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

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Cascading Failures: State-of-the-Art

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.

- *Methodologies for cascading outage analysis*
  - *static computation*
  - ***dynamic computation***
  - *combination of both*

IEEE Cascading Failure Working Group

High Impact Low Probability Event (HILP) as classified by **NERC**

- Outage process divided into two phases: the slow cascade and fast cascade phases[1] .
- **Fast phase** -- often driven by the transient dynamics of the system and triggering of protection devices.

[1] P. Henneaux, J. Song E. Cotilla-Sanchez, "Dynamic probabilistic risk assessment of cascading outages," *2015 IEEE Power & Energy Society General Meeting*, 2015, pp. 1-5. and

Motivation and Research Gap

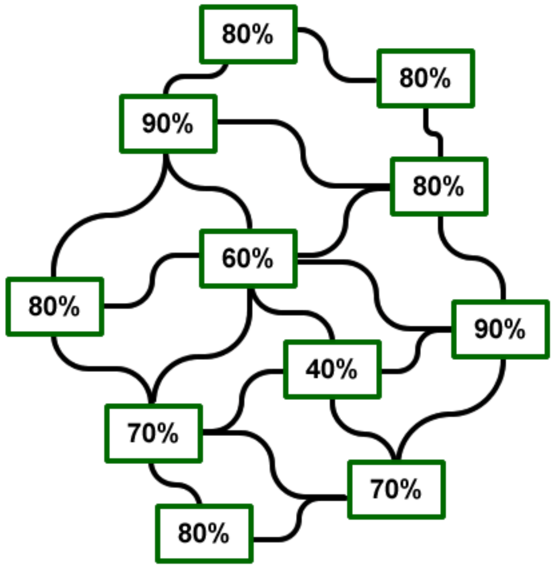
- **Fast phase of cascade** ---*too fast (inter-failure characteristic times ~ ms/10s)* to allow SO to take corrective actions.
  - *occurrence order and timing are driven by the power system's dynamic evolution in the course of the transient.*

- Key enablers for a resilient response include the capacity to anticipate, absorb, rapidly recover from, adapt to, and learn from such an event -- *defined by IEEE PES Task Force[2].*

- Fast Prediction in real-world settings is critical --- use of Machine Learning!

- Dynamic modelling+ Protection devices + varying operating conditions --- large scale combinatorial problem !

- Power system dynamic trajectories – spatio-temporal in nature!



Network running normally

[2] IEEE PES Task Force: et al., "Methods for Analysis and Quantification of Power System Resilience," in *IEEE Trans. on Power Syst.*, 2022 [Early Access].

Graph Theoretic Modelling

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***Power system weighted graph*[3], $G(V, E)$**

Graph: Nodes (V) – buses, Edges (E) – lines.

$$card[V] = n, card[E] = l$$

$$n \in (n_g, n_l)$$

Electrical grid signals indexed by such a graph.

