Predicting Cascading Failures in Power Systems using Graph Convolutional Networks

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Abstract

Worldwide targets are set for the increase of renewable power generation in electricity networks on the way to combat climate change. Consequently, a secure power system that can handle the complexities resulted from the increased renewable power integration is crucial. One particular complexity is the possibility of cascading failures — a quick succession of multiple component failures that takes down the system and might also lead to a blackout. Viewing the prediction of cascading failures as a binary classification task, we explore the efficacy of Graph Convolution Networks (GCNs), to detect the early onset of a cascading failure. We perform experiments based on simulated data from a benchmark IEEE test system. Our preliminary findings show that GCNs achieve higher accuracy scores than other baselines which bodes well for detecting cascading failures. It also motivates a more comprehensive study of graph-based deep learning techniques for the current problem.

1 Introduction

One of the greatest challenges of today's world is tackling the problem of climate change and mitigate its effects on the ecosystem and mankind. The Paris Agreement on climate change as a part of COP26 to be held in Glasgow during November 2021 has set a target to minimize global warming to 1.5^oC [1]. However, in order to meet this ambitious target, the emission of greenhouse gases like CO_2 need to be drastically cut down. These gases are emitted to a large extent in serving the energy demands of modern society (around 25% greenhouse gas emissions are estimated to come from electricity and heating [2]). Therefore, in order to cut down emissions of greenhouse gases, it is a global trend to integrate more renewable sources (wind, solar, etc.) for electric power generation. According to the National Grid, a major Electricity Systems Operator (ESO) in UK, the average carbon intensity in 2020 fell to 181g of CO_2 per kilowatt hour, a reduction of 66% over the last seven years [3]. Along similar lines, achievement of portfolio standards for renewable energy is one of the major thrust areas of the COP26 in reducing the impact of climate change [1]. However, integration of renewable energy sources (RES) into the power system can add *uncertainty* (due to their intermittent nature) and *complexity* (due to their power-electronics converters) to its dynamic behaviour. For instance, of particular concern for power system operators is the possibility of *cascading failures*. Therefore, accurate detection of those cascading failures in on their early stage is critical to maintaining the reliability and security of electric supply.

In [4], the definition of cascading failure and its mitigating strategies are systematically introduced and summarized. Previous studies are mainly focused either on mitigation of cascading failures in the planning time frame (steady-state)[5, 6] or simulating a simplified model of cascading failures [7]. In [8], an influence graph based techniques is proposed to model the evolution of cascading

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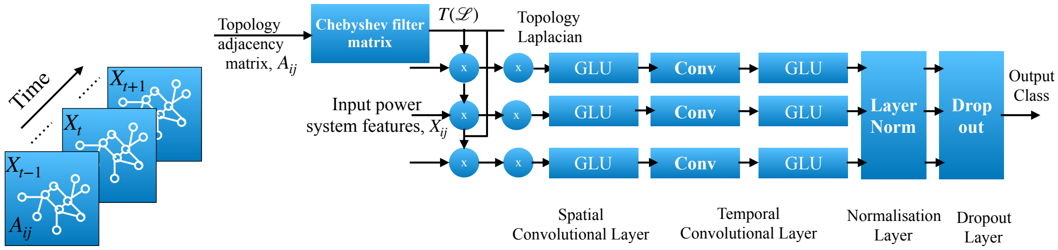

(a) Structure of input data

(b) Framework for GCN techqniue

Figure 1: GCN for predicting cascading failures in power system

failures. Physics based methods for analysis of power system cascading failures[7] are expected to be computationally intensive due to the nature and scale of power systems (nonlinear dynamical systems represented by thousands of differential algebraic equations). This motivates the use of online measurements and machine learning techniques to predict cascading failures in a real-time manner. While near real-time security and stability assessment through machine learning has been studied in [9] and reinforcement based topology controllers in [10], prediction of cascading failures has not been well represented in literature.

Motivated by the spatio-temporal aspects of cascading failures, in this work we seek to explore the efficacy of a Graph Convolutional Networks (GCNs) for predicting the occurrence of cascading failures in power system and comparison of performance with other baseline ML techniques. To authors' best knowledge, this paper is among few earliest studies that adopt GCN for cascading failure problems. An accurate prediction of cascading failures is expected to enhance the security and resiliency of power systems, thereby supporting higher penetration of RES and thus forming pathways to a positive climate impact.

