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Prediction of Cascading Failures and Simultaneous Learning of Functional Connectivity in Power System

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***Abstract*—The prediction of power system cascading failures is a challenging task, especially with increasing uncertainty and complexity in power system dynamics due to integration of renewable energy sources (RES). Given the spatio-temporal and combinatorial nature of the problem, physics based approaches for characterizing cascading failures are often limited by their scope and/or speed, thereby prompting the use of a spatio-temporal learning technique. This paper proposes prediction of cascading failures using a spatio-temporal Graph Convolution Network (GCN) based machine learning (ML) framework. Additionally, the model also learns an *importance* matrix to reveal power system interconnections (graph nodes/edges) which are crucial to the prediction. The elements of learnt importance matrix are further projected as power system functional connectivities. Using these connectivities, insights on vulnerable power system interconnections may be derived for enhanced situational awareness. The proposed method has been tested on a modified IEEE 10 machine 39 bus test system, with RES and action of protection devices.**

***Index Terms*—Graph theory, machine learning, phasor measurement units, power system failures, power system dynamics.**

I. Introduction

The rising integration of RES into the present day power system adds *uncertainty* (due to their intermittent nature) and *complexity* (due to power electronic interfaced devices with faster dynamic response and commensurately fast control) in its dynamic behaviour. Of particular concern for system operators and power system security is the possibility of cascading failures – *a quick succession of multiple component failures usually triggered by one or more disturbance events such as extreme weather, equipment failure, or operational errors*, and might also lead to a blackout [1]. Early detection and containment of such failures is critical to secure and reliable operation of power systems and minimize economic and social costs.

Conventional approaches for studying cascading failures in power systems are mostly physics based [2]. Previous studies in literature are mainly focused on modelling such failures using steady state approaches or simulating a dynamic model for a set of credible contingencies [2]. In [3], [4] different approaches are proposed using influence graphs to represent how these failures evolve in a specific network topology. In [5], statistical method based on *Random Chemistry* is used to sample most-likely set of failures. However, dynamic modelling of power system cascading failures has also gained interest, as these simulations can capture dynamic phenomena related to voltage, frequency and transient instability. In [6] [7] comparisons between static and dynamic time domain simulations are presented. The results in these studies highlight that the initial cascading events can be captured by both models, but dynamic phenomena occurring towards the later stage of cascading sequences cannot be represented adequately by static models. Dynamic probabilistic risk assessment of cascading failures has been reported in [8], [9]. The proposed method is applied to a realistic network model with protection devices and the uncertainty due to renewables is simulated by a probabilistic model. Recent literature also consists of few studies utilizing machine learning techniques for the assessment of voltage and transient stability of power systems [10], [11]. The use of machine learning/deep learning techniques for predicting cascading failures has shown to offer computational savings [12], [13]. However, learning based models for predicting cascading failures, trained using dynamic model of the power system components along with associated protection devices, has been scarcely represented in literature. Also, while black-box machine learning algorithms have shown promising results in power system stability/security assessment problems, they lack interpretability. As a result, explainable artificial intelligence, has become an emerging research direction, which addresses this problem and helps understanding why and how these models make predictions [14]. Thus, there are two key challenges to investigating the occurrence of cascading failures in power system. The size of the contingency set to be tested and the level of detail of the power system model used, which is often constrained by computational power. Secondly, such failures in power systems exhibit non-local propagation patterns which make the purely topological analysis of failures unrealistic [3].

Key Contributions: In the above context, the current work seeks to explore the efficacy of spatio-temporal GCN, to

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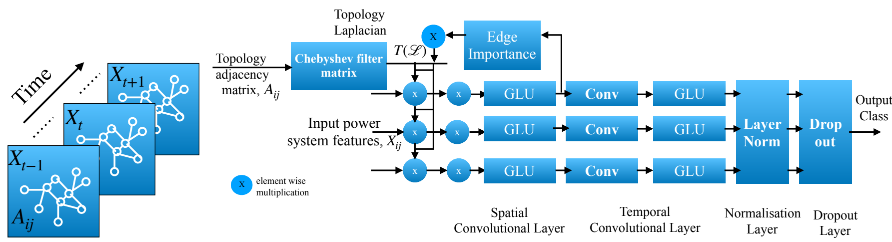