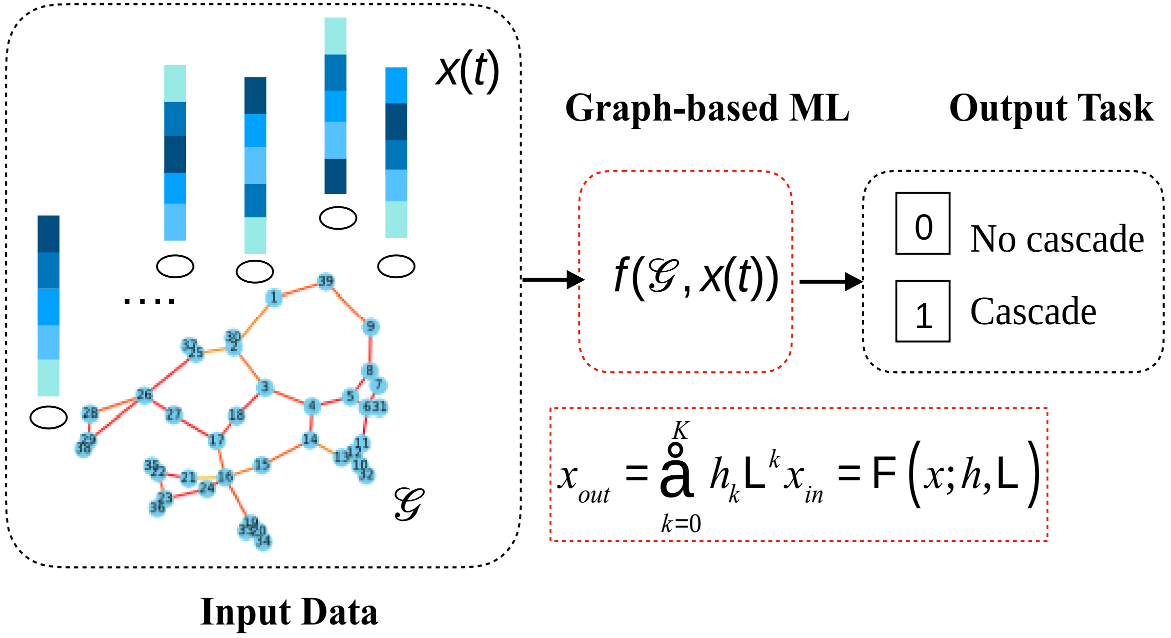
Spatial correlations between different power system buses represented by ***weighted adjacency matrix,*** $\widetilde{\boldsymbol{A}}$

$$\tilde{A} = |Y_{bus}|$$

Normalized Graph Laplacian, $\mathcal{L}$

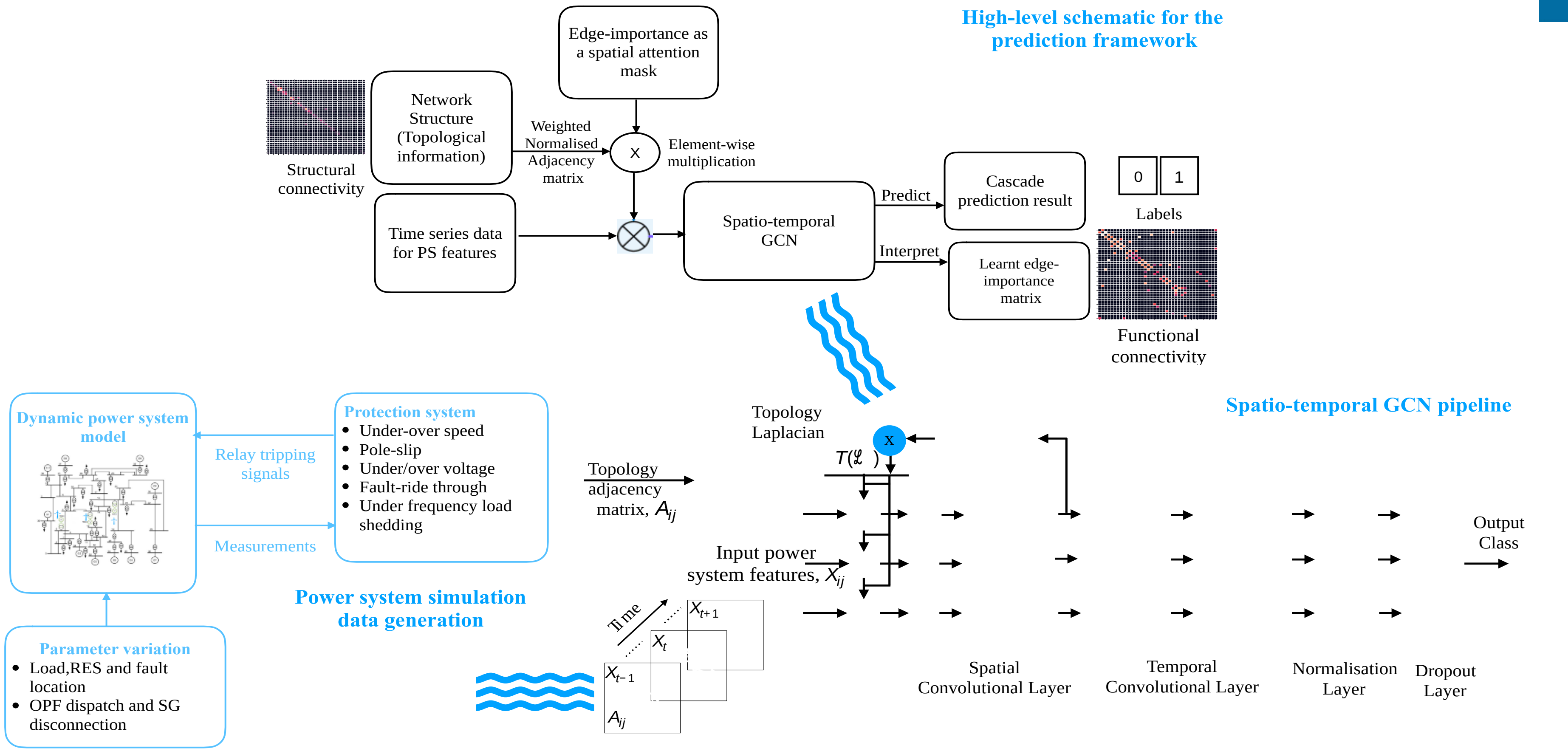
$$\mathcal{L} = D^{-\frac{1}{2}}\,\tilde{A}\,D^{\frac{1}{2}}$$

