DATS 6203 Machine Learning II

Final Project Group 4 Proposal

Team members:

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Problem:

Identify and estimate the topology of power grids with real time phasor measurement units (PMUs) detection data inputs.

Motivation:

With the increase of the requirement for high electricity quality and the number of end-use consumers, it brings more and more challenges in the operation and control of power grids. It is particularly important to ensure acceptable reliability and quality of the electricity supply for any aspects of the electrified economy. Due to the growing deployment of PMUs in power distribution networks (PDNs), an abundance of high-resolution measurements is available that can be harnessed for smarter operation and fault analysis in PDNs. Traditional models on the network topology identification are limited and might occupy too much human and material resources. Hence, it is essential to propose a resource saving and economical model to identify and estimate the topology of PDNs based on real-time PMUs data.

This project will investigate a real problem that can make progress in the PDNs topology detection by applying deep learning methods to check the online power grid status in real-time. Meanwhile, all members in this group major in Electrical Engineering. This project will be our major related problem.

Database:

The data is from Yifu's master thesis [1], which was generated from IEEE 34 test feeder [2]. This data was detected using PMUs. A PMU is a device used to estimate the magnitude and phase angle of an electrical phasor quantity (such as voltage or current) in the electricity grid using a common time source for synchronization. Time synchronization is usually provided by GPS or IEEE 1588 Precision Time Protocol, which allows synchronized real-time measurements of multiple remote points on the grid.

To gain a full observation of the IEEE 34-node test feeder shown in Figure 1, we set 33 PMUs on each node except node 800 (substation bus). We also added 5 breakers (SW 1-5) in order to generate different electrical network topologies for the training dataset. To generate more scenarios under one topology, we marked 5 loads, so the PMU data could be varying under different realization of the load demand. Different colors are here used to mark the phasing status, e.g., we used pink to mark the line 800-812 as BACN, meaning that it is a three-phase four-wire segment in the distribution grid. The proposed network topology identification approach is applied on a three-phase unbalanced electrical distribution system. As the breakers in Figure 1 changed between on and off, we were able to generate 8 different topologies (labels) as shown in Figure 2.

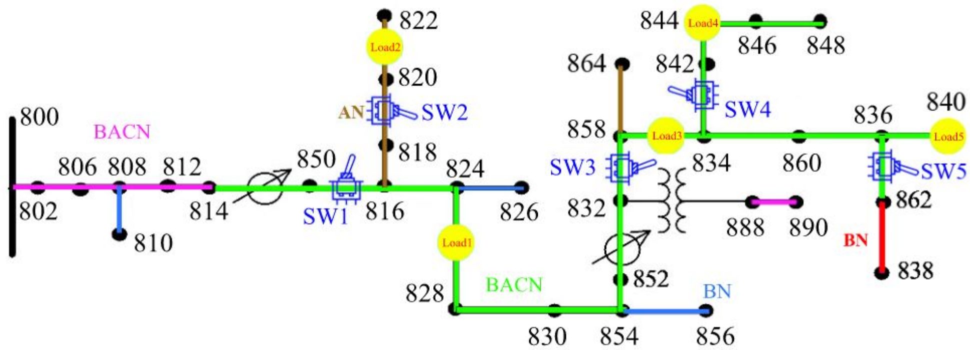

Fig. 1. IEEE 34-Node Test Feeder.

