Predicting Cascading Failures in Power System Graph Convolutional Networks

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NeurIPS 2021 Workshop
Tackling Climate Change with Machine Learning

Future Power System Networks

Carbon free operation in UK by 2025

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[1].

Greenhouse gases like CO_2 emitted in serving the energy needs of modern society.

Affordability

Energy Trilemma

Sustainability

Security

Increased **Uncertainty** and **Complexity**

High Impact Low Probability Events: cascading failures!

Maintain power system stability (voltage, small signal, frequency)

[1] Ringo Doe, " Goals of UK COP26 conference on climate change", May 2021.

Cascading Failures in Power Systems

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[2]

Notable Blackouts in the past

- Western US, August 10 1996, cascading failure
- Northeast US and Canada, August 14, 2003 ~ 50 million people
- California, Mexico, Arizona, September 8, 2011
- South Australia, 28 September, 2016
- Northern India, July 30-31 ~ 30 million people
- UK Blackout, 09 August 2019
- Texas Rotating Blackout, February 2021

Important to consider : Size of blackout (in MW) as well social cost of blackouts !

[2] Kai Sun, Yunhe Hou, Wei Sun, and Junjian Qi. *Power system control under cascading failures: understanding, mitigation, and system restoration*. John Wiley & Sons, 2019.

State of the Art

Model based[3]

• **Purely topological model** - neglect the physics of power flow - do not address the non-local behaviour of cascading failures.
• **Quasi steady state** based on AC/DC power flow - do not address the system behaviour in case of islanding as power flow does not converge.
• **Full blown dynamic models** - hybrid models of power system, along with dynamic components, RE, protection devices, etc—- hidden failures of protection systems, huge computational effort, modelling detail, incorrect parameter settings/changes in parameters in field.
• **Hybrid models** with exogenous inputs like weather related events.

Data-driven

•Early warning signs of critical transitions
•Markov Chain based cascade evolution
•PDF of blackout size
•Sampling of test cases (Random Chemistry approach etc,)
•Graph based
•Interaction Graph
•Tree-partition

Machine Learning/Deep learning

[3] Vaiman *et al.*, "Risk Assessment of Cascading Outages: Methodologies and Challenges," in *IEEE Trans. on Power Syst.*, vol. 27, no. 2, pp. 631-641, May 2012.

Why Graph Convolutional Networks?

Motivated by the spatial aspects of cascading failures, in this work we seek to explore the efficacy of a Graph Convolutional Networks (GCNs)[4][5] for predicting the occurrence of cascading failures in power system and comparison of performance with other baseline ML techniques.

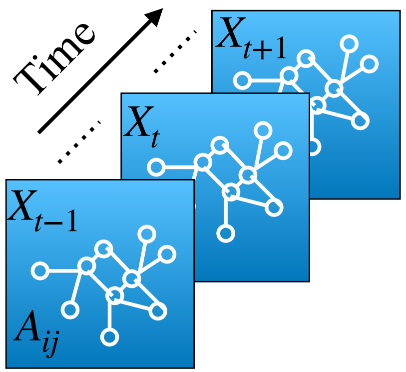
Cascading failures in power systems exhibit non-local propagation patterns which make the purely topological analysis of failures unrealistic.

Mainly four ways by exploiting graph convolution:

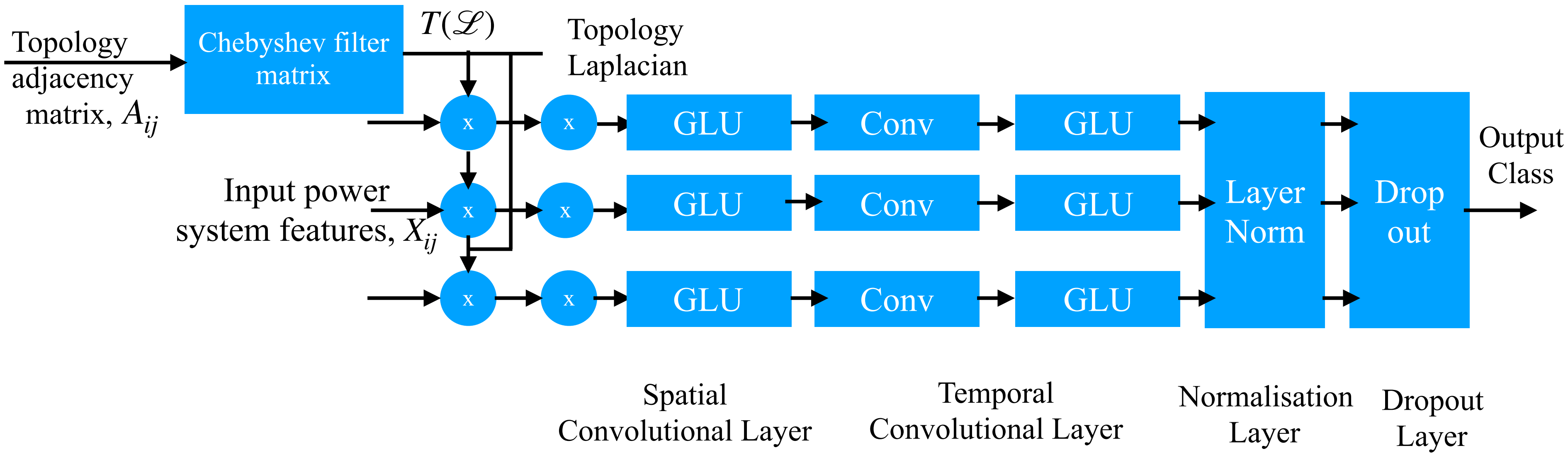
- adding a one-dimensional convolutional layer behind the graph convolutional layer.
- adding a long short-term (LSTM) layer or gated recurrent unit (GRU) behind the graph convolutional layer.
- modifying the original LSTM or GRU, to replace the fully connected layer in LSTM or GRU by graph convolution.
- representing temporal correlations as new edges of the graph and constructing a new graph with spatial-temporal correlations.

[4] Bing Yu, Haoteng Yin, and Zhanxing Zhu. Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. *arXiv preprint arXiv:1709.04875*, 2017.
[5] Michaël Defferrard, Xavier Bresson, and Pierre Vandergheynst. Convolutional neural networks on graphs with fast localized spectral filtering. In *Advances in Neural Information Processing Systems*, 2016.

Methodology

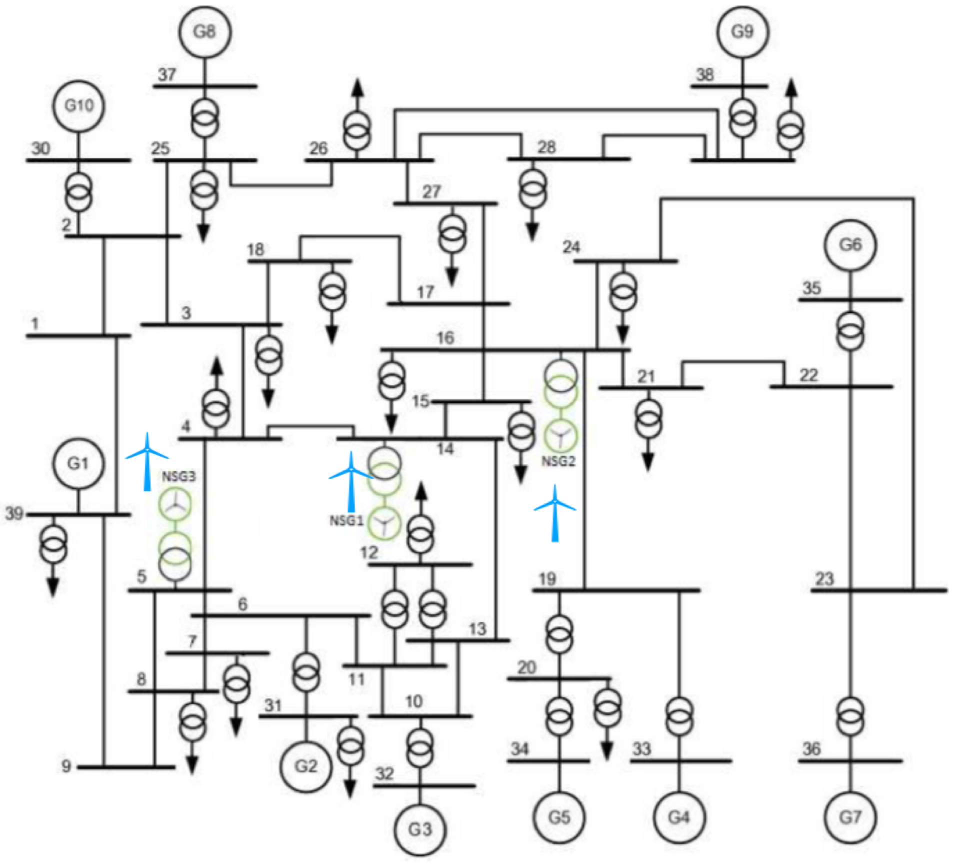


Structure of the input data
(Power system features recorded at different nodes across time)



