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A Transductive Graph Neural Network learning for Grid Resilience Analysis

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Abstract— **Power grids are critical infrastructures that require robust resilience analysis to ensure reliable and uninterrupted electricity supply. Traditional simulation-based methods for grid resilience analysis suffer from computational complexity and limited ability to capture the full spectrum of potential disruptions. This paper presents a novel approach to enhance grid resilience by leveraging transductive graph neural network (GNN) learning to identify critical nodes and links. By leveraging the graph structure and system features, GNNs effectively learn resilience metrics and accurately identify critical nodes based on actual grid operational behavior. The efficacy of the proposed approach is demonstrated through case studies on node criticality scoring and critical node/line identification in cascading outage scenarios. The results highlight the advantages of learning-based methods over traditional simulation-based approaches and their potential to revolutionize grid resilience analysis. The contributions of this paper include a graph-based scalable approach for fast cascading analysis, an inductive formulation for training GNN models, and a transfer learning-based approach to scale the model to large-scale power systems.**

Keywords: **grid resilience, graph neural networks, transductive learning, resilience metrics, cascading outage**

I. Introduction

Power grids are critical infrastructures that provide essential services to society. Ensuring the resilience of these grids is of paramount importance to maintain a reliable and uninterrupted electricity supply, particularly in the face of increasing threats and uncertainties. Traditional approaches to grid resilience analysis often rely on simulation-based methods that simulate system behavior under various conditions. While these methods have provided valuable insights, one major drawback of simulation-based resilience analysis is its computational complexity. Power grids are complex networks with thousands of nodes and intricate interdependencies, making exhaustive simulations time-consuming and resource-intensive. Moreover, simulations are typically based on specific scenarios and assumptions, limiting their ability to capture the full spectrum of potential disruptions and failures that a grid may experience. This restricts the effectiveness of traditional methods that heavily rely on pre-defined event scenarios and simulation parameters for identifying critical nodes whose failure can negatively impact grid operations

To address these limitations, there is a growing interest in leveraging machine learning techniques, particularly graph neural networks (GNNs), to enhance grid resilience analysis. Learning-based methods offer the advantage of capturing the inherent complex relationships and dynamics within power grids, without relying on explicit modeling assumptions. By utilizing historical data, GNNs can learn resilience metrics and identify critical nodes based on the grid's actual operational behavior, rather than predefined scenarios.

The introduction of transductive GNN learning for grid resilience analysis presents a promising solution. Transductive learning allows the algorithm to generalize well to unseen scenarios and adapt to dynamic changes in the grid's topology, enabling a proactive approach to grid resilience. By combining the expressive power of GNNs with the data-driven nature of the approach, the identification of critical nodes can be more accurate, efficient, and effective in enhancing grid resilience.

In this paper, we propose a novel algorithm that utilizes transductive GNN learning for improved grid resilience analysis. We present two case studies that demonstrate the efficacy of the approach: node criticality scoring for a power network and identification of critical lines in cascading outage studies. Identification of critical elements and links can be used for strategic hardening to improve the overall resilience of the power system. Through these case studies, we showcase the advantages of learning-based methods over traditional simulation-based approaches, highlighting their potential to revolutionize grid resilience analysis.

A. Literature Review

Existing literature has explored large-scale blackout problems using historical outage data which is limited to very few scenarios, and future failure scenarios might not be related to past events. Other researchers resort to simulation-based analytics which is computationally expensive and become infeasible for large transmission systems [1].

The various techniques developed to identify critical elements in the system can be broadly classified as

1) Topological Analysis: This approach involves studying the topology of power systems [2] to identify potential

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weaknesses or vulnerable points that could trigger cascading outages. It helps in finding potential cascading paths and predicts the extent and duration of cascading outages

2) Dynamic Simulation: Dynamic simulation models the power system's behavior under different operating conditions and contingencies. It models the cascading behavior through dynamic modeling of components of the power system [3], [4], taking into account the physical and electrical characteristics of the equipment. The simulation can be used to predict the system's response to various disturbances, including cascading outages and identification of critical points in the system that may trigger these cascades.

