Physics-Informed Graph Neural Networks for Robust Fault Location in Power Grids

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Motivations: Why faults matter?

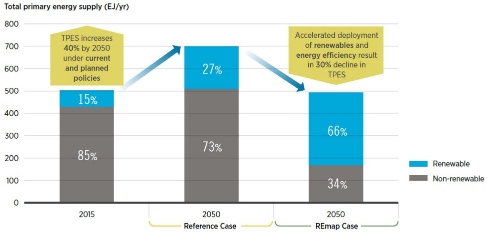

Fig.: Global Energy Transformation Prediction and Los Angeles wildfire

`https://www.irena.org`, `https://www.marketwatch.com/story`

- Renewable energy, such as solar and wind power, is growing to accelerate energy transformation, but these **random, intermittent** powers **increase faults in power grids**[1];
- Fast response to faulty conditions is crucial to prevent the further power **blackouts or wildfires**, which cost huge economic loss.
- We focus on **locating faults** in the efficient and robust way.

[1] Novosel et al. 2009; *Smart Grid System Report* 2018.

State of the Art & Problem Formulation

- State of the Art:
  - Device-based approaches:
    - e.g., Relays, circuit breakers, fault indicators[2].
    - **Fail to adapt** to the characteristics of renewable energy resources;
    - **Real-time and accurate** location is difficult.
  - Measurement-based approaches:
    - e.g., Impedance-based, Traveling-wave-based, Knowledge-based[3].
    - **Expensive requirements**: full network observability, exact system parameters, high data resolution, sufficient labels.
    - **Not robust to** : Load variations, topology changes.
- Problem Formulation:
  - Given datasets $V^p \in R^{n \times 6}, p = 1, \cdots, N$ of the three phase voltage **from a few measured nodes**, and partial labels $y^q \in \{1, \cdots, n\}, q = 1, \cdots, m, m \ll N$, denoting the faulted node;
  - **Goals:** Predict the **location of faulty node** in the disturbing environment.

[2] Brahma 2011; Džafić et al. 2016.

[3] Majidi, Etezadi-Amoli, and Fadali 2014; Chen et al. 2019; Dashti, Ghasemi, and Daisy 2018.

Our Main Contributions

- Propose a **two-stage** graph learning framework:
  - Stage I: $\mathcal{G}_{\mathrm{I}}$, a GNN with n nodes, learns the **graph embedding** or representation for the efficient prediction of fault location;
  - Stage II: $\mathcal{G}_{\mathrm{II}}$, a GNN with N nodes, improves the location accuracy employing **correlations of labeled and unlabeled** data samples.
- Define **adjustable adjacency matrices** to address the challenges of sparse observability and low label rates.

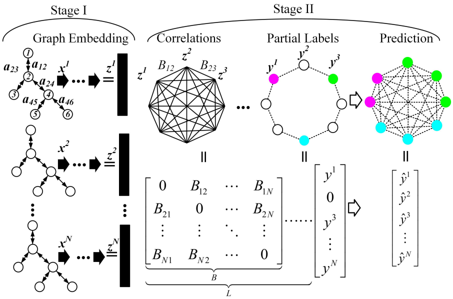

Fig.: The structure of our two-stage graph learning framework

Location Accuracy Rate (LAR) Comparison

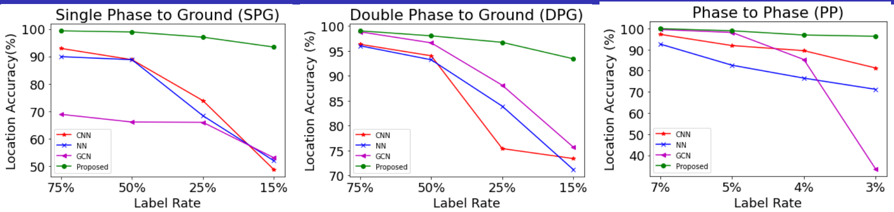

Fig.: LAR Comparison at different label rates[4]

- 24480 data samples are simulated by OpenDSS[5] in the IEEE 123-node benchmark system[6] with 16% of measured nodes(**21 measured nodes**);
- The proposed method **outperforms CNN, NN, and GCN** for various faults, including single phase to ground (SPG), double phase to ground (DPG), and phase to phase faults (PP).

[4] LAR = $\frac{\text{The number of correctly located faults}}{\text{The total number of faults}}$, Label rate = $\frac{\text{The number of training data}}{\text{The total number of data}}$

[5] Dugan and McDermott 2011.

[6] Jiang et al. 2021.

Robust to Load Variations and Topology Changes

Table: *LARs (%) When Loads Vary or Topology Changes*

	Changes	$\Delta p = 0.53$	$\Delta p = 0.64$	$\Delta p = 0.74$	Open 1-6	Open 1-3	Open 1&2
SPG	CNN	93.9	84	82	84.4	88.8	89.2
	NN	92.5	77.4	74	82.5	81.7	84.5
	GCN	64.3	56.4	55.1	58.3	59.6	62.2
	Proposed	**98.9**	**96.3**	**95.1**	**94.5**	**96.9**	**97.9**
DPG	Changes	$\Delta p = 0.53$	$\Delta p = 0.64$	$\Delta p = 0.74$	Open 1-6	Open 1-3	Open 1&2
	CNN	96.5	87.8	82.5	88.3	90.3	92.5
	NN	98	88.2	85.1	91.0	89.3	93.7
	GCN	98.3	83.7	78.8	66.9	85.6	89.4
	Proposed	**98.4**	**93.7**	**92.2**	**94.4**	**96.5**	**96.1**
PP	Changes	$\Delta p = 0.53$	$\Delta p = 0.64$	$\Delta p = 0.74$	Open 1-6	Open 1-3	Open 1&2
	CNN	97.5	96.1	94.6	95.0	96.9	96.8
	NN	95.6	90.3	85.9	94.1	94.1	95.2
	GCN	99.5	96.5	96.7	95.6	97.3	99.1
	Proposed	**99.9**	**99.4**	**98.4**	**99.0**	**99.9**	**99.8**

- Generate **another 110160 faults** when Δp, the averaged load variations, increases from 0.53 to 0.74 p.u. (Δp for training is 0.53) and topology changes due to various states of switches, e.g., “Open 1-6” denotes opening the switches 1 to 6;
- Compared with the baselines, our model (**without retraining**) shows **higher LAR** and less variations than the other baselines.

Conclusions and Future Works

- Propose the **physics-informed** graph neural networks for fault location in distribution systems;
- Overcome the challenges of sparse observation and low label rates by constructing particular **adjacency matrices**;
- Our method outperforms the baseline classifiers by significant margins, showing **robustness** to the out-of-distribution-data (ODD) due to load variations and topology changes.
- The **future work** is to study the **optimal deployment of sensors** at a low cost, and to **extend our graph learning framework** to other applications.

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Q & A

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The Long Version Paper: http://arxiv.org/abs/2107.02275