2 Methods

Power system cascading failures and eventual blackouts are rare events and thus, field data related to such events is scarce and also not easily available from power utility companies due to confidentiality. Therefore, data is generated by simulating a hybrid dynamic model (including synchronous machines, RES, and associated protection devices) of a benchmark IEEE test system, 10 machine 39 bus (i.e. node) New England Test system[11]. It should be noted that including system dynamics as well as the actions of protection devices is important, since it more accurately captures the complexity of the real power system, when compared to approaches that use simulations in steady-state time frame. Then, a database of power system features (assumed to be captured by measurement devices like Phasor Measurement Units (PMU)[12]) located at every node, and the initial faults on different locations of the power network is formed. This database, the tensor-like data X_t along with the topology information, the adjacent matrix A are used as the inputs to the GCN model. A Gaussian kernel learning using the K nearest neighbors[13] is used for construction of A_{ij}. In this work, the prediction of cascading failures in power system is posed as a binary classification problem. The model output, y is a label depicting the cascading status,(whereby 0 signifies *no cascading failure* will happen and 1 signifies a *cascading failure* will happen. Detailed model architecture and parameters are described in Appendix.

2.1 Brief Mathematical Framework

To be self-contained, we first present a brief introduction to spectral graph theory. Let the power system network be represented by an undirected weighted graph, $G = (V, E, W)$ where V is the set of vertices and $|V| = n$, E is the set of edges and $A \epsilon R^{nxn}$ is the weighted adjacency matrix[14]. The unnormalized graph Laplacian of G is defined as, $\mathcal{L} = D - A$ where, D is the degree matrix of the graph with diagonal entries $D_{ii} = \Sigma_j W_{ij}$. Then the normalized graph Laplacian is given as

$$\mathcal{L} = I_n - D^{-1/2} AD \tag{1}$$

where I_n is the identity matrix. The normalized Laplacian matrix is a real symmetric semi-definite matrix, which can be decomposed as a product of Fourier basis $V = [v_0, v_1, ...v_n]$ and diagonal

Table 1: Performance Metrics in Testing Stage (%) and seed = 17

Classifier	Accuracy	F1	Precision	Recall
Logistic Regression	78.9	78.8	78.9	78.8
SVM	81.0	80.6	83.1	80.9
ANN	85.0	84.9	84.9	84.9
GCN	**92.1**	**92.2**	**91.4**	**93.2**

matrix of eigenvalues, $\Delta = [\lambda_1, \lambda_2 ....\lambda_n] \epsilon R^{nxn}$ as

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

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 is proposed in [14]. The graph convolution of the input signal x with filter g is defined as

$$x * G_g = V(V^T x \odot V^T g) \tag{3}$$

where $\odot$ denotes the Hadamard product. The convolution theorem [15] defines convolutions as linear operators that diagonalize in the Fourier basis (represented by the eigenvectors of the Laplacian operator). Polynomial filters like the Chebyshev filter are used to realise a fast spectral graph convolution. The current framework and structure of data-set is depicted in the schematic diagram shown in Figure 1.

3 Results

Time series data of power system features at all spatial locations until 10 samples post fault are utilized for the current model. This is done to investigate the performance of the technique in detecting cascading failures before their onset. For the benchmark power system, 178 features (i.e.,bus voltages, line currents, bus electrical frequency, line active power injection, line reactive power injection) are utilized in this study. A data-set with post fault time-series (Appendix) from 14000 independent simulations are obtained with different fault locations, loading levels and RES (wind-power) penetration levels. Training, validation and testing database were created using a 70%, 10% and 20% split. With the prepared database, GCN along with baseline ML models, namely, Logistic Regresssion, Support Vector Machine (SVM) and Artificial Neural Network (ANN) are trained. The training performance (the highest validation accuracy = 89.06%) and hyperparameters for the GCN classifier are present in Appendix. The performance metrics for all models are depicted in Table 1. Our preliminary findings show that GCNs achieve an average accuracy of 92.2% over multi-seed runs. Since our data-set is highly imbalanced we use weighted precision, recall and F1 score (weighted harmonic average of precision and recall) as model performance metrics. The *Recall* score (*Recall* for GCN is 93.2%) is particularly important for the cascading failures problem because the implications of a false negative could result in cascading failures going undetected and possibly manifesting into a blackout. From Table 1, it is also inferred that for a mid or large-scale system as ours, the performance of simple ML methods is not as good. The superior performance of GCN as compared to other baselines reflects that the detection of cascading failures indeed benefits from adding the spatial information.

4 Conclusion and Future Scope

This work is intended to be an initial study to illustrate the potential of spatial machine learning algorithms like GCNs to predict the occurrence of power system cascading failures. Our research shows promising results and will motivate a more extensive study of machine/deep learning methods for the current problem. Lastly, the findings of present work could help in deployment of mechanisms for predicting cascading failures (in real-time) in a power system with high penetration of RES. This in turn serves the higher-level goal of reducing carbon emissions by increasing integration of renewable sources while still keeping system secure, and thus helping address climate change.