3) Statistical Analysis: Probabilistic analysis involves assessing the likelihood of cascading outages occurring in the power system. It analyzes historical outage data to identify patterns and correlations that could indicate the likelihood of cascading outages. This method can also be used to develop predictive models to estimate the probability and severity of cascading outages [5], [6], [7].

In contrast to earlier works, [8] addresses this issue using a data-driven method incorporating a security index to score the cascading outage. In addition, they use deep convolution and depth-first algorithms to reduce computational burden and find scenarios for cascading outages. Few works have proposed graph-based network approaches for risk and vulnerability assessment. In general, a combination of these techniques can be used to model cascading outages in power systems and identify strategies to prevent and mitigate them.

B. Research Gap and Contributions

The primary challenge of resilience analysis is the nonlinear and dynamic behavior due to multiple interconnected components and systems, and the failure of one component can lead to a cascading effect that can rapidly spread throughout the system. This behavior of the system can quickly become complex and unpredictable. Cascading failures are often triggered by events that are unpredictable, such as natural disasters or cyber-attacks. This makes it difficult to prepare for and respond to such events, as it can be difficult to accurately predict when and where they will occur. Furthermore, obtaining complete and accurate information about the system's state and topology can be challenging during emergencies, further complicating the response efforts. While various methods exist, such as contingency analysis and dynamic simulation, they have their limitations. Improving resilience often requires significant resource investments, such as increasing redundancy, improving system monitoring, or implementing new protection devices. Resource constraints can limit the ability of system operators and planners to implement measures to prevent and mitigate cascading failures. The detailed challenges and risk assessment methodologies is discussed in [9].

Addressing these challenges requires a collaborative effort between system operators, researchers, and policymakers to develop effective risk management strategies and improve the overall resilience of power systems. Advances in data analytics, machine learning, and real-time monitoring can also help in detecting and preventing cascading failures.

Though there is a large literature on Cascading on the graphs and modeling them using the graph topology [10], [11], they are not scalable which limits their application to large power systems. For graph-based models, several methods are available for the identification of critical nodes/links based on an iterative approach that explores each node/link of a graph at a time. The authors in [12] proposed a scalable graph-based model for identifying the critical nodes in the graph that can be used to train on a small or subset of the graph which can be further scalable to the large graph. For the post-outage recovery, whether the current outage leads to a further outage, a forward and backward Markov tree algorithm has been proposed in [13]. Another approach proposed in [14] is a Markovian influence graph for transmission line outage data using the transitions probability matrix for modeling the cascading line outage generation. In real word scenarios, all these graphs become large and it becomes infeasible to use traditional approaches. This motivates us to explore the graph neural network-based approaches to make the proposed algorithm scalable and more generalized.

Based on the identified gaps in literature, the paper has the following contributions,

1) We propose a resilience analysis framework to identify critical elements in a power system using a graph neural network approach. This graph-based method exploits the local neighborhood information of nodes and links for fast and scalable cascading analysis.
2) The formulation has an inductive nature which is utilized to train the GNN model on a portion of the power system and the trained model is applied to the rest of the system.
3) Finally, a transfer learning-based approach is proposed to scale the model trained on a smaller system to larger power systems utilizing the transductive nature of the proposed algorithm.

The paper is organized as follows. Section II provides an overview of the system model and problem formulation. Section III presents the proposed resilience analysis framework using graph neural networks and transductive learning. Section IV discusses the experimental setup and presents the results for various power system models. Section V concludes the paper and outlines future research directions.