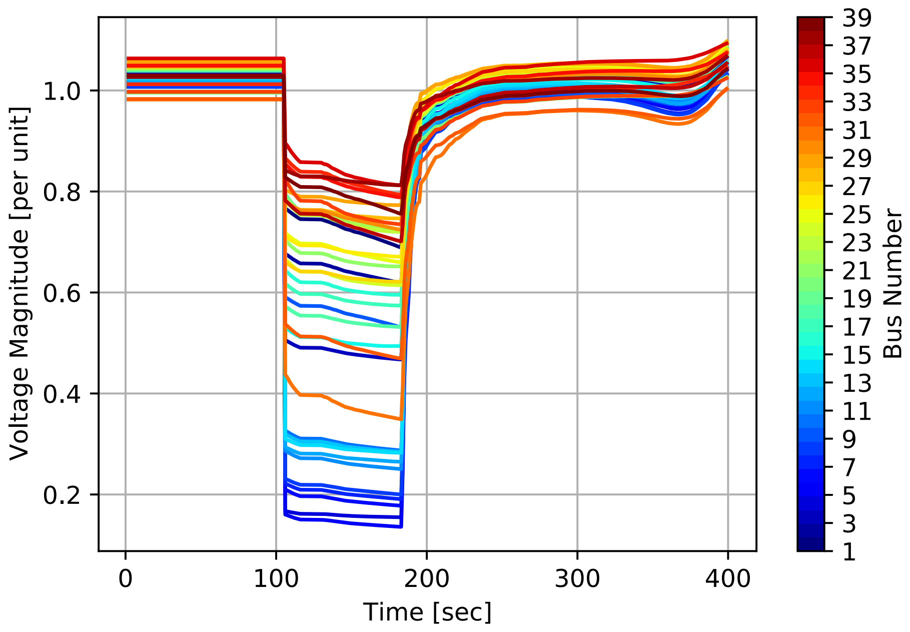
Framework for spatio—temporal GCN technique

Case Study



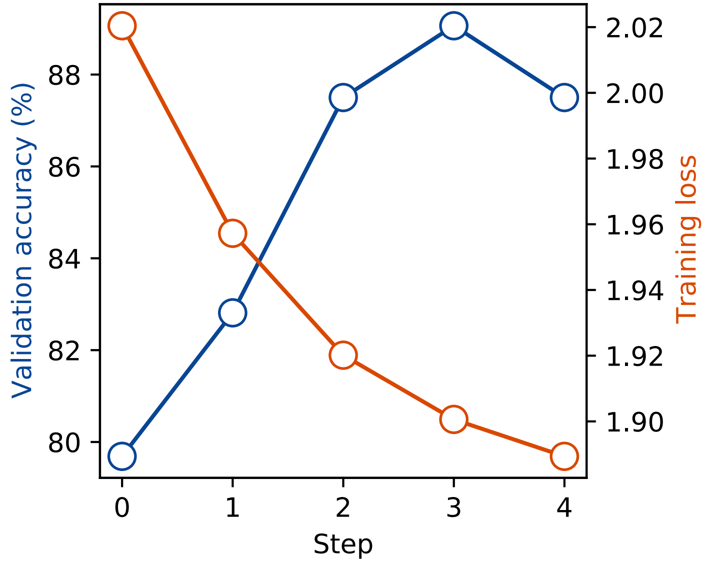
Wind generators

G Synchronous generators



- Training and testing data is generated by simulating a hybrid model (including synchronous machines, RES, and associated protection devices) of modified IEEE 10 machine 39 bus New England Test System.
- Database of power system features assumed to be captured by PMU located at every node, and initial faults on different locations of the power system ~ **spatio-temporal data**
- Gaussian Kernel Learning using K nearest neighbours is used to form the adjacency matrix, A_{ij} .
- Binary classification problem

Results



Training Performance

Table 1: Model parameters

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

Table 2: Performance metrics (%)

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**

- Preliminary findings show that GCNs achieve an accuracy of 92.1%
- The *Recall* score for GCN is 93.2% which signifies that the GCN technique correctly predicts the cascade most of the times.
- 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.

Conclusion & Future Work

- This work is intended to be an initial study to illustrate the potential of spatial machine learning for studying cascading failures.

- Data-sets with realistic representation of noise and missing data that are representative of real-life power systems might improve the robustness of our model.

- Findings of present work could help algorithms like GCNs to predict the occurrence of power system cascading failures with high RES penetration.

- This in turn serves the higher-level goal of reducing carbon emissions for the current problem.

Any questions?

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