Physics Based GNNs for Locating Faults in Power Grids

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Abstract—The reducing cost of renewable energy resources, such as solar photovoltaics (PV) and wind farms, is accelerating global energy transformation to mitigate climate change. However, a high level of intermittent renewable energy causes power grids to have more stability issues. This accentuates the need for quick location of system failures and follow-up control actions. In recent events such as in California, line failures have resulted in large-scale wildfires leading to loss of life and property. In this article, we propose a two-stage graph learning framework to locate power grid faults in the challenging but practical regime characterized by (a) sparse observations, (b) low label rates, and (c) system variability. Our approach embeds the geometrical structure of power grids into the graph neural networks (GNN) in stage I for fast fault location, and then stage II further enhances the location accuracy by employing the physical similarity of the labeled and unlabeled data samples. We compare our approach with three baselines in the IEEE 123-node benchmark system and show that it outperforms the others by significant margins in various scenarios.

I. INTRODUCTION

Renewable energies, including wind and solar distributed energy resources (DERs), can help to meet the ever-increasing energy demand without further accelerating climate changes. However, these random and intermittent DERs cause power systems to have more dynamics due to reduced stability. As such, abnormal transmission line failures (faults), if undetected in the grid, may trigger disastrous blackouts and wildfires as observed in recent events across the Western USA. Quickly locating and isolating the faults can help mitigate the situation. Traditional data-driven methods for fault localization, such as impedance-based approaches and traveling-wave-based approaches can enable that but they either require a high ratio of measured nodes or high sampling rates, that are expensive for large-scale systems. Furthermore, variable ambient environments due to load variations and topology changes complicate the detection of such faults due to changing signatures.

In recent years, electric utilities have installed various sensors, such as micro-phaser measurement units (µPMUs), to improve the network visibility for sensing and detection. However, the available data is often poorly labeled, which prevents the straightforward use of data-driven methods. Even worse, black-box data-driven algorithms lacking clear physical interpretations and hence are vulnerable to evolving system states. In this paper, we propose to overcome these issues by employing the unique physics in power grids to inform data-driven algorithms and augment both their transparency and robustness.

Key contributions: We formulate a realistic fault location problem in a sparsely observed power network with a small number of datasets. Our strategy is to establish graph neural networks (GNNs) $G_1, G_2$ to represent power grids topology and the dynamic correlations in two stages respectively. We employ $G_1$ to efficiently locate faults in real time and $G_2$ to further improve the accuracy with the unlabeled data samples. The core novelty is the adjustable adjacency matrices $A$ and $B$ of our GNNs that improve the observability and the exact location accuracy. The proposed method is tested in the IEEE 123 node testing feeder simulated by OpenDSS. Compared with three typical baselines (fully connected neural networks (NN), convolutional neural networks (CNN), and graph neural networks (GCN), our method has superior performance in various situations.

II. RELATED WORK

The intuition of embedding physics into deep learning structures for power grids stems from the general physics-informed neural networks. Though we share some common structures with the popular graph configurations, i.e., GraphSage and GCN (Graph convolutional networks), we define our own distinctive neural network architecture using adjustable grid-aware adjacency matrices in two different GNNs to solve the sparse observation and low label rates challenges. Compared to black-box NN-based methods, this enhances the robustness of our method for insufficiently labeled and out-of-distribution (OOD) datasets.

III. PROBLEM FORMULATION

Consider a power grid with $n$ nodes in the set $V$ and $l$ branches in $E$, where voltages of $s$ nodes in the set $\Omega$ are measured. Given datasets $X^p \in \mathbb{R}^{n \times 6} = [V^a, \theta^a, V^b, \theta^b, V^c, \theta^c], p = 1, \ldots, N$ of the three phase voltage from the $s \ll n$ measured nodes. The target is to predict the location of unknown faults with the minimum number of labeled data samples. Practically, loads at multiple nodes fluctuate randomly and the power grid topology varies occasionally when faults occur.
IV. Our Approach

We treat fault location as a classification problem when given a few labels \(y^p \in \{1, \ldots, c\}, p = 1, \ldots, m, m \ll N\), denoting the locations of faulted nodes, and propose a two-stage graph learning framework to address the practical challenges: sparse observability and insufficient labeled data samples.

A. Stage I: Graph Embedding Learning

By analyzing voltage variations according to Kirchhoff’s circuit laws [6, 17], we find those nodes having significant variations after faults are geometrically near the faulty location. This inspires us to design a GNN \(G_1\) as the graph embedding of power grid topology to enhance robustness. However, as the measured nodes of power grids are sparse, directly learning from the available measurements causes some blind nodes. Instead, we construct an adjustable adjacency matrix for \(G_1\) to deal with sparse observability. Then our \(G_1\) can efficiently locate faults through two main components: aggregation and transformation.