II. System Model and Preliminaries

The proposed approach exploits the graphical representations of a power system and identifies critical elements based on desired properties and metrics. The graph representation along with the GNN-based learning approach is discussed in the following subsections:

A. Problem Formulation

We consider a graph $G = (V, E)$, where V is the set of nodes/vertices that represent buses in the system and E is the set of edges/links, representing transmission lines that connect neighboring buses. The features for each node can include standard power system information such as the bus type, Base voltage, zone, Voltage limits, etc. while the features for each edge can include information such as the line resistance and reactance, line ratings, tap, shift, and status. The graphical representation can be used to analyze the power transmission line outages in this system as a link classification task, where the goal is to predict whether a transmission line will fail under certain conditions. Critical points are components or elements within a system that are vulnerable to failure and have the potential to initiate cascading failures. Identification of these critical lines/links can guide hardening solutions to protect the system and prevent cascading failure scenarios.

Contingency analysis methods can be employed to identify critical components, which involve analyzing the system's behavior under disruptive events that cause failure of specific components while assuming all other components remain operational. Disruptions can occur due to various factors, including stress, hazards, external attacks, or sudden load increases. However, identifying critical nodes/links is a challenging combinatorial problem that is NP-complete, as discussed in [15].

In this paper, we present a transductive GNN-based learning approach to the critical nodes/links identification. Graph Neural Network (GNN) is a neural network architecture that leverages the properties as well as the structure of graphs. A high-level flow for the identification of critical components using GNNs for power systems is shown in Fig.1.

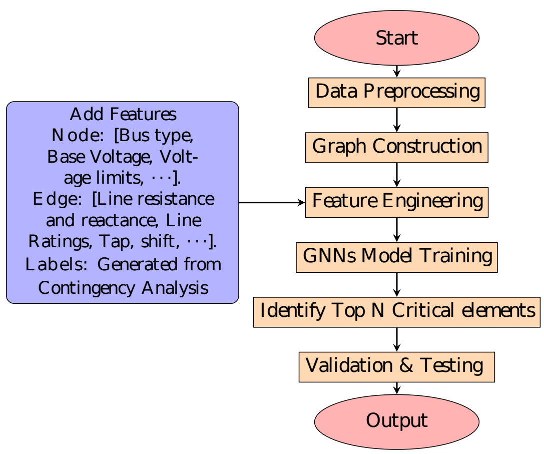

Fig. 1. Learning Based Resilience Analysis Flow Chart

Preliminaries on GNN and the proposed approach will be explained in detail in the subsequent sections.

B. Preliminaries of Graph Neural Networks

A GNN typically operates on graphs by creating a computation graph using the graph's structure information and incorporating node features. The basic computation graph for a 6-bus system is illustrated in Fig.2. Assume we have a graph $G = (V, A, X)$, where V is the vertex set, A is the adjacency matrix, and X is a matrix of node features, where node $v \in V$ and $N(v)$ represents the set of neighbors of v. A node embedding is a vector representation for each node in a graph to capture essential information about the node's features and its relationships with neighboring nodes in the graph. GNN involves the learning of a function f that maps the graph G to a space $\mathbb{R}^{m\times d}$, where m is the number of nodes and d represents the dimension of the node embedding. f updates the node representations iteratively by integrating information from neighboring nodes.

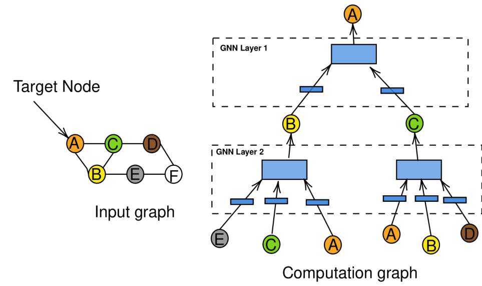

Fig. 2. Input and Computation graph

Graph Neural Networks (GNNs) perform two crucial tasks, namely message passing and neighbor aggregation, to process graph-structured data. The basic idea is that each node constructs a computation graph based on the information from its neighbors, with the node embedding generated at each layer. The input feature of a node is represented as the Layer-0 embedding, denoted by $h_v^{(0)} \in \mathbb{R}^d$, while the embedding in Layer-k incorporates information from nodes that are k hops away. For example, in Fig.2, $h_v^{(0)}$ would be the input feature for node A, $h_v^{(1)}$ would include features from the immediate neighbor nodes of A (nodes B and C), and $h_v^{(2)}$ includes features of neighbors of B and C. For this study, we limit the maximum hop distance to 2. The process can be mathematically formalized using the following equations.