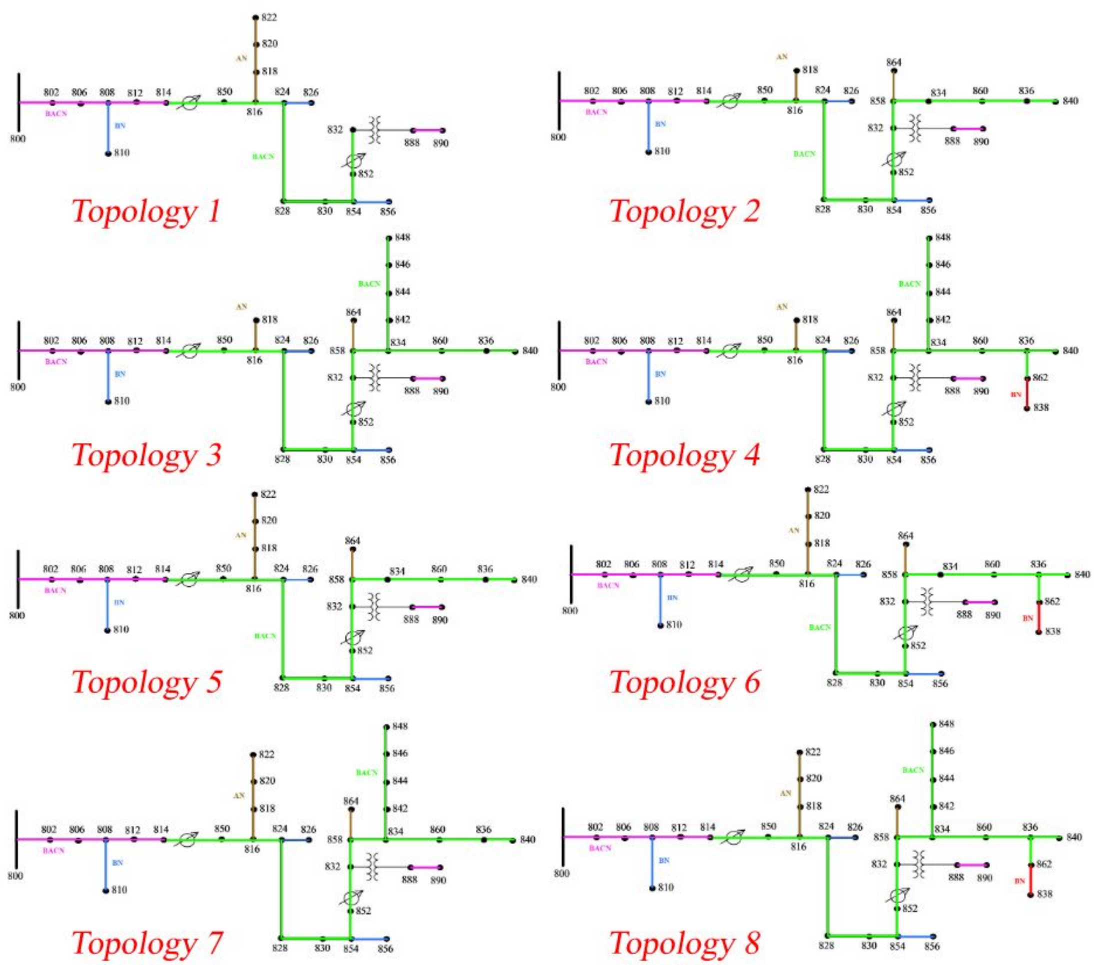

Fig. 2. All Studied Grid Topologies

Nearly 20K data would be used in training a deep network, which is big enough for deep learning training. A sample of the input data is shown as an Excel screenshot in Figure 3 and as a heatmap in Figure 4. In the Excel screenshot, columns A, B, and C stand for the three-phase normalized voltage values (divided by nominal voltage), columns D, E, and F stand for the voltage phase angle radian values divided by π, and the last 6 columns G to L are the same as the previous 6 columns but the voltage variables are replaced with the current. The rows 1 to 33 represent the 33 PMUs.