(a) Structure of input data

(b) Framework for GCN technique

Fig. 1: Spatio-temporal GCN framework for predicting cascading failure

detect the early onset of such failures. In addition to the temporal evolution of failures, the proposed framework also takes into account the spatial connectivity of the network for the prediction task. A salient feature of the proposed framework is that the a spatial attention based *importance* mask is also learnt as an additional trainable parameter. In addition to improving model performance, the learnt importance matrix allows us to identify the importance of power system interconnections significantly contributing to the prediction of cascading failures. The trained importance matrix thus represents an improved graph connectivity obtained in a data-driven manner and thus could be helpful in the absence of accurate knowledge of power system topological parameters. Such a connectivity could offer interpretable insights that can support informed decisions for the system operators. It has also been found that GCNs require fewer parameters than time-series based learning methods [15], thus prompting the usage of the current framework for real-time operations. Simulation studies are conducted using data generated from dynamic simulation of cascading failures, along with the action of protection devices, on a modified IEEE 39 bus 10 machine test system.

The remainder of paper is structured as follows: Section II introduces the methodology of the proposed ML framework, Section III discusses the case studies and results, while Section IV enumerates the key conclusions of the current work.

II. Methodology

This paper explores the use of spatio-temporal GCN based machine learning framework (as shown in Fig. 1) to predict the occurrence of cascading failures, using binary classification. The proposed work also attempts to interpret the predictions of the ML model as opposed to black box machine learning models, using a spatial attention based *importance* mask, which is further projected as *dynamic functional connectivity* of the power system. Intuitively, the spatio-temporal GCN model trained along with the importance matrix is expected to perform better than its vanilla counterpart.

A. Background of Graph Signal Processing and Machine Learning Framework

Let the power system network be represented by an undirected weighted graph, $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where $\mathcal{V}$ $(card[|\mathcal{V}|] = n)$ is the set of vertices represented by buses and $\mathcal{E}$ $(card[|\mathcal{E}|] = l)$ is the set of edges, represented by transmission lines and transformers. Let $n \in (n_g, n_l)$ be the number of buses equipped with generator and load respectively. The spatial connectivity between different power system buses (nodes) is represented by the weighted adjacency matrix, $\tilde{A}$ [16]. In line with previous works related to graph based power system stability assessment, we utilize the bus admittance matrix, $Y_{bus}^{n\times n}$ as the weighted normalised adjacency matrix [17], [18]. For the weighted adjacency matrix $\tilde{A}$, the symmetrically normalised graph Laplacian matrix can be defined as

$$\mathcal{L} = D^{-1/2}\tilde{A}D^{1/2} \tag{1}$$

where D is the degree matrix of the graph (diagonal matrix with nodal degree on the diagonal).

Spatial Convolution: : The normalized Laplacian matrix is a symmetric semi-definite matrix, which can be decomposed as a product of Fourier basis $V = [v_1, v_2, ...v_n]$ and diagonal matrix of eigenvalues, $\Delta = [\lambda_1, \lambda_2....\lambda_n]$ as

$$\mathcal{L} = V\Delta V^T \tag{2}$$

The *Convolution Theorem* defines convolution as linear operators that diagonalize in the Fourier basis (represented by the eigenvectors of the Laplacian operator). In order to calculate the Graph Fourier Transform of a signal on non-Euclidean spaces like irregular graphs (e.g., the power system network), efficient spectral filter based discretization proposed in [16] is utilized. The graph convolution of the input signal x_{in} (which represents the set of power system input features), with spectral filter G_g is defined as

$$x_{in} * G_g = V(V^T x_{in} \odot V^T G_g) \tag{3}$$

where $\odot$ denotes the Hadamard product. The current framework also shares similarities with [15] for implementation of a spatio-temporal module.

Temporal Convolution: : After the extraction of spatial features, one dimensional convolution is adopted to incorporate temporal information. Gated Linear Unit (GLU) based activation function is utilized to model the time-varying non-linear characteristics. Then, a *Normalization* layer and a *Dropout* layer is added to prevent over-fitting. The output of the last spatio-temporal GCN layer is fed to a *global average pooling* and its output vector is transformed to class probabilities by a fully connected layer *Softmax* layer. Output 1 represents that a cascading failure is about to happen and 0 represents *no cascade*. The structure of input data and the proposed spatio-temporal GCN pipeline is represented in Fig. 1(a) and 1(b) respectively.