Message Passing: Each node u receives messages from its neighbors and aggregates them to update its own state:

$$m_u^{(l)} = \mathrm{MSG}^{(l)}\left(W^{(l)}h_u^{(k-1)}\right) : u \in \mathcal{N}(v) \tag{1}$$

where, MSG is the message passing function and $W^{(l)}$ is the trainable parameter. Node Update: Each node v updates its own representation using its previous state and the aggregated messages from its neighbors:

$$h_v^{(l)} = \mathrm{CONCAT}\left(\mathrm{AGG}\left(\left\{m_u^{(l)} : u \in \mathcal{N}(v)\right\}\right), m_v^{(l)}\right) \tag{2}$$

where, $CONCAT$ and AGG are the concatenation and sggregation function respectively.

The message-passing mechanism involves propagating information between adjacent nodes in the graph using the adjacency matrix. This way, each node gradually incorporates more global information about the graph structure into its embedding by recursively aggregating information from neighboring nodes. The neighbor aggregation operation computes an aggregation function over the embeddings of a node's neighbors, producing a summary representation of its local neighborhood. Thus, each node can consider the collective properties of its immediate neighbors, in addition to its own input features, when computing its embedding. In summary, GNNs provide an effective framework for learning expressive

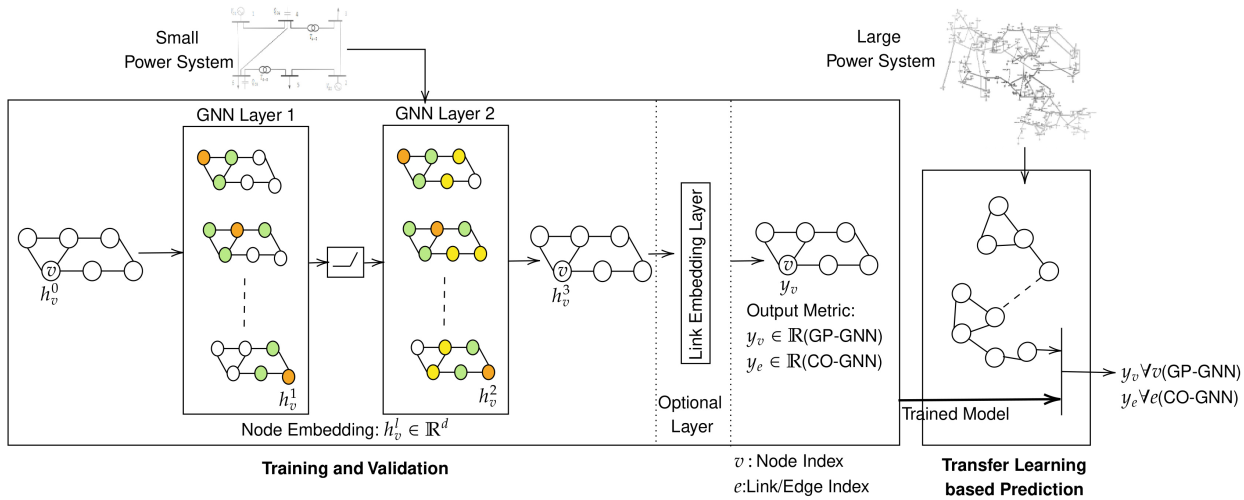

Fig. 3. Propose Approach for GP-GNN and CO-GNN

node embeddings for downstream tasks by leveraging both the local and global information encoded in the graph.