33 μPMUs

	V_a	V_b	V_c	θ_{Va}	θ_{Vb}	θ_{Vc}	I_a	I_b	I_c	θ_{Ia}	θ_{Ib}	θ_{Ic}
	A	B	C	D	E	F	G	H	I	J	K	L
1	1.048623	1.049323	1.049391	-8.42E-05	-0.66681	0.666655	0.70592	0.54974	0.417023	-0.11972	-0.77278	0.559939
2	1.04769	1.048916	1.049007	-0.00014	-0.66691	0.666651	0.706332	0.486436	0.363541	-0.1201	-0.76787	0.567628
3	1.030076	1.042183	1.042223	-0.00131	-0.66862	0.666715	0.714104	0.489543	0.36934	-0.12702	-0.77828	0.555288
4	0	1.042034	0	0	-0.66863	0	1.45E-15	0.018129	1.45E-15	-0.32245	-0.81621	-0.32245
5	1.009424	1.035278	1.033791	-0.00273	-0.67041	0.666909	0.723361	0.458324	0.376668	-0.13478	-0.78936	0.541531
6	0.992866	1.029663	1.026907	-0.00381	-0.67176	0.667135	0.730844	0.462029	0.382887	-0.14071	-0.79924	0.531091
7	0.992859	1.02966	1.026904	-0.00381	-0.67176	0.667135	0.730847	0.462031	0.382889	-0.14071	-0.79924	0.531087
8	0.992631	1.029569	1.0268	-0.00382	-0.67177	0.667143	0.73092	0.462073	0.382951	-0.14077	-0.79934	0.530987
9	0.991771	0	0	-0.00384	0	0	0.347288	1.45E-15	1.45E-15	-0.13913	-0.32245	-0.32245
10	0.969833	0	0	-0.00416	0	0	0.28177	1.45E-15	1.45E-15	-0.15202	-0.32245	-0.32245
11	0.967027	0	0	-0.00418	0	0	0.141679	1.45E-15	1.45E-15	-0.15644	-0.32245	-0.32245
12	0.988977	1.025492	1.023638	-0.0037	-0.67195	0.6671	0.386352	0.458374	0.379662	-0.14635	-0.80477	0.530013
13	0	1.025294	0	0	-0.67195	0	1.45E-15	0.045128	1.45E-15	-0.32245	-0.81953	-0.32245
14	0.98868	1.02524	1.023364	-0.0037	-0.67196	0.667099	0.386558	0.368755	0.371345	-0.14664	-0.8023	0.529973
15	0.981551	1.019039	1.016776	-0.0036	-0.67217	0.667087	0.376879	0.371703	0.375541	-0.15461	-0.81023	0.523259
16	0.981392	1.018888	1.016624	-0.0036	-0.67218	0.667088	0.337099	0.348934	0.338178	-0.14875	-0.81001	0.513234
17	0	1.018796	0	0	-0.67222	0	1.45E-15	0.004574	1.45E-15	-0.32245	-0.8198	-0.32245
18	0.970044	1.008306	1.005683	-0.00336	-0.67231	0.667246	0.346462	0.34932	0.346529	-0.16309	-0.83123	0.50061
19	0.970041	1.008303	1.00568	-0.00336	-0.67231	0.667247	0.346464	0.349322	0.346531	-0.1631	-0.83123	0.500607
20	0.93274	0.970755	0.967741	-0.01281	-0.6815	0.658411	0.345628	0.348452	0.345657	-0.16285	-0.83097	0.500847
21	0.844252	0.891217	0.887066	-0.01511	-0.68958	0.654236	0.345699	0.348494	0.34572	-0.16295	-0.83109	0.500749
22	1.88E-13	3.81E-13	2.15E-13	-0.14854	0.812369	-0.31514	4.17E-14	7.99E-14	4.81E-14	-0.23005	0.63634	-0.50397
23	1.90E-13	0	0	-0.14943	0	0	3.97E-16	1.45E-15	1.45E-15	-0.29701	-0.32245	-0.32245
24	1.87E-13	3.81E-13	2.15E-13	-0.14918	0.812413	-0.31507	3.91E-14	7.27E-14	4.18E-14	-0.23895	0.634222	-0.52047
25	1.60E-28	1.61E-28	1.95E-28	0.972053	-0.99934	0.656793	1.67E-29	1.66E-29	1.52E-28	-0.54412	-0.54673	0.782888
26	1.60E-28	1.60E-28	1.95E-28	0.97197	-0.99952	0.655245	1.79E-29	1.65E-29	1.52E-28	-0.48332	-0.54082	0.782446
27	1.59E-28	1.60E-28	1.95E-28	0.97074	0.999207	0.654979	4.63E-29	5.03E-29	1.04E-28	-0.15256	-0.12641	0.861525
28	1.59E-28	1.60E-28	1.94E-28	0.972372	-0.99844	0.65486	4.58E-29	5.80E-29	1.04E-28	-0.15209	-0.12833	0.861182
29	1.88E-13	3.80E-13	2.15E-13	-0.14823	0.812295	-0.31514	3.18E-14	5.84E-14	2.96E-14	-0.30348	0.629856	-0.49288
30	1.88E-13	3.80E-13	2.15E-13	-0.14851	0.812352	-0.31463	1.13E-14	2.42E-14	1.33E-14	-0.3428	0.632022	-0.41788
31	1.88E-13	3.80E-13	2.15E-13	-0.14961	0.812534	-0.31464	4.04E-15	8.19E-15	4.61E-15	-0.36002	0.602117	-0.52506
32	3.69E-15	1.51E-15	4.07E-16	0.010447	0.973447	-0.1555	3.58E-32	1.13E-15	0	0.221224	0.968464	0
33	0	1.59E-18	0	0	0.624155	0	1.45E-15	4.69E-20	1.45E-15	-0.32245	0.476571	-0.32245