B. Importance Matrix and Power System Functional Connectivity

The spatio-temporal GCN output features, x_{out} are calculated as,

$$x_{out} = G_g^{-\frac{1}{2}} \left(\tilde{A}\right) G_g^{-\frac{1}{2}} x_{in} W \tag{4}$$

where W is the weights matrix and G_g is the kernel obtained from graph convolution in spatial domain as discussed in Section II-A. To determine the importance of spatial graph edges in defining class probabilities, a spatial attention mask in the form of *importance* matrix, $M^{n\times n}$ may be integrated into the model. This matrix is shared across all spatio-temporal GCN layers by replacing $\tilde{A}$ in (4) with $\tilde{A} \times M$ (element-wise multiplication). As such, while performing spatial graph convolution on a node, the contribution from its neighbouring nodes, will be re-scaled according to the importance weights learnt in the i^{th} row of M. Thus, the diagonal entries of M (self-connectivity) quantify importance for each node, while off-diagonal entries do so for each edge.

Conceptual proof for importance matrix, M as scaled dynamic functional connectivity of power system: The generator and network dynamics of power system are given by

$$\begin{aligned} \dot{x} &= f(x, u) \\ 0 &= g(x, u) \end{aligned} \tag{5}$$

where, x are the states of the power system and u is the external input. The algebraic equations, $g(.)$ indicating active/reactive power injections, P_i/Q_i at bus i are given by

$$\begin{aligned} P_i &= V_i \sum_{k=1}^{n} V_k \left(G_{ik} \cos\left(\theta_{ik}\right) + B_{ik} \sin\left(\theta_{ik}\right)\right) \\ Q_i &= V_i \sum_{k=1}^{n} V_k \left(G_{ik} \sin\left(\theta_{ik}\right) - B_{ik} \cos\left(\theta_{ik}\right)\right) \end{aligned} \tag{6}$$

where, G_{ik} and B_{ik} are the real and imaginary parts of Y_{bus} respectively, for a power system consisting of n buses. For high voltage transmission lines, the line conductances, G_{ik} are usually neglected, thus Y_{bus} is assumed to consist of only bus susceptances, B_{ik}. For the power system graph as described in Section II-A, the weighted graph Laplacian is given as [19],

$$\mathbf{L}_{ij} = \begin{cases} -w_{i,j}, & \text{for } i \neq j \& \ i \ j \in \mathcal{E} \\ \\ \sum\limits_{k=1}^{n} w_{ij}, & \text{for } i = j \ \& k \neq i \end{cases} \tag{7}$$

where w_{ij} represents the connectivity between the elements of the graph, usually given by B_{ik}. For assessing vulnerability to cascading failures the underlying electrical network encoded in B_{ik} may not be sufficient and an auxiliary re-weighted network with the same topology as the physical network, but with new edge weights encoding generator voltage levels, the topology and strength of connections between loads and generators may be useful. We thus refer to [20] for creation of a re-weighted power system graph Laplacian with *dimensionless voltage magnitude deviations to reactive power demand* as the new edge weights and assumed to represent the dynamic functional connection between nodes.

Concurrently, the proposed spatio-temporal GCN framework achieves prediction of class probabilities (using normalised V_{mag} based features) through key signal processing operations on the graph Laplacian like spectral filtering, graph coarsening and pooling [16]. *Additionally, there is simultaneous learning of importance matrix based spatial attention mask. This importance matrix (see (4)) can thus be projected as a scaled version of the dynamic functional connectivity of the power system learnt using V_{mag} features (thus creating a re-weighted power system graph as explained above).* Graph signal processing based theoretical underpinnings of spatio-temporal GCN with importance are the basis for this analogy.

