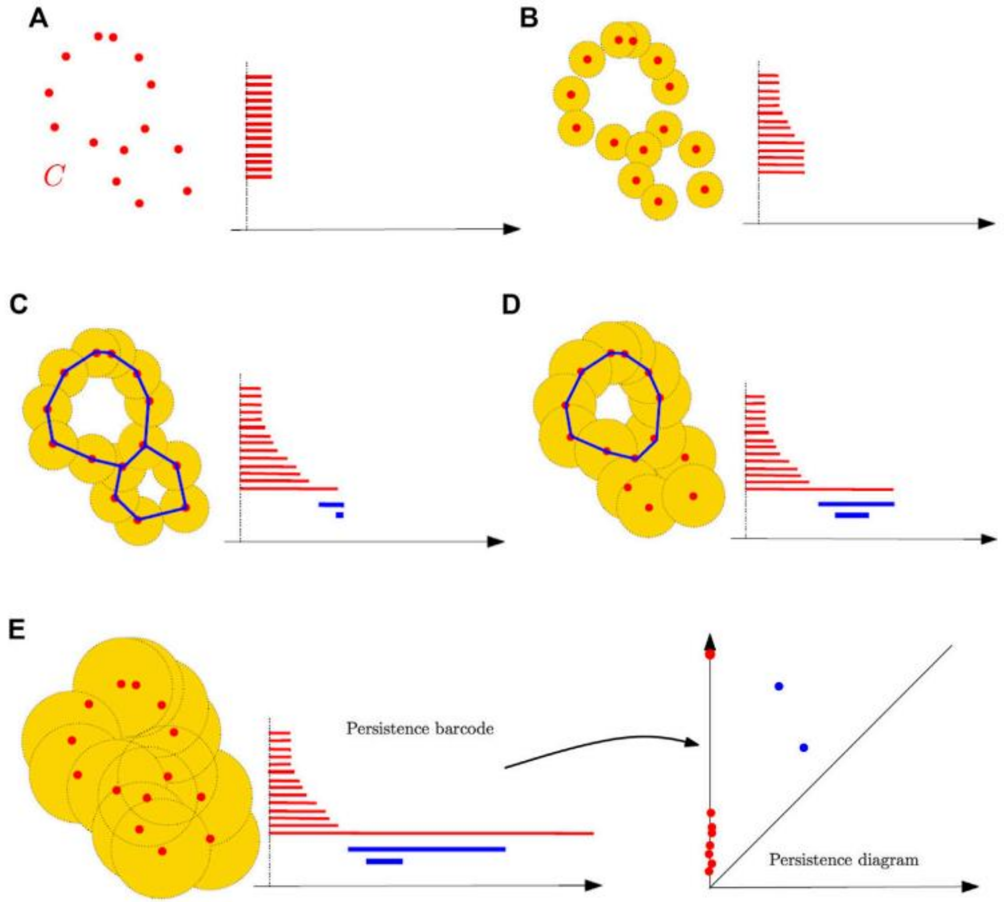
Persistent Homology

Two noisy clusters of data and the corresponding 0-d persistence diagram



https://towardsdatascience.com/persistent-homology-with-examples-1974d4b9c3d0

Filtration given by a union of growing balls and extraction of persistence image

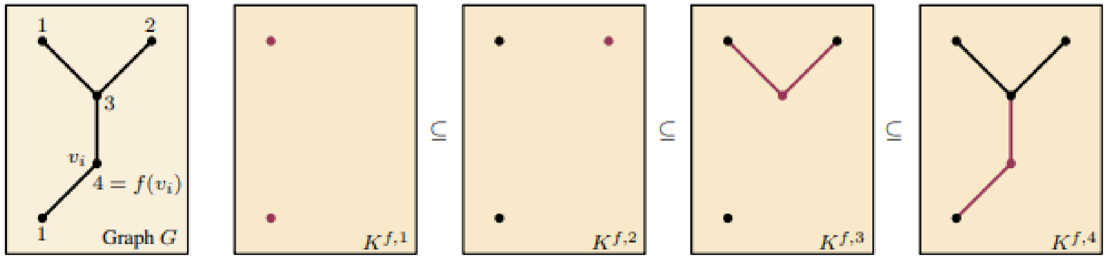


Chazal, Frédéric, and Bertrand Michel. "An introduction to topological data analysis: fundamental and practical aspects for data scientists." Frontiers in artificial intelligence 4 (2021): 108.

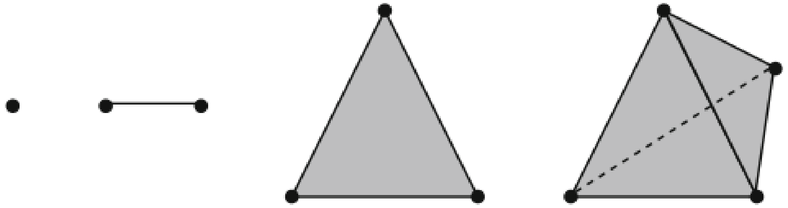
Research Background

Filtration on graphs and simplices

Illustration of 0-d persistent homology on a toy graph G using a node-based filter function *f*



Hofer, Christoph, et al. "Graph filtration learning." International Conference on Machine Learning. PMLR, 2020.



0-, 1-, 2-, and 3- simplex from left to right.

Example of generating simplicial complexes from a distribution network (DN) where each node represents a bus.

Node-to-edge incidence matrix

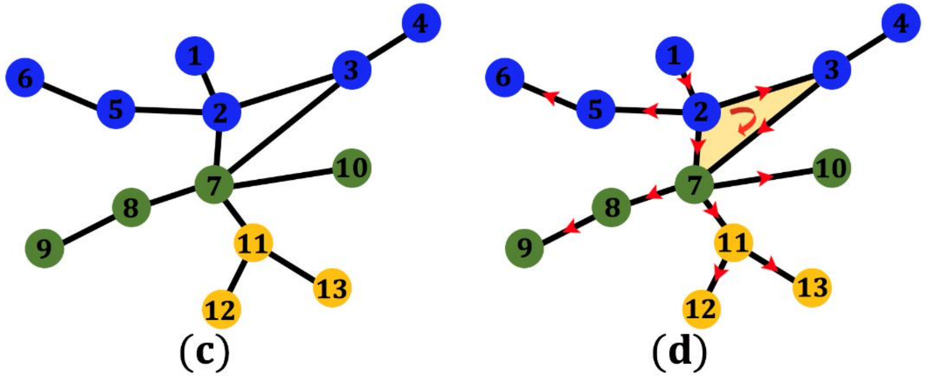
$$B_1 = \begin{array}{cc} & \begin{matrix} (1,2) & (2,3) & (2,5) & (2,7) & (3,4) & (3,7) & (5,6) & (7,8) & (7,10) & (7,11) & (8,9) & (11,12) & (11,13) \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \\ 10 \\ 11 \\ 12 \\ 13 \end{matrix} & \begin{pmatrix} -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & -1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 & -1 & -1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0. & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & -1 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \end{array}$$

(a)

Edge-to-face incidence matrix

$$B_2 = \begin{array}{cc} & (2,3,7) \\ \begin{matrix} (1,2) \\ (2,3) \\ (2,5) \\ (2,7) \\ (3,4) \\ (3,7) \\ (5,6) \\ (7,8) \\ (7,10) \\ (7,11) \\ (8,9) \\ (11,12) \\ (11,13) \end{matrix} & \begin{pmatrix} 0 \\ 1 \\ 0 \\ -1 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \end{array}$$

(b)



Graph structure of power network.

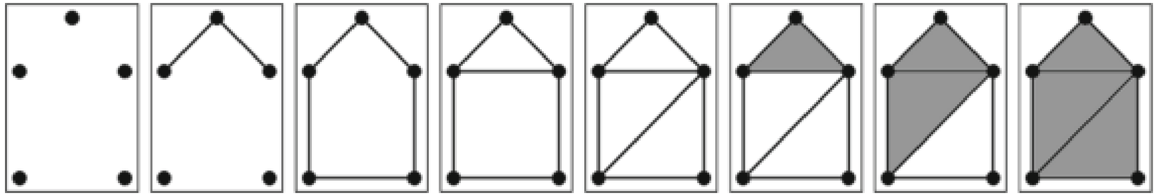
Simplicial complexes of power network.