where, D is the degree matrix of the graph.



[3] R. Ramakrishna and A. Scaglione, "Grid-Graph Signal Processing (Grid-GSP): A Graph Signal Processing Framework for the Power Grid," in IEEE Transactions on Signal Processing, vol. 69, pp. 2725-2739, 2021.

Model Framework



[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] T. Ahmad, PN Papadopoulos, "Prediction of Cascading Failures and Simultaneous Learning of Functional Connectivity in Power System "ISGT Europe, Novi Sad, Serbia, 2022.

Edge-Importance Matrix: Functional Connectivity in Power System

Edge-Importance based Spatial Attention Mask

For ST-GCN output/input features, x_{out} are calculated as

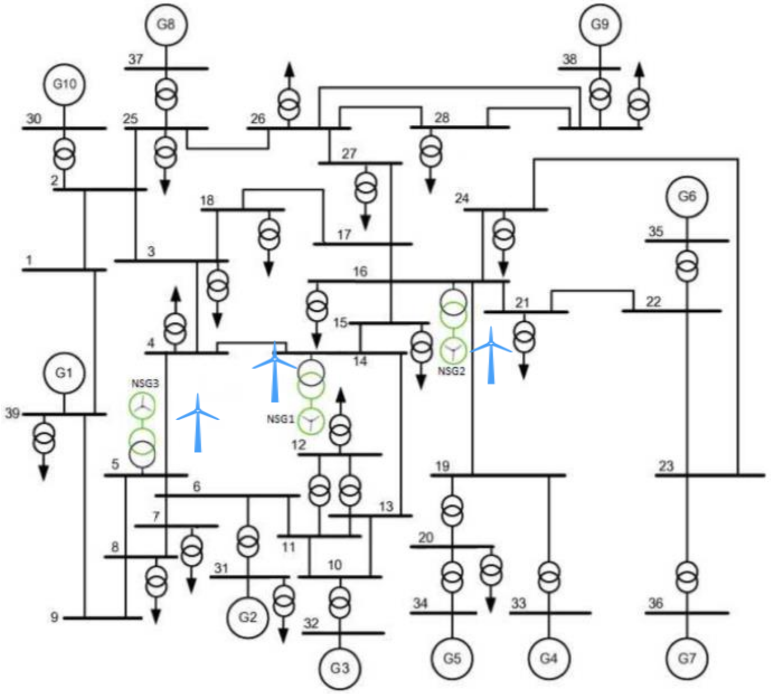
$$x_{out} = G_g^{-\frac{1}{2}} (\tilde{A})\, G_g^{-\frac{1}{2}}\, x_{in} W$$