III. Case Studies & Results

A. Description of Dataset

In order to predict cascading failure events in a comprehensive manner there is a need for detailed modelling of power system dynamics. It is also imperative to consider dynamics in both fast as well as slow time scales, the operation of protection devices, initial operating conditions governed by dispatch of generators, appropriate representation of system load and renewable generation. In this work, a dynamic root mean square (RMS) model of a modified IEEE 39 bus 10 machine New England system with high penetration of wind and protection devices is used to generate power system features. The power system features assumed to be measurable in field by Phasor Measurement Units (PMU) are suitably pre-processed and resampled to the PMU sampling rate of 10 milli-sec [21]. Automatic voltage regulators, over-excitation limiters, power system stabilizers, detailed controllers for wind generators, tap changer actions and governors are also modeled to capture voltage related phenomena and primary frequency response actions. In addition to this, a basic load shedding scheme to arrest significant frequency drops after loss of generation is modelled. The details related to modelling of dynamic components and their protection devices is present in [22].

Simulations are performed for different operating conditions which include changes in load (in the range of 0.7 - 1.2 p.u. in steps of 0.1) and wind power (in the range of 0-1 p.u. in steps of 0.2). After taking into account these initial operating conditions and dispatch of conventional generators, three phase faults on transmission lines are introduced into the system as initiating events at 1.0 second and removed at 1.07 seconds. The faults get cleared by the protection devices included in the model, and in some cases lead to cascading events involving multiple failures. The cascading events are caused by tripping of components, due to intentional interventions of the protection devices after the relevant limits are violated

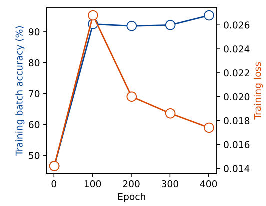
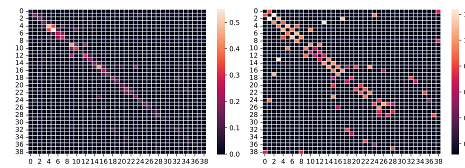


Fig. 2: Training performance for the $st{-}GCN{+}Imp$ classifier averaged over validation folds



(a) (b)

Fig. 3: Comparison of sparsity structure (a) bus admittance matrix, Y_{bus} (b) trained importance matrix, M

(e.g. under-/over- voltage or frequency). Time series data of power system bus voltages until $t = 2$ minutes for each simulation case are recorded. However, post-fault data up to a time window, $T_w = 0.1$ sec $= 10$ time-steps is utilized for the spatio-temporal GCN prediction. This optimal window has been pre-determined, by studying the time of occurrence of first cascading events. This is done to investigate the performance of the current technique in detecting cascading failures before their onset. We consider here that a cascading event has happened if any protection devices are activated, following the initial fault and disconnection of faulted line. *It should be noted that the focus of this study is to capture the evolution of the cascading events related to the detailed dynamic response of the system and their protection devices, following an initial disturbance.*

B. Results for spatio-temporal GCN based prediction

For the modified IEEE 10 machine 39 bus New England power system, voltage magnitude, V_{mag} (in p.u.) at all the buses, are utilized in this study. Initiating faults on all 34 lines and incremental loads and wind power leads to 44064 independent scenarios. It is found that cascading failures occur in 5500 scenarios (unsafe cases). Thus, a balanced dataset consisting of an equal number of safe-unsafe cases is created for the ML model. The input weighted adjacency matrix, $\tilde{A}$ for $n = 39$ nodes is constructed using the power system bus admittance matrix, Y_{bus} matrix (neglecting line resistances). The input dataset (as shown in Fig. 1(a)) is a tensor of order $(X \times n \times T_w) = (11000 \times 39 \times 10)$, where V_{mag} recorded at all 39 buses for 11000 cases and for 10 time-steps is used.The output is a vector of size $(Y) = (11000 \times 1)$. Stratified K-fold cross validation for $k = 5$ splits is used for different training and testing data splits. With the prepared database and filter parameters as present in Table I, the spatio-temporal GCN model with importance is trained for the binary classification problem. Standard libraries in Pytorch are used to implement the proposed spatio-temporal GCN pipeline.