Research Background

Key take aways:

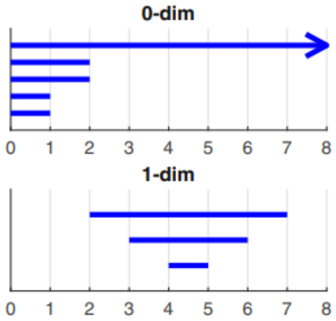
1

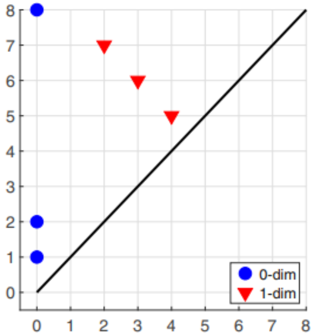
Track the evolution of various patterns in the DN that (dis)appear as we change the (dis)similarity threshold and record the birth and death information of each topological feature. Those with longer lifespan are called persistent (or topological signals) and contain information about key mechanisms behind DN functionality.



2

Summarize all extracted topological features as persistence diagram (PD), persistence landscape (PL), persistent image (PI), etc.





Also…

Hodge Laplacian analytics can be used to extend the convolutional operation within graph neural networks (GNNs) to account for complex interactions among multi-node substructures. It generalizes the node-to-node diffusion to diffusion over high order substructures.

Methodology: Higher-Order Topological Neural Networks

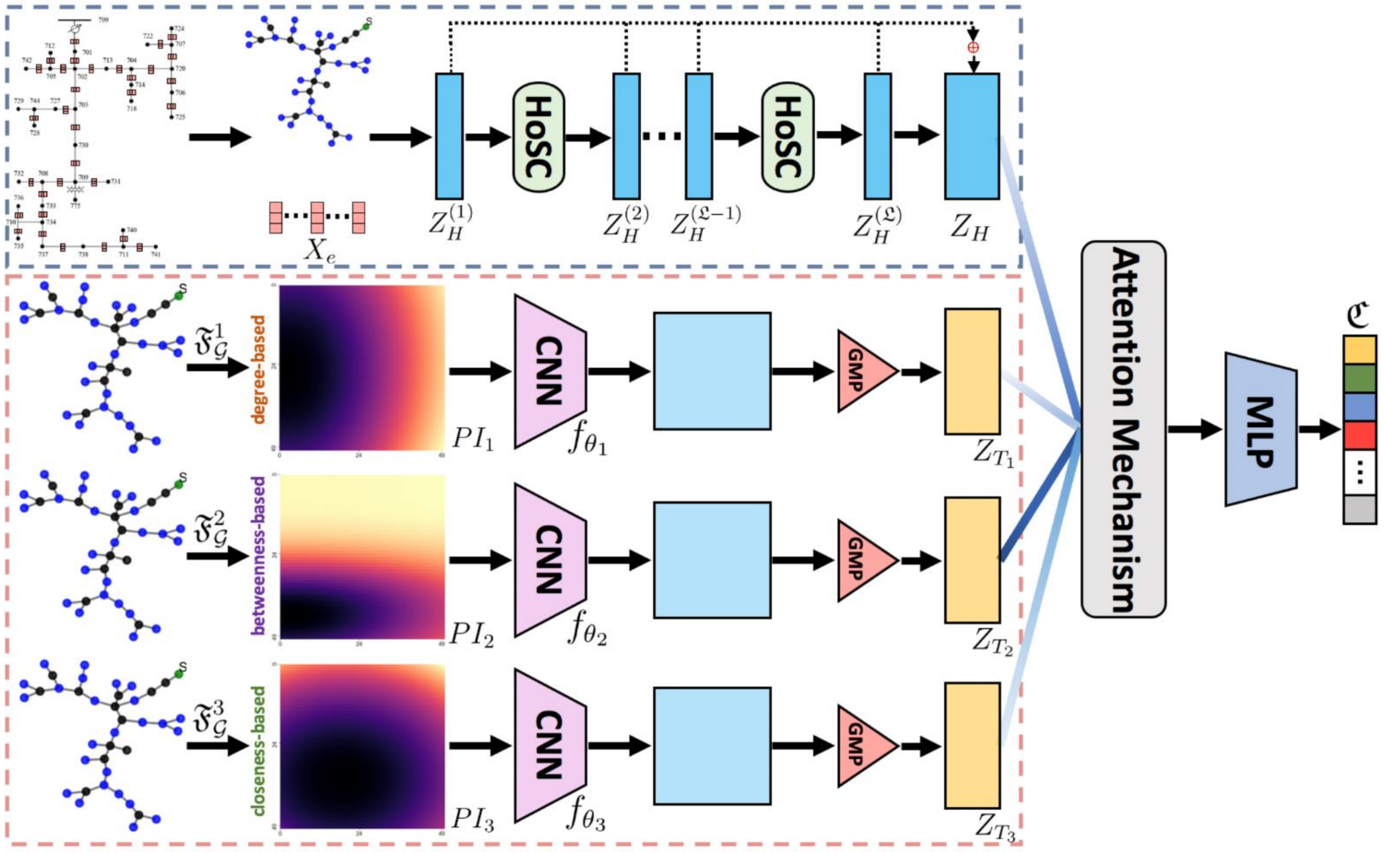


Fig. 1: Framework of our HOT-Nets model for graph classification. *Top row*: The higher-order simplices convolution (HoSC) module is used to extract higher-order simplices embeddings and form a primary higher-order simplex descriptor (i.e., Z_H) via the concatenate operation $\oplus$. *Bottom row*: First, we generate a persistence image PI_i for the input graph using the filtration $\mathfrak{F}_{\mathcal{G}}^i$ (where $i = \{1, 2, 3\}$, i.e., here we display 3 different filtrations including degree-based, betweenness-based, and closeness-based filtrations); we then feed these PIs into a CNN based model to obtain the image-level topological features. An attention mechanism is used to adaptively learn the correlation information among higher-order structures and different topological representations.

- The **power DN has an inherent graph structure** and can be represented as:

  $\mathcal{G} = (\boldsymbol{V}, \boldsymbol{\mathcal{E}}, \boldsymbol{A})$, where $\mathbf{V}$ is the set of nodes (buses), $\boldsymbol{\mathcal{E}}$ is the set of edges (lines/ transformers), $\boldsymbol{A} \epsilon \mathbb{R}^{N \times N}$ is the adjacency matrix with N nodes.

- The **node feature** matrix $\boldsymbol{X_V} \epsilon \mathbb{R}^{\boldsymbol{N} \times \boldsymbol{d_v}}$ consists of active/reactive power demands, active/reactive power generation forecasted at the buses, and the voltage measurements.
- The **edge feature** matrix $\mathbf{X}_{\boldsymbol{e}} \epsilon \mathbb{R}^{\boldsymbol{M} \times \mathbf{d}_{\boldsymbol{e}}}$ consists of the resistance, reactance, base load capacity, maximum capacity, residual capacity, and power flow through branches.
- The outage detection is a **graph level classification task.**

[1] Chen, Y., Jacob, R. A., Gel, Y. R., Zhang, J., & Poor, H. V. (2023). Learning Power Grid Outages with Higher-Order Topological Neural Networks. *IEEE Transactions on Power Systems*.

hotnets/HOT-Nets (github.com)

Methodology: Higher-Order Topological Neural Networks

Generation of synthetic data and simulation of contingency events

- The circuit definition of the test networks in OpenDSS simulation software is used to emulate actual network flow measurements with varying scenarios.
- Considering the localized effect of contingency events in DNs, a subgraph approach is used for simulating network outages.