Construction of \(A\): Our adjacency matrix defines the neighborhood of each node according to the power grid topology and observability. We first calculate the shortest distances of any two nodes and convert them into probability through Gaussian kernel [18]. Notice that we only take the top \(k_1\) nearest nodes as the neighborhood of each node, where \(k_1\) can be adjusted to ensure at least each node has one observed neighbor.

The \(k_1\) of our adjacency matrix \(A\) can flexibly control the size of each node’s neighborhood. A large \(k_1\) causes each node to be influenced by a wider region while a small \(k_1\) narrows down the size of neighborhood. When the observation is too sparse, we can increase \(k_1\) to ensure no nodes are out of the graph model’s horizon.

The aggregation component means that each node in the first \(K\) layers collects the values from its neighbors weighted by the corresponding entry in \(A\), and then concatenates with itself to formulate the hidden variable as the output of this layer.

The transformation component denotes that we convert the output of the aggregation component to the graph embedding \(z^p\) for the \(p\)th data sample as the prediction probability through fully connected layers. The output of the transformation component is compared with the labels \(y^p\) through the cross entropy loss function.

B. Stage II: Propagate the Labels

\(G_II\) takes advantages of the physical similarity of the labeled and unlabeled data samples to further improve the location accuracy. To do this, we construct the adjacency matrix \(B\) as follows:

Construction of \(B\): The critical technique is to cut off misleading correlations among data samples using \(z^p\). Precisely, we first zero out the entries of \(z^p\) that are corresponding to the nodes geometrically far beyond the predicted location, to obtain \(\bar{z}^p\), i.e., \(\bar{z}^p_k = 0\) if \(k \notin S_{ps}\), where \(S_{ps}\) is the immediate neighborhood of the node \(p_s = \arg \max_i z^p_i \in G_i\). Otherwise \(\bar{z}^p = z^p\). Second, we calculate the similarity \(s(p, q)\) of the embedding between any pair of data samples \(z^p, z^q\) through distance metrics, such as the subspace angle [19].

Similarly, we apply the cross entropy loss function on the output of \(G_{II}\) and the partial labels as well as the \(l_2\) norm regularization item.

V. Numerical Results

A. Data and Evaluation

Datasets are generated by the OpenDss software [12]. We simulate \(N = 24480\) data samples covering various fault types (including single phase to ground (SPG) faults, phase to phase (PP) faults, and Double-phase to ground (DPG) faults in three phases), locations, and load variations. Each data sample is a matrix \(X^p \in \mathbb{R}^{n \times 6}, n = 128\), where only the rows corresponding to the 21 measured nodes have nonzero values. We normalize each dataset \(X_i\) by subtracting the mean values \(\bar{X} = \frac{\sum p \in N \{X_p\}}{N}\) and scaling with the standard deviation of all datasets. We measure the location performance with three popular metrics: F1-score, location accuracy rate (LAR), and LAR\(_{1-hop}\) [20].

\[
\text{LAR}_{1-hop} = \frac{\text{The number of faults located within 1-hop}}{\text{Total number of data samples}}
\]

where “located within 1 hop” denotes that the predicted node is or connected with the true faulty node.

B. Performance of the proposed approach

We train a model using different label rates \(\beta\) (The ratio of labeled data number to the total number of data samples). The location performance in terms of the three metrics when \(\beta\) varies from 75\% to 15\%, where labeled data samples are randomly selected for each location to avoid the issue of data imbalance. We observe that the F1 Score and LAR of our model are stable and remain higher than 97\% even if only 15\% training datasets are employed. Crucially, the LAR\(_{1-hop}\) is close to 100\%, indicating that the predicted node is or at least connected to the true faulty node with a high probability, which is useful in realistic operations.

C. Comparing with Baselines

We compare our model with three baseline classifiers for different types of faults at various label rates and illustrate results in Fig. [1]. The propose method shows high location accuracy regardless of fault types. Other classifiers can also reach high accuracy if labels are sufficient, but their performances decline rapidly with decreasing the label rates.

VI. Conclusion

We incorporate the physics of power grids through a two-stage graph learning framework for efficient fault location, which shows superior performance than the state of art in accuracy and robustness to low observation, insufficiently labeled datasets, variations in operating environments. Our
method reaches an average location accuracy rate of 98.0% for various types of faults, even while using only 15% of data samples for training, and the predicted node has more than 99.9% accuracy to be the true faulty node or at least connected to it. Furthermore, we notice the influence of the deployment of measured nodes on the location accuracy rates and plan to study the optimal placement of sensors to minimize cost in the near future.

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