In this work we explore two variants of GNNs namely, the Graph Convolutional Network (GCN) and GraphSAGE. GCN extends the generalized GNN framework by incorporating multiple graph convolutional layers to capture local neighborhood information. By propagating information across the graph and aggregating neighboring node features, GCN learns to capture higher-order dependencies and gain a deeper understanding of the critical nodes in the power network. This enables us to accurately classify nodes based on their importance and impact on grid resilience. GraphSAGE, on the other hand, adopts a neighborhood sampling approach to enhance scalability and generalization. By sampling a subset of neighboring nodes for each node and aggregating their features, GraphSAGE reduces computational complexity while retaining the ability to capture essential information from the graph. This allows us to effectively model large-scale power systems and accurately predict critical nodes.

III. Proposed Approach

In this section we build two GNN models for power system resilience studies namely:

1) Generalized Power GNN (GP-GNN): To identify Critical nodes in the power network based on generalized criticality score.
2) Cascading Outage GNN (CO-GNN): To identify critical transmission lines that could initiate cascading outages.

The general approach is as shown in Fig.3. The training phase involves building a GNN model based on the input graph and output metrics. The input graph is defined by the graph structure G and feature vectors h_v^0. For each node, the multiple GNN layers are executed to generate a node embedding $h_v^l \forall v$ based on the message passing and aggregation described in Section.II.B. The final step is to train the model to convert the embeddings h_v^l into the desired metric $y_v/y_e \in \mathbb{R}$. This trained model is then used to predict the output metrics for unlabelled nodes and links and also for analysing larger systems.

A. *Generalized Power GNN: Identifying Critical Nodes*

In order to identify critical nodes in a power network based on a generalized criticality score, we propose the Generalized Power Graph Neural Network (Generalized Power GNN) approach. The objective of this approach is to classify nodes in the power system as critical or non-critical, considering the overall structure of the power system graph.

For the generalized power GNN, we use a graph robustness metric called effective graph resistance (R_g) as the output metric y_v. R_g is a metric that quantifies the resilience of a graph. It is calculated by summing the effective resistances between all pairs of nodes in the graph thus taking into account both the number of paths between nodes and their lengths. This metric provides an intuitive measure of the presence and quality of backup possibilities within the system and thus can be effectively used for resilience studies. A spectral form equation for R_g is given by (3),

$$R_g = \frac{2}{m-1} \sum_{i=1}^{m-c} \frac{1}{\lambda_i} \tag{3}$$

where, λ_i are eigenvalues of the Laplacian matrix of graph G with m nodes, and c is the number of connected components in the graph. This expression in (3) is normalized, enabling comparison of the metric across graphs of varying dimensions.

The problem is framed as a node classification task within a graph structure, where each node is a bus in the power network. The output of the approach is a criticality score $y_v \in \mathbb{R}$ based on R_g of the residual graph (Graph obtained by removing the node of interest). Higher the criticality score, larger is the impact of that node on the system.

B. *CO-GNN: Cascading Outage Graph Neural Network*

To address the classification of power transmission lines as critical or non-critical, we propose the Cascading Outage Graph Neural Network (CO-GNN) model. The lines that contribute to multiple outages and lead to blackouts are called as critical lines and are the vulnerable sets in the transmission system. For resilience studies, the time in which the cascade propagates is also important as fast cascades as more severe compared to slower propagating outages. So the Outage Indices developed in [16] are leveraged to quantify the cascading criticality. The advantage of the above indices is that they quantify the outage in terms of time in addition to number of outages. The outage indices are as defined below,

1) Load Shedding Index (r_{LS}): Ratio of Total Load Shed to time till blackout/Islanding.
2) Line Outage Index (r_{LO}): Ratio of number of line outages to time till blackout/Islanding.