Acknowledgments

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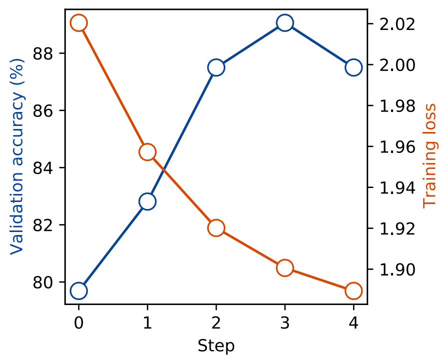

Hyperparameter	Description
Initial Learning Rate	0.0002
Learning Rate Decay	0.95
Batch Size	64
Dropout Probability	0.5
Regularization Weight	$5 * 10^{-4}$
Size of Chebyshev Filter	$5 * 5$
Polynomial Order of Filter	20
Activation Function	GLU

Figure 2: Training performance and hyperparameters for GCN classifier

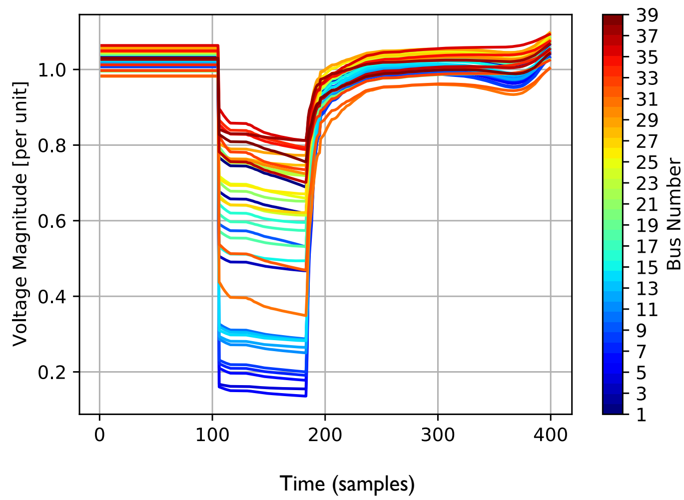

Figure 3: Voltage magnitude at all buses

5 Appendix

5.1 Model Architecture

All the methods use random number generators with $seed = 17$, for reproducibility.
Logistic Regression : Sigmoidal activation function, Adam optimizer and binary crossentropy based loss function, is used for the single layer Logistic Regression model. The parameters of the estimator are optimized by cross-validated grid-search.
SVM : The 3 layer SVM model has been trained using ReLU activation function, hinge based loss function and adadelta optimizer.
ANN : The 3 ANN has been trained ReLU activation function, Adam optimizer and binary crossentropy based loss function.
GCN : Spectral GCN is trained with a gradient descent algorithm, namely the Adam algorithm. The model hyper-parameters have been tuned using a validation accuracy of 84.3%. The tuned hyper-parameters include - batch size (64), dropout probability (0.5), regularization weight $(5 * 10^{-4})$, initial learning rate (0.0002), learning rate decay (0.95), size of Chebyshev filter $(5 * 5)$ and polynomial order of filter (20). Gated Linear Unit (GLU) based activation functions have been used for both spatial and temporal layers. The training performance and the hyper-parameters for the GCN classifier are shown in Figure 2.

5.2 Description of Data-set

: In order to accurately predict cascading failure events there is a need for detailed modelling of power system dynamics, considering 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 RMS model of modified IEEE 39 bus 10 machine New England system with high penetration of wind generation and including models for protection devices is used to generate power system features. The features which are measurable in field by PMUs (i.e.,bus voltages, line currents, bus electrical frequency, line active power injection, line reactive power injection) are utilized in this study. Time-series measurements for voltage magnitudes (in per unit) at all buses for a simulation case are shown in Figure 3 for reference. The data is also suitably pre-processed and resampled to the PMU sampling rate of 10 milli-sec. Automatic voltage regulators, over-excitation limiters, power system stabilizers, detailed controllers for wind generators, tap changer actions and governors are also modeled to capture slower voltage related phenomena and primary frequency response actions. In addition to this, a basic load shedding scheme is to arrest significant frequency drops after loss of generation is modelled. Simulations are performed for different operating conditions which include changing, a)fault location (line on which the fault happens), b) system loading (in the range of 0.7 - 1.2 per unit in steps of 0.1), c) active power output of three wind generators (in the range of 0-1 per unit in steps of 0.2). After taking into account the initial operating conditions for load and wind power generation, an Optimal Power Flow (OPF) problem is solved in order to determine the dispatch of conventional generators. Three phase faults 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 a cascading event 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 (e.g. under-/over- voltage or frequency).