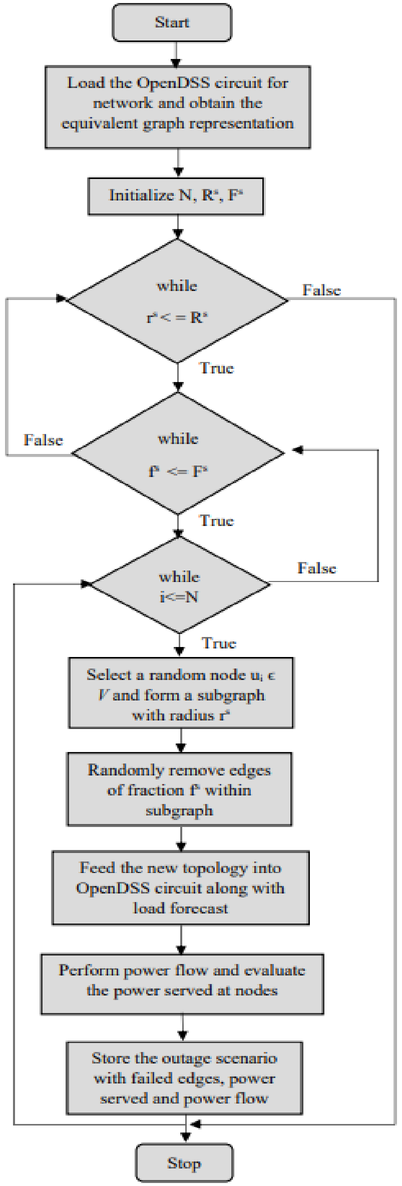


TABLE I
SUMMARY OF DATASETS USED IN GRAPH CLASSIFICATION TASK WITH FULL OBSERVABILITY AT BUSES.

Dataset	**Graphs**	**Nodes**	**Edges**†	**Features**$_{\mathcal{V}}$	**Features**$_{\mathcal{E}}$	**Classes**
IEEE 37 Bus	200	39	35.34	2	8	2
IEEE 123 Bus	300	132	126.56	2	8	2
342 Bus LVN	500	390	432.39	2	8	2

The [†] means the average number of edges in a distribution network under contingency (edge failed).

TABLE II
SUMMARY OF DATASETS USED IN GRAPH CLASSIFICATION TASK WITH PARTIALLY OBSERVABLE BUSES AND LINES.

Dataset	**Graphs**	**Nodes**	**Edges**†	**Features**$_{\mathcal{V}}$	**Features**$_{\mathcal{E}}$	**Classes**
IEEE 37 Bus$'$	300	39	37.34	5	6	2
IEEE 123 Bus$'$	300	132	122.87	5	6	2
342 Bus LVN$'$	300	390	446.74	5	6	2

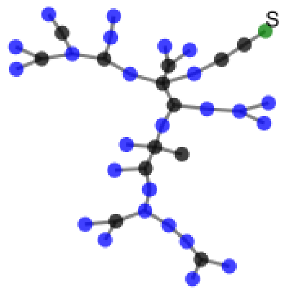
The [†] means the average number of edges in distribution network under contingency (edge failed).

Dataset

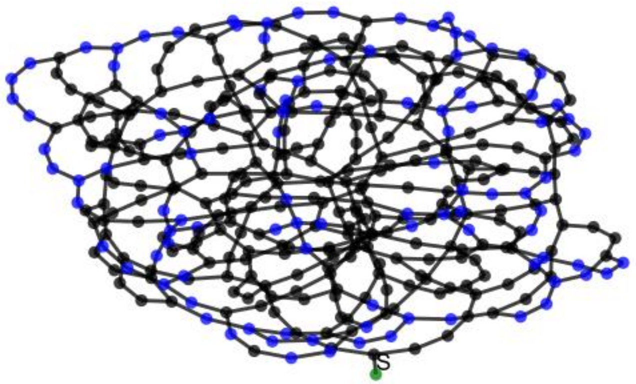
Test Networks

The test networks used to validate the HOT-Nets model for outage detection include IEEE 37-bus, IEEE 123-bus, and 342-bus Low voltage network (meshed).

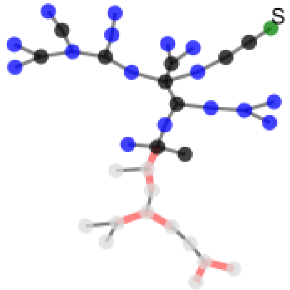
IEEE 37-bus DN



342-bus low voltage North American DN



Base network- normal operating conditions. The source node is marked as ‘S’ with green color. The buses with loads are marked using blue and the interconnecting buses are colored black.



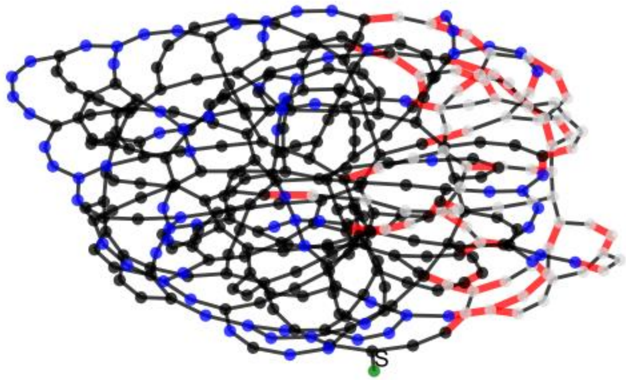


Illustration of a contingency event. The grey nodes are isolated by network failure and red edges represent failed components.

Results

Model Performance

1 OVERALL CLASSIFICATION PERFORMANCE (%) (± STANDARD DEVIATION) OF DIFFERENT METHODS ON TEST NETWORKS FOR A CASE WITH ALL BUSES OBSERVABLE. *** DENOTES THE HIGHLY STATISTICALLY SIGNIFICANT RESULT.

Datasets	RF	ANN	GCN	GAT	GIN	GraphSage	Set2Set	DiffPool	EigenGCN	AM-GCN	SNNs	HOT-Nets (ours)
IEEE 37 Bus	77.61±1.55	78.21±1.48	84.45±1.67	85.02±1.74	87.28±1.97	86.96±2.25	88.20±1.94	90.25±2.32	87.50±2.36	83.98±2.03	86.65±1.80	***97.70±1.64
IEEE 123 Bus	68.50±0.25	73.15±0.85	84.33±0.77	83.80±0.76	81.91±0.79	86.00±1.30	76.67±0.82	87.67±0.90	87.73±0.89	87.68±0.15	86.69±1.01	***90.33±0.73
342-bus LVN	63.32±0.18	68.07±0.72	75.05±1.70	73.62±1.98	74.80±1.91	76.47±1.67	78.39±1.79	77.93±1.22	80.61±1.97	76.20±2.00	79.26±1.31	***83.68±2.03

2 CLASSIFICATION PERFORMANCE (%) (± STANDARD DEVIATION) OF DIFFERENT METHODS ON IEEE 37 Bus′, IEEE 123 Bus′, AND 342 Bus LVN′ (I.E., NEW TEST CASE ON NETWORKS) WITH PARTIALLY OBSERVABLE DISTRIBUTION GRIDS. *** DENOTES THE HIGHLY STATISTICALLY SIGNIFICANT RESULT.

Datasets	RF	ANN	GCN	GAT	GIN	GraphSage	Set2Set	DiffPool	EigenGCN	AM-GCN	SNNs	HOT-Nets (ours)
IEEE 37 Bus′	83.60±0.16	85.28±0.49	91.96±0.37	93.82±0.25	92.81±0.63	93.70±0.50	92.00±0.26	94.60±0.40	93.66 ±0.23	94.24±0.25	94.42±0.19	***95.67±0.15
IEEE 123 Bus′	84.29±0.30	87.26±0.92	93.50±0.50	94.44±0.75	94.62±0.73	95.03±0.37	91.43±0.22	95.29±0.43	94.33±0.86	95.12±0.66	95.30±0.43	***97.66±0.33
342 Bus LVN′	76.49±0.20	76.57±0.30	83.11±0.34	83.95±0.46	85.44±0.52	84.67±0.59	83.95±0.93	87.24±0.78	83.76±0.50	85.95±0.61	89.47±0.17	***91.11±0.46

3 OVERALL CLASSIFICATION PERFORMANCE (%) (± STANDARD DEVIATION) OF DIFFERENT METHODS ON IEEE 123 BUS″ WITH 30% SENSOR DENSITY. *** DENOTES THE HIGHLY STATISTICALLY SIGNIFICANT RESULT.

Datasets	RF	ANN	GCN	GAT	GIN	GraphSage	Set2Set	DiffPool	EigenGCN	AM-GCN	SNNs	HOT-Nets (ours)
IEEE 123 Bus″	70.43±0.34	78.23±0.20	81.53±0.57	82.37±0.72	83.92±0.56	83.75±0.38	84.53±0.58	85.20±0.43	86.36±0.75	87.69±0.74	88.11±0.69	***91.37±0.67

Results

Ablation study

ABLATION STUDY OF THE NETWORK ARCHITECTURE.