This matrix is shared across all $\mathrm{st}-\mathrm{GCN}$ layers by replacing $(\tilde{A})$ by $(\tilde{A})$x M (element-wise multiplication)

where, x_{in}, x_{out} are the input/output features, W is the weights Matrix and G_g is the kernel obtained from spatial graph convolution.

Diagonal entries of M (self-connection) quantify the importance for each node, while off-diagonal entries do so for each functional connection (edge)

Case Study



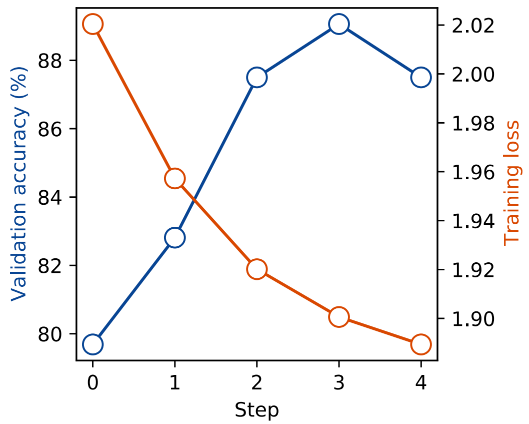
Wind generators   G Synchronous generators

- ***Features*** $\left(X \times n \times T_w\right) = \left(11000 \times 39 \times 10\right)$
- ***Adjacency matrix*** $\tilde{A} \in R^{n\times n} = |Y_{bus}|$
- ***Labels*** $\left(Y\right) = \left(11000 \times 1\right)$

- Training and testing data generated by simulating a ***hybrid dynamic model (including synchronous machines, RES (wind-generation), associated controls and protection devices)*** for ***IEEE 10 machine 39 bus New England Test System*** *[2].*
- ***3-phase fault on transmission lines*** as initiating events; ***incremental load and wind power demand.***
- ***Power system features*** (voltage magnitude, V_{mag} (in p.u.) assumed to be captured by PMU.
- Posed as a ***binary classification problem.***

Results

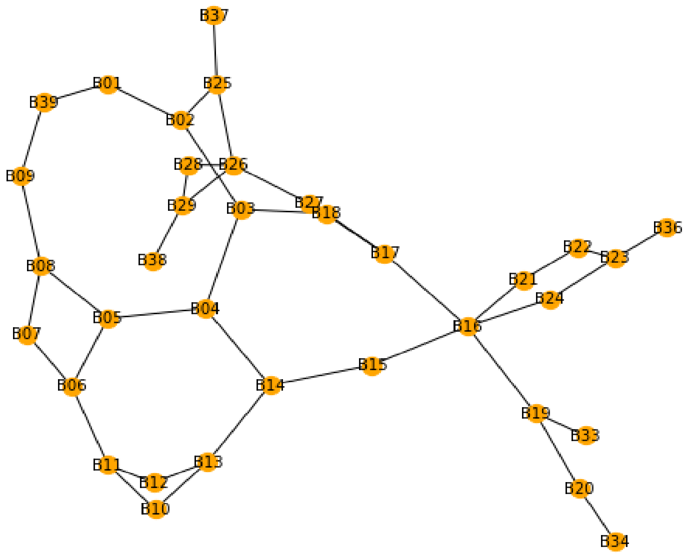
- Stratified K-fold cross validation for k = 5 splits is used for different training and testing data splits.



Training performance for the st – GCN + EdgeImp classifier averaged over validation folds.