Previous works determine these indices using extensive simulation based approaches, which is not computationally efficient and consumes a high amount of time for real large scale networks. In this work these indices are used as criticality scores and we propose the GNN approach to learn these indices in a fast, accurate and efficient way.

The objective of CO-GNN is to solve the link classification problem, which involves predicting the criticality of edges between nodes. Given a training set of labeled edges E, where each edge e connecting nodes (i, j) has a binary label $y_{i,j}$ (1= critical; 0= non-critical), the CO-GNN model learns to classify the edges based on the node feature vectors.

The update function in CO-GNN can be expressed as:

$$h^{(l+1)} = \sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}h^{(l)}W^{(l)}) \tag{4}$$

where $h^{(l)}$ represents the node feature matrix at layer l, $W^{(l)}$ is the weight matrix at layer l, $\tilde{A}$ is the adjacency matrix of the graph with added self-loops, and $\tilde{D}$ is the degree matrix of the graph with self-loops. The activation function σ introduces non-linearity to the model.

The LO-GCN model learns to predict the probability of an edge being critical based on the node feature vectors $\mathbf{h}_i$ and $\mathbf{h}_j$ by computing a score $z_{i,j}$ given by,

$$z_{i,j} = f(\mathbf{h}_i^T \mathbf{W} \mathbf{h}_j) \tag{5}$$

where f represents an activation function.

The probability of observing the binary label $y_{i,j}$ given the predicted score $z_{i,j}$ is determined by the sigmoid function:

$$p(y_{i,j} \mid z_{i,j}) = \sigma(z_{i,j})^{y_{i,j}}(1 - \sigma(z_{i,j}))^{1-y_{i,j}} \tag{6}$$

The CO-GNN model is trained using cross-entropy loss function, that measures dissimilarity between predicted scores and observed labels. The loss is calculated over the labeled edges in the training set E and minimized using gradient-based optimization methods, such as stochastic gradient descent.

C. *Transfer Learning for Scalable Resilience Analysis*

Transfer learning is a method that leverages knowledge learned from a smaller power system and applies it to a larger system, thus enhancing model performance and reducing data requirements. It has proved to be a promising tool for various smart grid applications [17], [18]. In the proposed work, we use transfer learning for pre-training a GNN model on a source power system and then fine-tuning it on a target power system with limited labeled data. By transferring learned representations from the source to the target system, GNNs can effectively capture structural and operational similarities between different power systems. This enables improved predictions of critical system states, fault detection, and other resilience-related tasks, even when data availability is limited in the target system. Transfer learning in GNNs for power systems holds great promise in addressing data scarcity issues, facilitating knowledge transfer, and enabling more accurate and efficient analysis of diverse power grid scenarios.

IV. Results

The proposed Generalized Power GNN and CO-GNN based algorithms are trained on a 39-bus New England test system and validated using larger real-life power systems like the 118-bus test network and US-Power grid network. Critical lines and outage metrics for the 39-bus test system and the 118-bus test system were obtained using extensive simulations using the dynamic cascading model [16]. Outputs were compared with existing simulation and analytical algorithms for accuracy and computation burden. The algorithms were implemented using Python programming on a personal computer equipped with a 2.93 GHz Intel processor and 4 GB RAM.

A. *Generalized Power GNN*

Table.I gives the accuracy and computation time for ranking the top 5% nodes using effective graph resistance metric, R_g. For the IEEE 39-bus test system, we trained the 39 node graph using both GCN and GraphSage architecture incorporating 70% node information for training + validation and predicted the remaining 30%. For the larger systems, we used the entire trained model of the IEEE Bus 39 system and used a transfer learning approach to train it with partial information of the larger system. We add 40% nodes and lines (Training + validation) from the 118 and US-Powergrid systems, and test it on the remaining 60% system.