The training performance (the highest training accuracy = 95.31%) is shown in Fig. 2. Our preliminary findings reported in Table II, show that the model achieves an accuracy of $96.83 \pm 4.61\%$ at the 95% confidence level, assuming independent trials. The F1 score (weighted harmonic average of precision and recall) is used as an additional model performance metric. The *Recall* score is also important for the power system cascading failures problem because the implications of a false negative could result in cascading failures going undetected and possibly manifesting into a blackout. The *Recall* score for the model is 96.36% which signifies that the technique correctly predicts the occurrence of cascade most of the times. In Table II, we also test the improvement in performance of the model from the case when *no importance matrix* is included while training the model which is referred to as the *vanilla st-GCN*. It is clear that the $st - GCN + Imp$ based training performs better in terms of all the performance metrics.

TABLE I: Model Parameters

Hyperparameter	Description
Initial learning rate	0.001
Weight decay	0.001
Batch size	64
Dropout probability	0.5
Kernel size of spatio-temporal filter	(39,11)
Window Size	0.1 sec

TABLE II: Classification Performance

Classifier	**Performance (seed = 17)**			
	Accuracy	***Precision***	***Recall***	***F1 score***
vanilla st-GCN	92.56 ± 2.94 %	84%	93.22%	88.36%
st-GCN+Imp	96.83 ± 4.61 %	96.45%	96.36%	96.41%

C. Model Interpretability in Terms of Functional Connectivity

In addition to post-hoc interpretability methods, model based interpretability may be used to explain the predictions of black-box NNs. In this work, we aim to interpret the predictions of the graph NN, by learning the dynamic functional connections significantly contributing to the prediction of a cascade. As mentioned earlier, the current work introduces, *importance* matrix, M as an additional trainable parameter inside the spatio-temporal GCN to reveal the influence of a set of nodes and edges in model prediction. For the current 39 bus test system, the sparsity structure of M and Y_{bus}, in the form of heatmaps is shown in the Fig. 3. In context of the power systems, the diagonal elements of the importance matrix depict the relative importance of various power system buses (graph nodes) , while the off diagonal elements depict the importance of power system lines (graph edges) in the prediction of cascades. It is anticipated that the matrix M offers insights into the connectivity structure of a power system graph, as

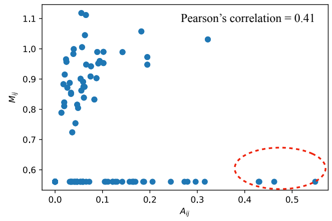


Fig. 4: Comparison between elements of $A_{ij} \in Y_{bus}$ and $M_{ij} \in M$

Y_{bus} weighted adjacency matrix, as discussed in Section II-B. However, it is also important to note that the functional connectivity given by M also take into account the spatio-temporal dynamics of power system trajectories and is learnt within the spatio-temporal GCN for a given time window. From the sparsity patterns of matrices Y_{bus} and M (as shown in Fig. 3) , it can be inferred that lighter the colour gradient, closer are the buses/lines in their admittance based electrical connectivity and functional connectivity respectively.

It should be noted that benchmarking the accuracy of learnt functional connectivity makes little sense as the its true value is unknown and dynamic. Thus, correlation between the functional and electrical connectivity is observed to establish the validity of the current framework. The correlation between elements of Y_{bus} and M is shown in Fig. 4. The scatter plot in Fig. 4 shows that elements of Y_{bus} and M are positively correlated (Pearson correlation = 0.41). However there are few cases when, tightly coupled nodes in electrical structure (larger value in Y_{bus}) are loosely coupled in flow (lower value of M) as shown by encircled region in Fig. 4. This counter-intuitive observation demonstrates that any two close nodes in structure may have very little or weak impact on function. This is also verified in literature, through non-local propagation of cascades [3], [23].

IV. Conclusion

This work illustrates the potential of an interpretable, spatio-temporal graph learning framework to predict the occurrence of cascading failures in a hybrid power system (i.e including power system dynamics and discrete actions of protection devices). The spatio-temporal GCN model achieves improved performance when trained along with *importance* matrix based spatial attention. The *importance* matrix indicates the importance of various buses and transmission lines in the prediction of failures and is projected to represent the dynamic functional connectivity of the power system network. Future works include mining the spectral properties of the importance based functional connectivity to reinforce informed control actions. The authors also seek to explore the possibility of importance matrix as an *improved* data-driven adjacency matrix to enhance the performance of graph based learning methods in the absence of accurate knowledge of power system topology.

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