Line 16 - 19	0.7	0	0	0	1	[('G 05', 'Over-Speed', '1.70')]
Line 01 - 02	0.7	0	0	0	1	[('G 01', 'Under-Speed', '5.00')]
Line 01 - 39	0.7	0	0	0	1	[('G 02', 'UV', '2.73'), ('G 01', 'Under-Speed', '5.79')]
Line 01 - 02	0.7	0	0	0.2	1	[('G 02', 'UV', '2.70'), ('G 03', 'UV', '2.92'), ('G 01', 'Under-Speed', '6.64'), ('NSG_3', 'UnderVoltage', '9.29')]
Line 16 - 19	0.7	0	0	0.4	1	[('G 05', 'Over-Speed', '1.73'), ('Load 29A_UF', '9.79'), ('Load 28A_UF', '9.79'), ('Load 25A_UF', '9.80'), ('Load 26A_UF', '9.80'), ('Load 08A_UF', '9.93'),
Line 16 - 21	0.7	0	0.2	0	1	[('NSG_2', 'OverVoltage', '2.12')]

The graph induced by dynamic functional connectivity correctly predicts the location within 1-hop and 2-hop neighborhood for all scenarios.



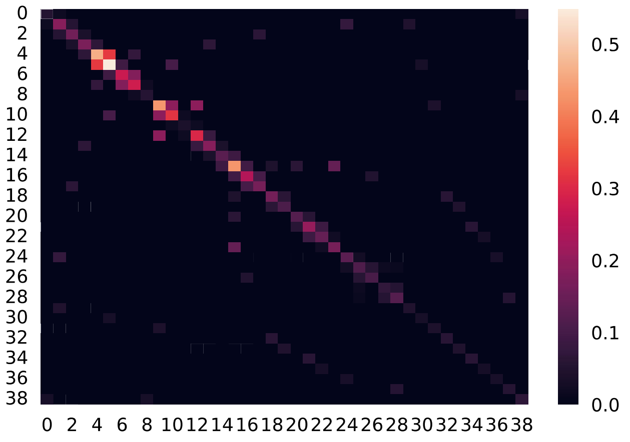
Classifier	Classification Performance (%) (seed = 17)			
	Accuracy	Precision	Recall	F1 score
vanilla st-GCN	92.56±1.55	84	93.22	88.36
st-GCN+EdgeImp	96.83±1.03	96.45	96.36	96.41

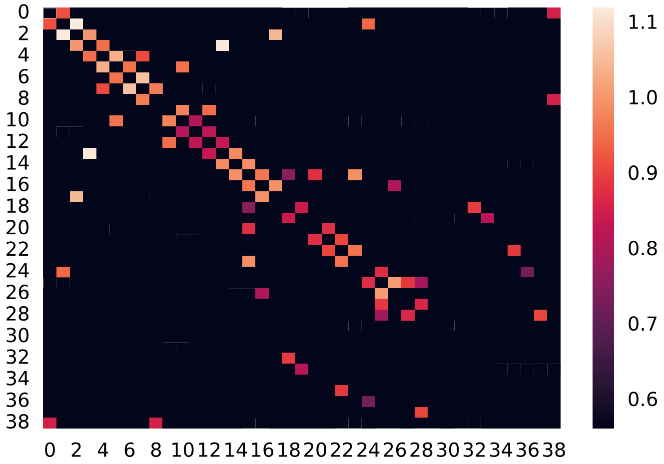
The inclusion of Edge Importance matrix in st-GCN further improves the key performance metrices than using the vanilla st-GCN.

Interpretable Insights

- Lack of interpretability in "black-box neural networks" - hinder their deployment under *mission critical systems such as the **power system.***
- Current work introduces***, edge importance* matrix**, ***M as an additional trainable parameter*** inside the *st-GCN* to reveal the influence of a set of nodes and edges in model prediction.
- ***Diagonal elements*** of M depict the relative importance of various ***power system buses (graph nodes)*** , while the ***off-diagonal elements of M*** depict the ***importance of power system lines (graph edges)*** in the prediction of cascades.