TABLE I
Performance Analysis for Generalized Power GNN

Power System Model	Method	Accuracy (%)	Computation time (s)
39-Bus	Simulation	100	10
	GCN	92.3	2.688
	Graphsage	100	2.14
118-Bus	Simulation	100	25
	GCN	94.4	2.689
	GraphSage	94.4	2.179
US- Powergrid (4941 nodes)	Simulation	100	64212
	GCN	92.8	16
	GraphSage	96	10

B. *Cascading Outage GNN*

The CO-GNN is tested for 39-bus and 118-bus test cases. In the 39-bus test system, we trained the IEEE Bus 39 system using both GCN and GraphSage architecture incorporating 70% node information for training + validation and predicted the remaining 30%. For the 118 bus system, we used the entire trained model of the IEEE Bus 39 system and used a transfer learning approach to train it with partial information of the larger system. We add 40% nodes and lines (Training + validation) from the 118 systems, and test it on the remaining 60% system. Table.II gives the accuracy and computation time for different models.

TABLE II
PERFORMANCE ANALYSIS FOR CO-GNN

Power System Model	Method	Accuracy (%)	Computation time (s)
39-Bus	Simulation	100	60
	GCN	92.9	2.688
	Graphsage	100	2.14
118-Bus	Simulation	100	180
	GCN	100	2.358
	GraphSage	100	2.687

From Tables.I and II, its can be observed that accuracy of GNN-based prediction of top 5% critical nodes and lines is very high and is acceptable for power system resilience studies. The computation time for simulation-based analysis is very high while that for the proposed approach is very small thus indicative of its benefits in real-time analysis. Theoretically, the computation complexity of the proposed algorithm is independent of the size of the graph m, and depends only on size of the feature vector d. Thus, with respect to graph size, the overall time complexity of the proposed framework is $O(1)$. The time complexity of conventional simulation or analytical based approaches is dependent on the number of nodes/links in the graph. For instance, an exhaustive search to identify a critical link is of order $O(m^5)$. This improved time complexity makes the proposed method more efficient than any of the conventional approaches for reslience analysis and improvement.

V. CONCLUSION

In this paper, we propose a novel approach for enhancing grid resilience by identifying critical nodes and links using transductive GNN learning. The proposed algorithms, GP-GNN and CO-GNN, address the limitations of traditional simulation-based methods and provide a more efficient and accurate approach for grid resilience analysis. The algorithms were evaluated on IEEE 39-bus test system, the 118-bus test system, and the US-Power grid system. The results demonstrated the effectiveness of proposed algorithms in accurately identifying critical nodes and lines. The Generalized Power GNN achieved high accuracy in ranking the top 5% critical nodes, with performance comparable to simulation-based methods but significantly lower computation time. The CO-GNN algorithm also achieved high accuracy in predicting critical nodes and lines, outperforming simulation-based approaches in terms of computation time.

Overall, the proposed algorithms offer a data-driven framework that leverages the power system's graph structure and system data to identify critical elements and enhance grid resilience. The computational efficiency and accuracy of the algorithms make them suitable for real-time analysis and proactive planning of mitigation strategies. Future work can focus on further improving the scalability of the algorithms to even larger power systems and incorporating additional factors, such as dynamic operational data and uncertainty analysis, to enhance the resilience analysis. Furthermore, the application of the proposed algorithms can be extended to the distribution system using a heterofunctional graph analysis.

REFERENCES

[1] R. Baldick, B. Chowdhury, I. Dobson, Z. Dong, B. Gou, D. Hawkins, H. Huang, M. Joung, D. Kirschen, F. Li, J. Li, Z. Li, C.-C. Liu, L. Mili, S. Miller, R. Podmore, K. Schneider, K. Sun, D. Wang, Z. Wu, P. Zhang, W. Zhang, and X. Zhang, "Initial review of methods for cascading failure analysis in electric power transmission systems ieee pes cams task force on understanding, prediction, mitigation and restoration of cascading failures," in *2008 IEEE PES General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century*, pp. 1–8, 2008.