Method	Architecture			Datasets	
	Hodge	*Topo.*	*Att.*	IEEE 37 Bus	IEEE 123 Bus
HOT-Nets	✓	✓	✓	******97.70***	******90.33***
Node & Topo.-Nets (NT-Nets)	✗	✓	✓	85.00	86.61
Edge & Topo.-Nets (ET-Nets)	✗	✓	✓	86.93	87.71
HOT-Nets W/o *Att.*	✓	✓	✗	93.49	88.59
HOT-Nets With One *Topo.*	✓	✗	✓	92.75	89.00
HOT-Nets W/o *Topo.*	✓	✗	✓	90.05	88.11

ABLATION STUDY OF THE NETWORK ARCHITECTURE ON IEEE 123-Bus$'$. * DENOTES THE SIGNIFICANT RESULT.

Method	Architecture			Datasets
	Hodge	*Topo.*	*Att.*	IEEE 123 Bus$'$
HOT-Nets	✓	✓	✓	***97.66**
Node & Topo.-Nets (NT-Nets)	✗	✓	✓	86.33
Edge & Topo.-Nets (ET-Nets)	✗	✓	✓	96.17
HOT-Nets W/o *Att.*	✓	✓	✗	94.53
HOT-Nets With One *Topo.*	✓	✗	✓	95.65
HOT-Nets W/o *Topo.*	✓	✗	✓	92.35

Key Observations

- Our HOT-Nets model **outperforms** all the **SOTA** methods. The improvement gain of HOT-Nets over the runners-up ranges from 2.88% to 7.63%.
- A common limitation of the SOA methods is that they are incapable of incorporating **both higher-order features and multi-scale local topological structures**.
- The **ablation study** shows that when replacing the **Hodge 1-Laplacian** with the node or edge-level Laplacian, the graph classification accuracy is **significantly** affected. HOT-Nets outperforms NT-Nets with relative gains of 12.99% and 4.12% for IEEE 37-bus and IEEE 123-bus networks.
- Combining the **simplicial convolutional layer** and the **fully trainable topological layer** results in more informative learning of the underlying graph structure.

Contents

1 Outage detection in power distribution networks using higher-order topological neural networks (HOT-Nets)

2 Outage detection in power distribution networks using multi-parameter persistence

- ❑ *Introduction* ❑ *Methodology* ❑ *Dataset* ❑ *Results* ❑ *Key observations*

[2] Uddin, Md. J., Olojede, D., Jacob, R. A., Coskunuzer, B., & Zhang, J., Detecting Power Grid Outages with Topological Machine Learning (Draft)

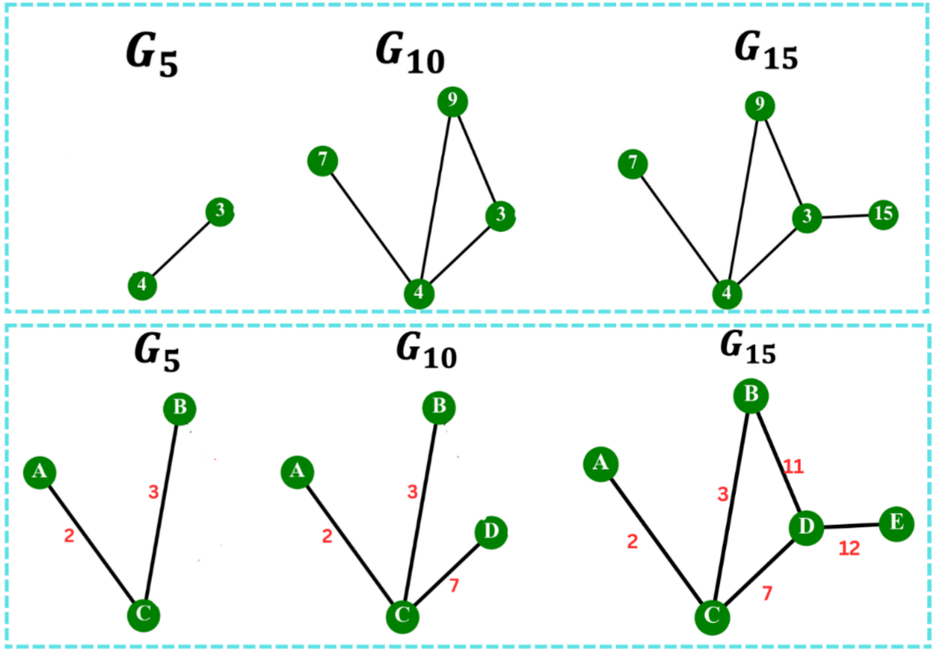
3 Outage management in power distribution networks using learning over graphs