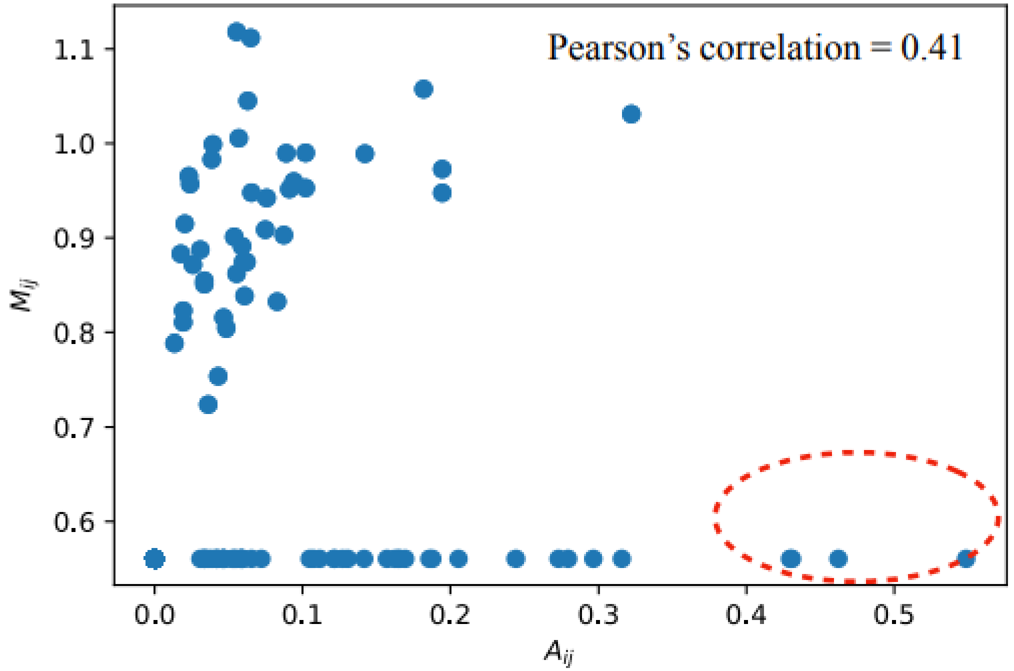
$|Y_{bus}|$ matrix is sparse matrix mirroring the **physical topology of the grid**





*M is a dense matrix, with **significant off diagonal elements,** mirroring the importance of **not only local but also multi-hop interactions.***

Interpretable Insights



- There is some positive correlation between ***admittance-based connectivity matrix*** and ***dynamic functional connectivity matrix.***

- Some counter-intuitive cases where *tightly coupled elements of admittance connectivity* have no impact on *dynamic functional connectivity for failures.*

Concluding Remarks

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- Work illustrates the potential of an interpretable, spatio-temporal graph learning framework to *predict the occurrence of dynamic cascading failures* in a *hybrid power system* (i.e. including power system dynamics and discrete actions of protection devices).

- The st-GCN model achieves improved performance when trained along with *importance matrix based spatial attention mask.*

- From the sparsity patterns of matrices $|Y_{bus}|$ and M, it can be inferred that *lighter the colour gradient, closer are the buses/lines in their admittance based electrical connectivity and functional connectivity respectively.*

- Could be useful in preventive (e.g., hardening critical components) and corrective control for mitigating the risk of catastrophic failures.

Future Work

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- In order to build trust in the learnt sensitivities to cascading failures (M learnt using V_{mag}) using the proposed method, comparison with relevant physics-based sensitivity[3] makes sense.
- Future work also includes investigating the transferability of the st-GCN based learning framework in case of topology changes and out of distribution data.
- Explore the possibility of *edge-importance matrix* as an ***actual distance metric*** to acquire additional (perhaps causal) insights into power system functional graph.

[3] Simpson-Porco, J. W, et al Voltage collapse in complex power grids. Nature communications, 7(1), 1-8.

Thank you !

Further reading at …

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