[2] J. Yan, Y. Tang, H. He, and Y. Sun, "Cascading failure analysis with dc power flow model and transient stability analysis," *IEEE Transactions on Power Systems*, vol. 30, no. 1, pp. 285–297, 2014.

[3] D. Bienstock, "Adaptive online control of cascading blackouts," in *2011 IEEE Power and Energy Society General Meeting*, pp. 1–8, IEEE, 2011.

[4] R. Fitzmaurice, E. Cotilla-Sanchez, and P. Hines, "Evaluating the impact of modeling assumptions for cascading failure simulation," in *2012 IEEE Power and Energy Society General Meeting*, pp. 1–8, IEEE, 2012.

[5] R. Yao and K. Sun, "Toward simulation and risk assessment of weather-related outages," *IEEE Transactions on Smart Grid*, vol. 10, no. 4, pp. 4391–4400, 2019.

[6] I. Dobson, "Estimating the propagation and extent of cascading line outages from utility data with a branching process," *IEEE Transactions on Power Systems*, vol. 27, pp. 2146–2155, 11 2012.

[7] K. Zhou, I. Dobson, Z. Wang, A. Roitershtein, and A. P. Ghosh, "A markovian influence graph formed from utility line outage data to mitigate large cascades," *IEEE transactions on power systems*, vol. 35, pp. 3224 – 3235, 2019.

[8] Y. Du, F. Li, T. Zheng, and J. Li, "Fast cascading outage screening based on deep convolutional neural network and depth-first search," *IEEE Transactions on Power Systems*, vol. 35, pp. 2704–2715, 2020.

[9] M. Vaiman, K. Bell, Y. Chen, B. Chowdhury, I. Dobson, P. Hines, M. Papic, S. Miller, and P. Zhang, "Risk assessment of cascading outages: Methodologies and challenges," *IEEE Transactions on Power Systems - IEEE TRANS POWER SYST*, vol. 27, pp. 631–641, 05 2012.

[10] M. E. J. Newman, "The structure and function of complex networks," *SIAM Review*, vol. 45, no. 2, pp. 167–256, 2003.

[11] S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, and D.-U. Hwang, "Complex networks: Structure and dynamics," *Physics Reports*, vol. 424, no. 4, pp. 175–308, 2006.

[12] S. Munikoti, L. Das, and B. Natarajan, "Scalable graph neural network-based framework for identifying critical nodes and links in complex networks," *Neurocomputing*, vol. 468, pp. 211–221, 2022.

[13] R. Yao and K. Sun, "Toward simulation and risk assessment of weather-related outages," *IEEE Transactions on Smart Grid*, vol. 10, no. 4, pp. 4391–4400, 2019.

[14] K. Zhou, I. Dobson, Z. Wang, A. Roitershtein, and A. P. Ghosh, "A markovian influence graph formed from utility line outage data to mitigate large cascades," *IEEE transactions on power systems*, vol. 35, pp. 3224 – 3235, 2019.

[15] A. Arulselvan, C. Commander, L. Elefteriadou, and P. Pardalos, "Detecting critical nodes in sparse graphs," *Computers & Operations Research*, vol. 36, pp. 2193–2200, 07 2009.

[16] Amulya, K. S. Swarup, and R. Ramanathan, "Risk assessment of cyber-attacks in multi area load frequency control," in *2020 21st National Power Systems Conference (NPSC)*, pp. 1–6, 2020.

[17] Y. Xia, Y. Xu, and N. Zhou, "A transferrable and noise-tolerant data-driven method for open-circuit fault diagnosis of multiple inverters in a microgrid," *IEEE Transactions on Industrial Electronics*, pp. 1–11, 2023.

[18] Y. Xia, Y. Xu, S. Mondal, and A. K. Gupta, "A transfer learning-based method for cyber-attack tolerance in distributed control of microgrids," *IEEE Transactions on Smart Grid*, pp. 1–1, 2023.