4 Conclusion and Future Works

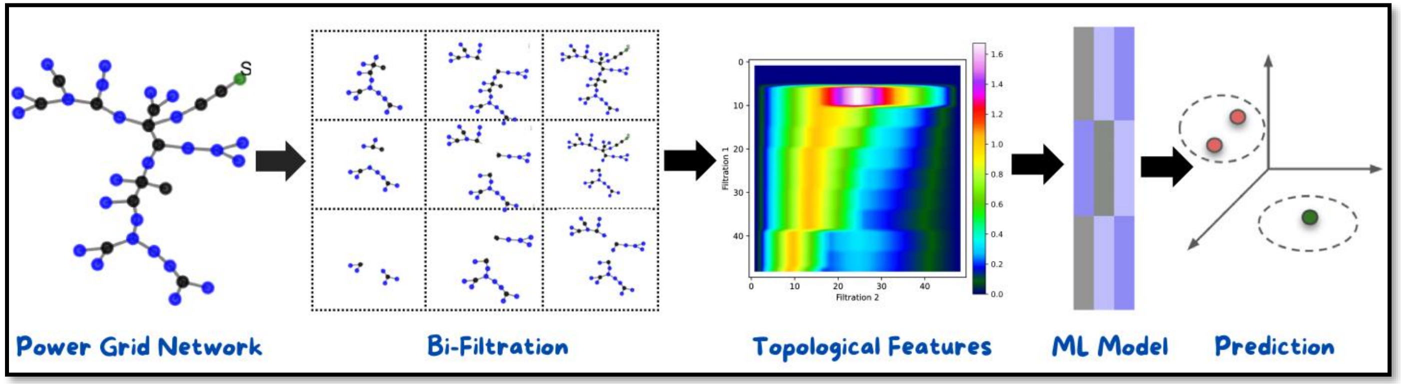
Introduction

Bi-level filtration approach

Node and edge filtrations

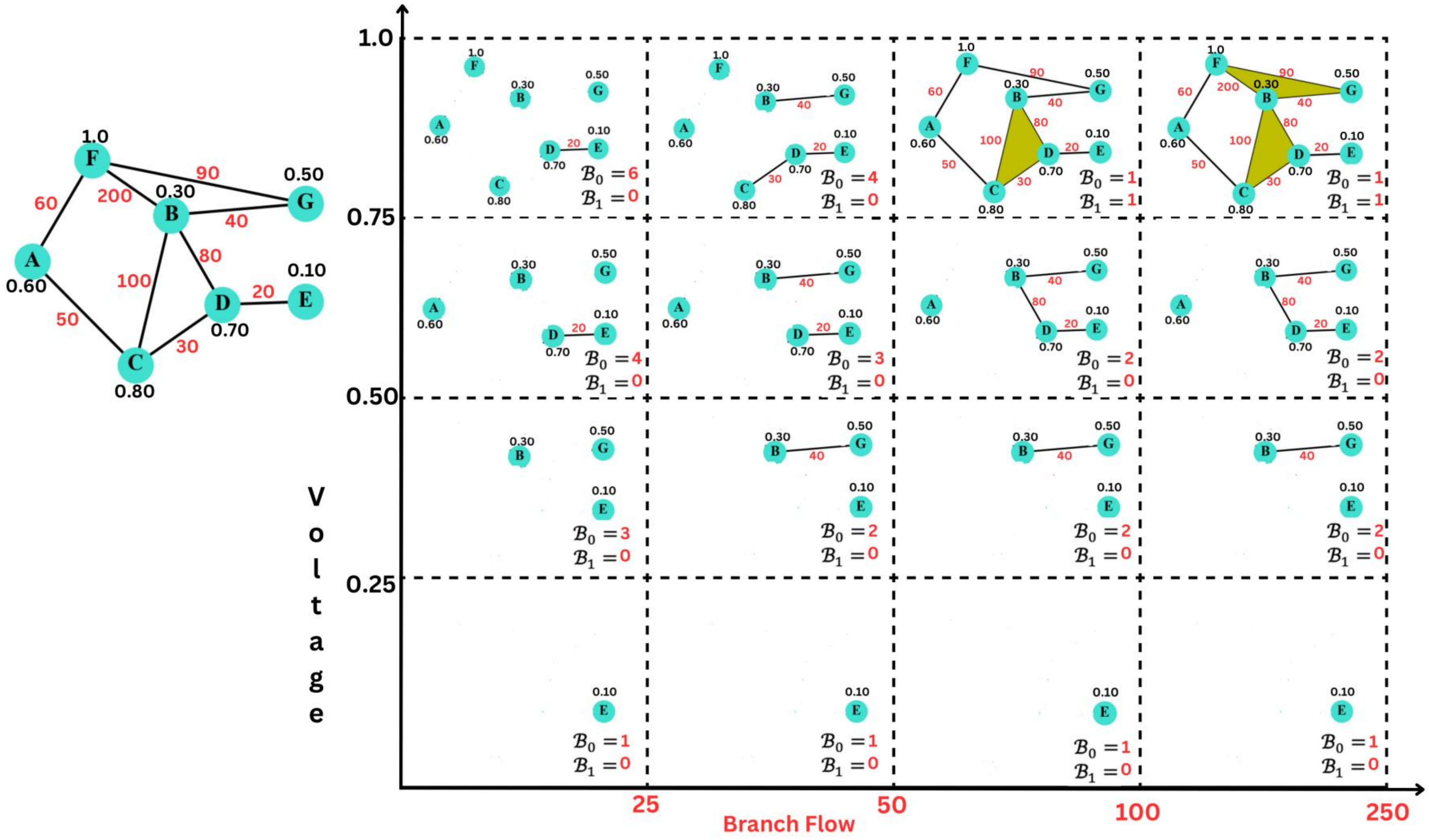


Pipeline of bi-level filtration-based graph classification



Methodology

A toy graph example demonstrating the extraction of multiparameter persistence information



Dataset

To test the **scalability** of the outage detection module, we have included the following large-size DNs:

- IEEE 8500-Bus Test Feeder: Contains both the primary and secondary levels of DN.
- Sub-Region P1U of San Francisco Bay Area: NREL's SMART-DS datasets. This is one of the 35 sub-regions and is close to a real-world network.

SUMMARY OF DATASETS USED IN GRAPH CLASSIFICATION TASK WITH PARTIALLY OBSERVABLE BUSES AND LINES.**BC:JOSHEM, PLEASE ADD OTHER DATASETS' DETAILS**

Dataset	Graphs	Nodes	Edges	Edges†	Features$_{\mathcal{V}}$	Features$_{\mathcal{E}}$	Classes
IEEE 37 Bus$'$	1,000	39	38	37.34	5	6	2
IEEE 123 Bus$'$	1,000	132	131	122.87	5	6	2
342 Bus LVN$'$	1,000	390	460	446.74	5	6	2
IEEE 8500 Bus	300	4,875	4,874				2
San Francisco	300	18,585	18,563				2

Results

1

CLASSIFICATION PERFORMANCE (%) (±STANDARD DEVIATION) OF DIFFERENT METHODS ON IEEE 37 Bus′, IEEE 123 Bus′, AND 342 Bus LVN′ (I.E., NEW TEST CASE ON NETWORKS) WITH PARTIALLY OBSERVABLE DISTRIBUTION GRIDS.

Datasets	GCN	GAT	GIN	GraphSage	Set2Set	DiffPool	EigenGCN	AM-GCN	SNNs	HOT-Nets	Ours
IEEE 37 Bus′	91.96±0.37	93.82±0.25	92.81±0.63	93.70±0.50	92.00±0.26	94.60±0.40	93.66 ±0.23	94.24±0.25	94.42±0.19	95.67±0.15	**96.33±0.03**
IEEE 123 Bus′	93.50±0.50	94.44±0.75	94.62±0.73	95.03±0.37	91.43±0.22	95.29±0.43	94.33±0.86	95.12±0.66	95.30±0.43	97.66±0.33	**98.40±0.01**
342 Bus LVN′	83.11±0.34	83.95±0.46	85.44±0.52	84.67±0.59	83.95±0.93	87.24±0.78	83.76±0.50	85.95±0.61	89.47±0.17	91.11±0.46	**92.20±0.03**

2

SINGLE VS. MULTIPERSISTENCE

Dataset	Voltage	Branch Flow	MP-XGB	MP-MLP
IEEE 37 Bus	91.33±0.06	86.33±0.05	**96.33±0.03**	96.00±0.04
IEEE 123 Bus	97.20±0.02	97.20±0.02	**98.40±0.01**	97.60±0.02
IEEE 342 Bus	**93.00±0.02**	90.00±0.02	92.20±0.03	91.50±0.03
IEEE 8500 Bus	98.67±0.02	97.67±0.02	**99.00±0.02**	98.00±0.02
San Francisco	96.67±0.02	98.33±0.02	99.33±0.01	**99.67±0.01**

Key Observations

- The **multi-persistence-based (MP)** model achieves outstanding **performance surpassing** all the **SOTA** methods. Our model utilizes multi-persistence to extract finer topological structures from the network when compared to the single persistence used in HOT-Nets.
- The model performs well on larger networks with high accuracy.

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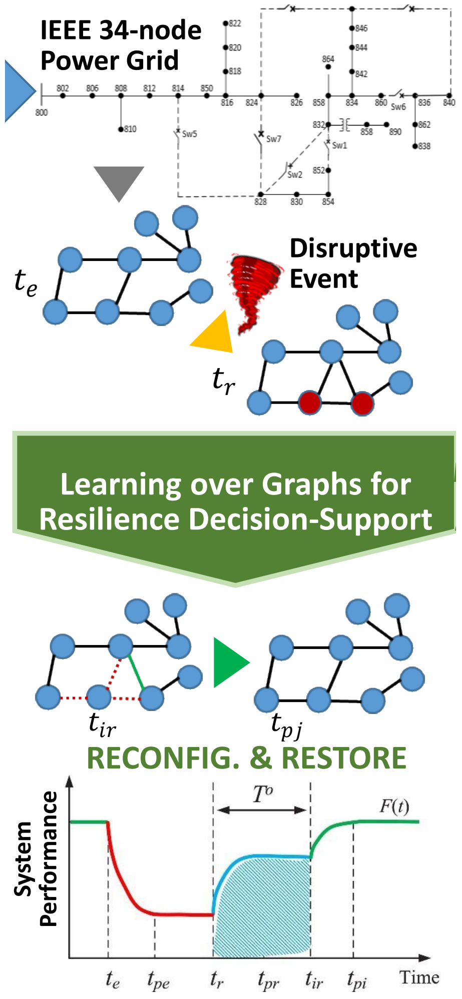
- ❑ *Introduction* ❑ *Methodology* ❑ *Testing on Networks* ❑ *Results* ❑ *Adding TDA*

[3] Jacob, R., Paul, S., Chowdhury, S., Gel, Y. & Zhang, J. (2023). Real-Time Outage Management in Active Distribution Networks Using Reinforcement Learning over Graphs. (Under Review)

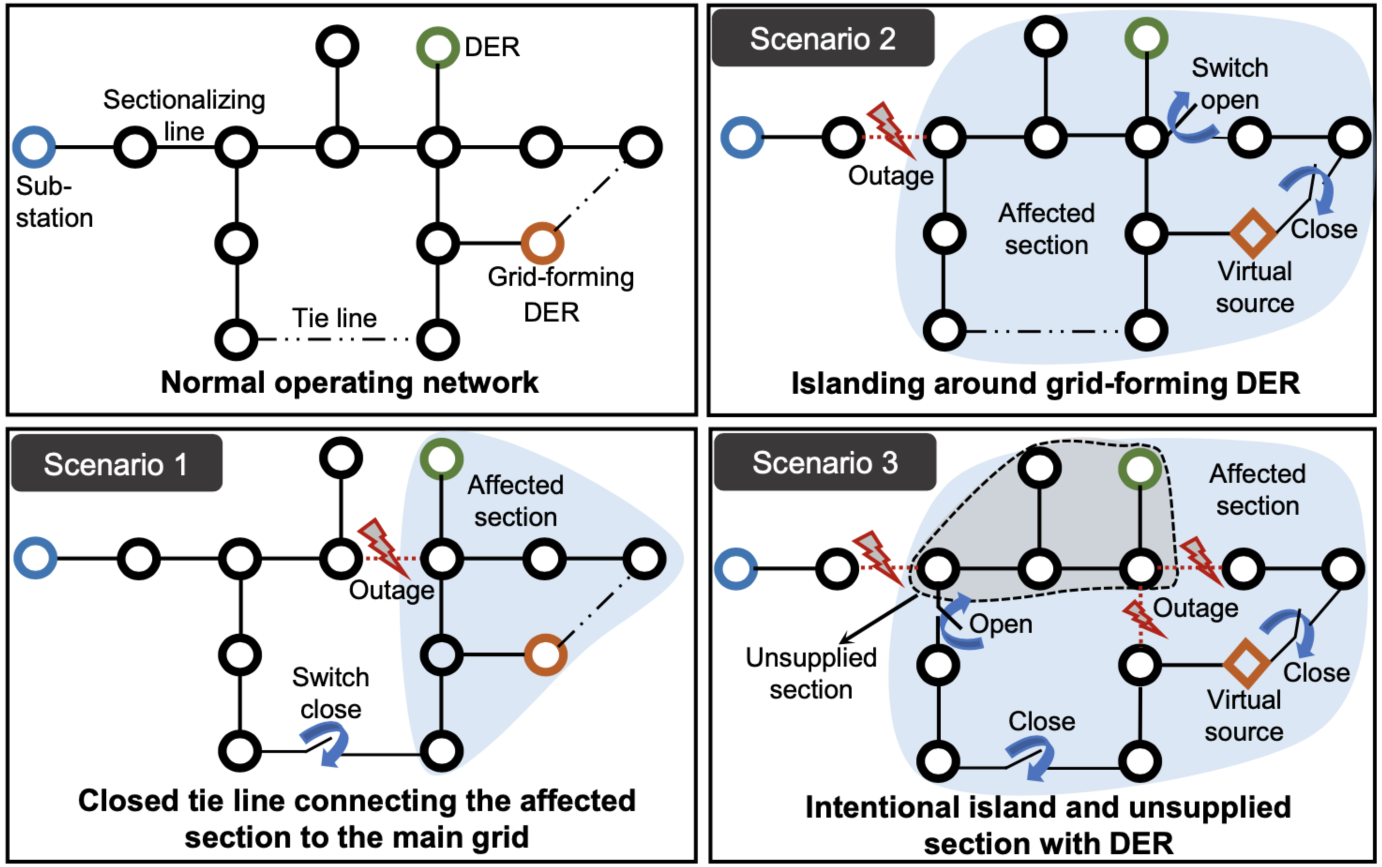
4 Conclusion and Future Works

Introduction

The concept of learning over graphs



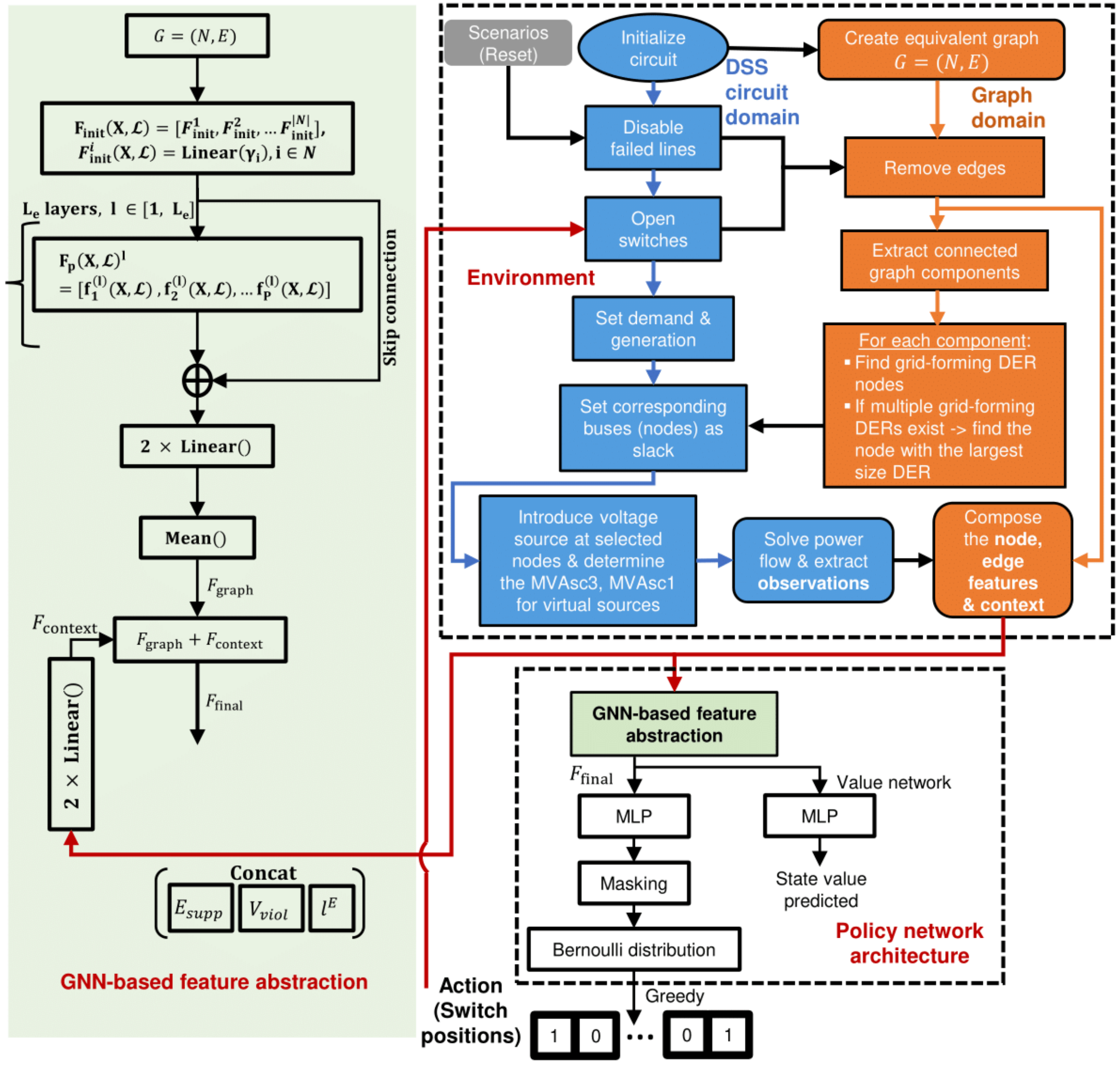
Schematic of outage management in an example network with DERs (with and without grid forming ability), and sectionalizing/tie switches



Methodology

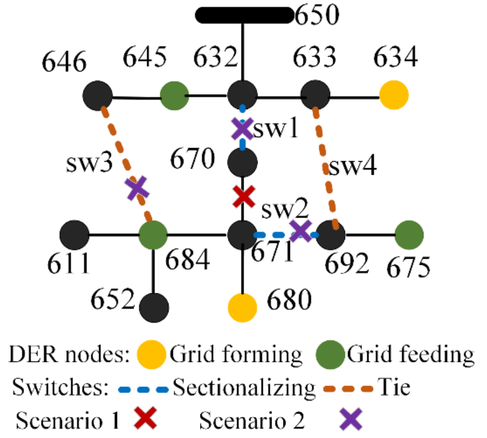
- A learning over-graphs approach, specifically reinforcement learning is developed for switching control during outages.
- Both reconfiguration and intentional islanding are considered for outage mitigation.
- The environment is composed of a DN model interface (DSS circuit) using a Python-based API and the graph replica of the DSS circuit.
- Policy network uses the state information from the environment to compute graph node embeddings and context embeddings using GNN and feedforward networks, respectively.
- A final feature vector that encompasses the two embeddings is computed by an MLP.

The learning framework developed includes the environment and the policy network architecture with GNN-based feature abstraction

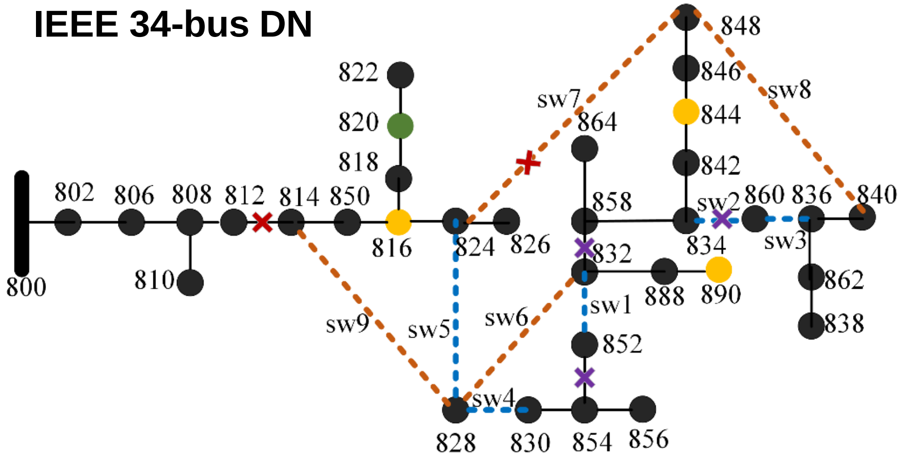


Testing on Networks

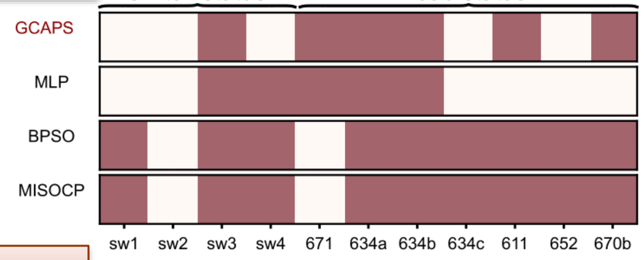
IEEE 13-bus DN



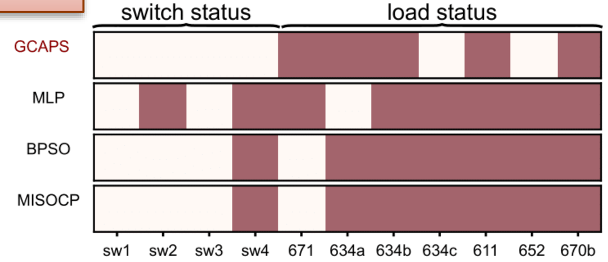
IEEE 34-bus DN



Scenario 1

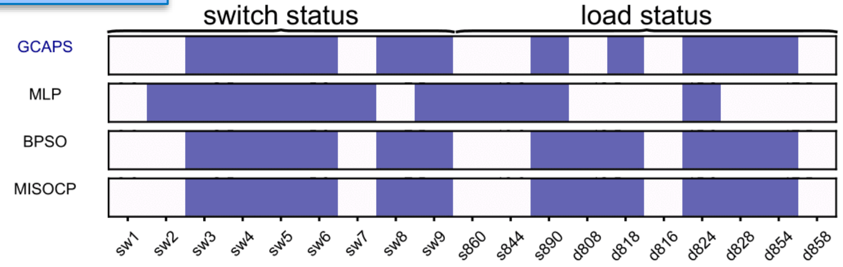


Scenario 2

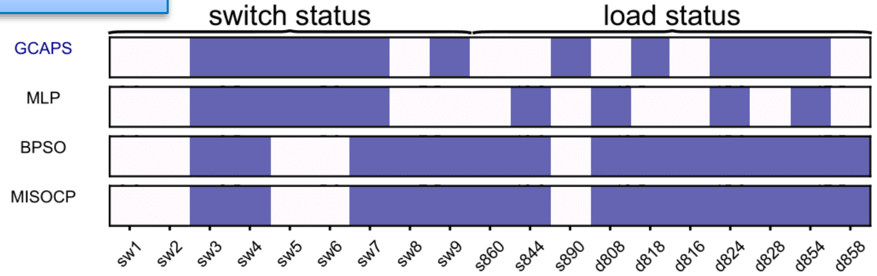


Decision Variables

Scenario 1

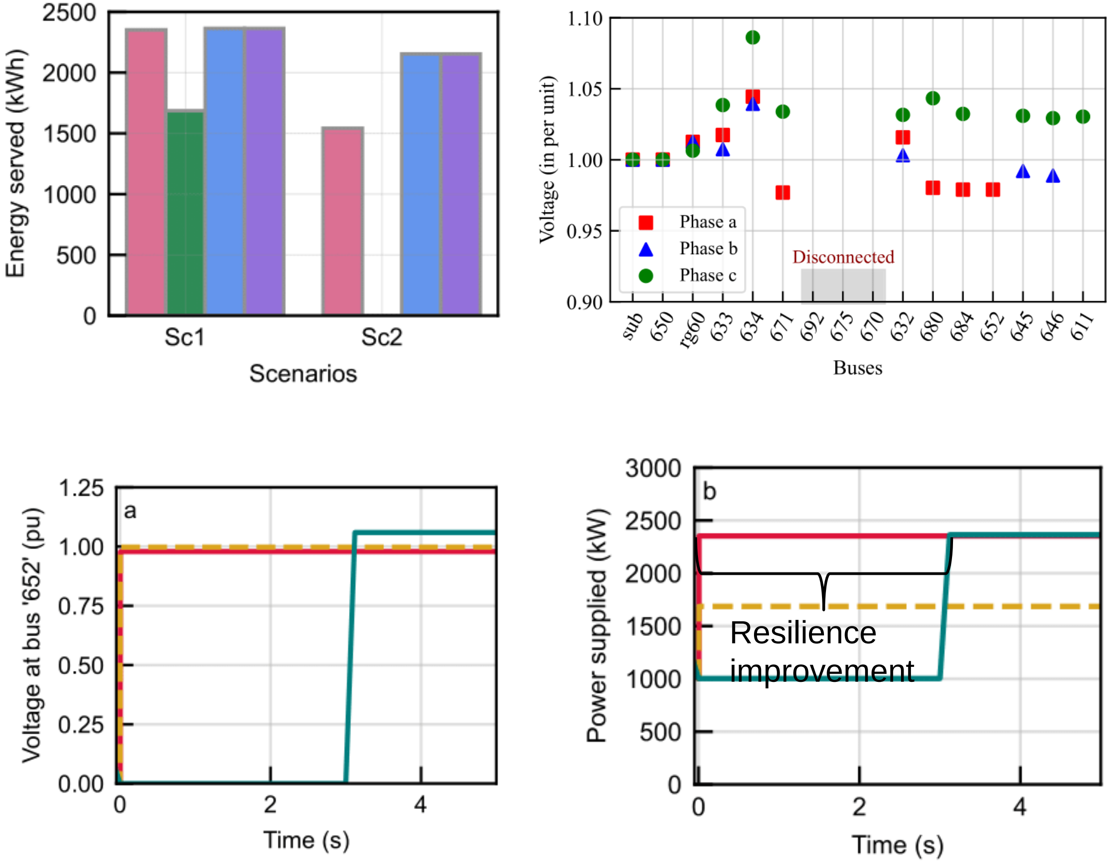


Scenario 2

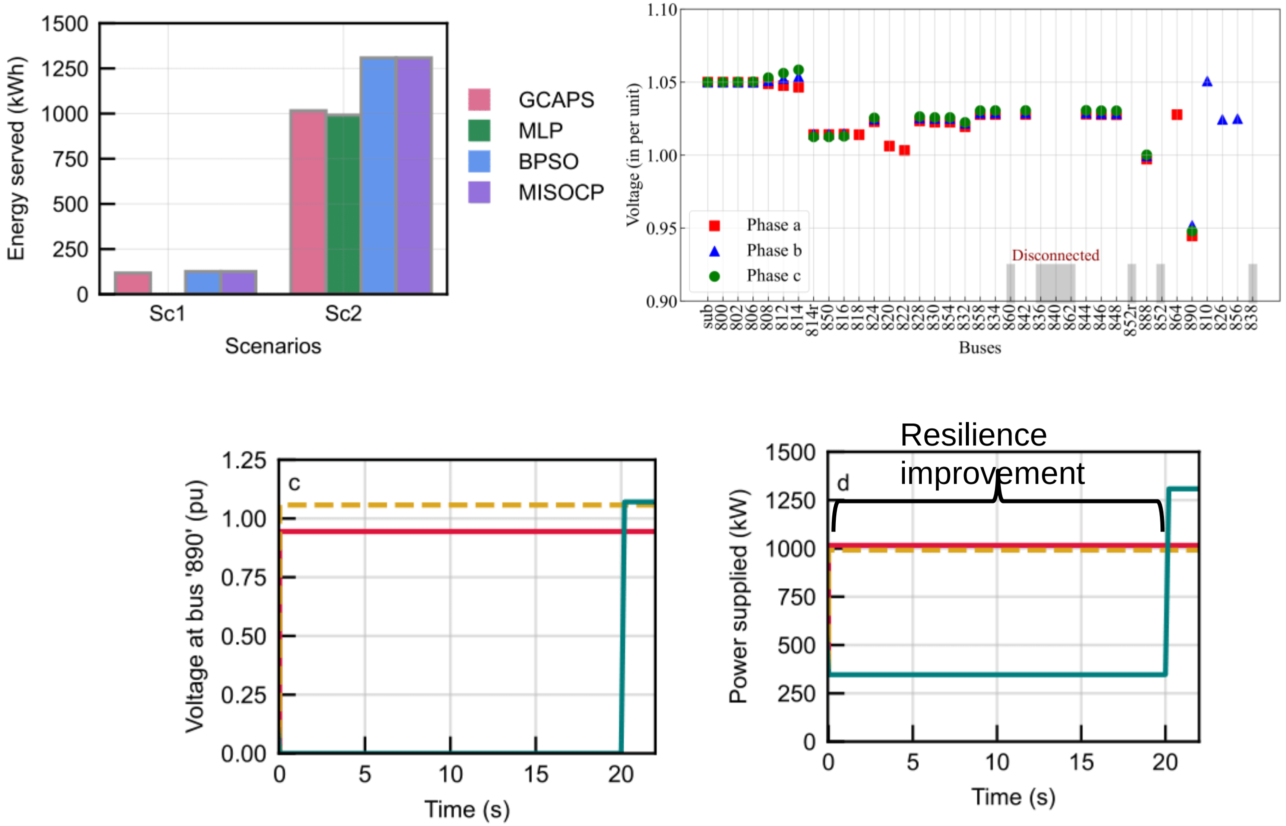


Results

IEEE 13-bus scenario 1



IEEE 34-bus scenario 2

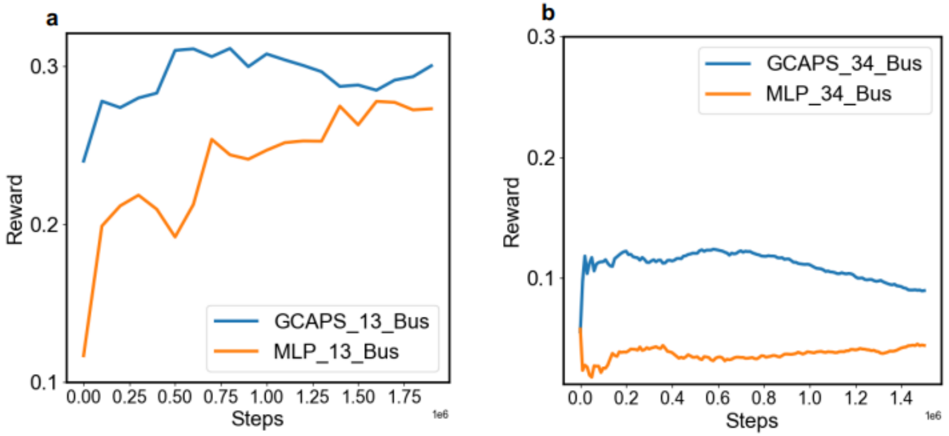


Results

Performance comparison of the proposed model with SOTA methods

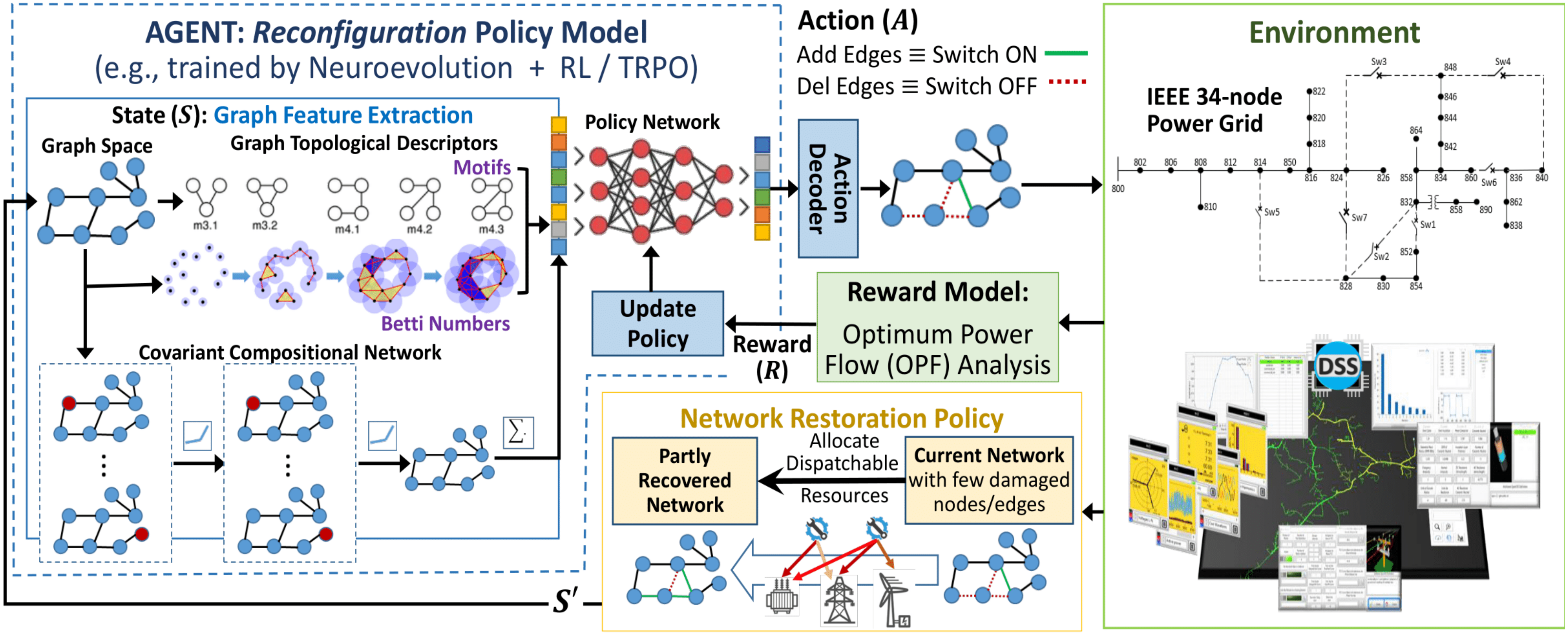
Network	Method	Scenario 1 Mean time (s)	Scenario 2 Mean time (s)
13-bus	GCAPS	0.0049	0.0056
	MLP	0.0039	0.0054
	BPSO	500.15	540.20
	MISOCP	3.12	5.23
34-bus	GCAPS	0.0030	0.0025
	MLP	0.0022	0.0020
	BPSO	2580.15	2540.20
	MISOCP	25.20	20.20

The training convergence plots for the policy models



- The response time for RL models is mostly agnostic to the network size.
- RL with MLP may result in invalid control actions.
- BPSO and MISOCP are about 5 and 3 orders of magnitude more expensive than the learned RL-based policies.

Adding TDA to the learning over graphs approach



Conclusion and Future Works

Conclusion

- The power distribution networks are inherent graphs, and the resilience-related tasks require considering the underlying topology of the DN.
- Integrating persistent homology into learning DNs allows us to extract the most characteristic topological descriptors of the distribution grid.
- The topological learning approaches used in power distribution networks exhibit resilience improvement and online decision-making capability.

Future direction

- ❑ Time-aware topological graph learning for DN/microgrid resilience improvement tasks.
- ❑ Multiparameter persistence-based learning for anomaly detection.
- ❑ TDA embedded graph learning approach for power DN restoration.

Thank You


multidisciplinary
design
optimization
linear
system
failure
solar
data
cost
engineering
deformation
statistical
battery
fidelity
optimum
surrogate
learning
energy
experiments
evaluation
reliability
methodology
decomposition
renewable
mathematical
stochastic
algorithm
bounds
illustration
exploration
minimization
approximation
objective
criteria
complex
equivalence
uncertainty
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recursive
structural