Fig. 3. Example of a PMU Data

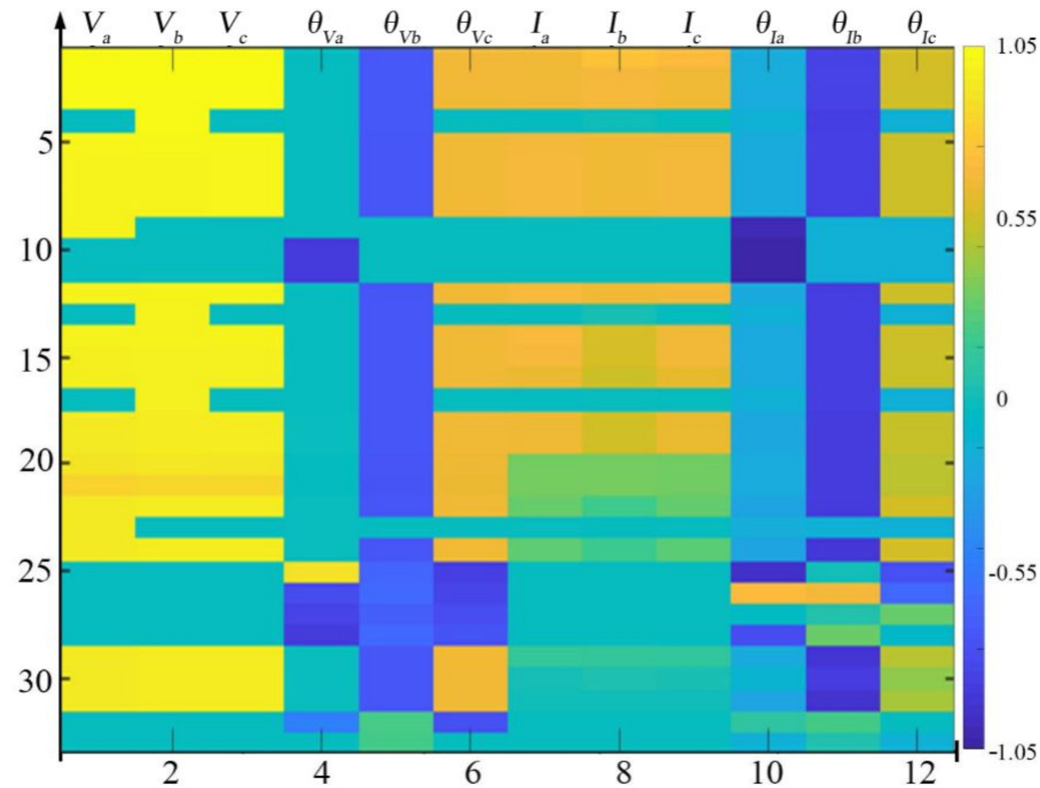

Fig. 4. A Heatmap Example of the Generated PMU Measurement Data Sample

Type:

In this project, the Autoencoder network will be used [3]. We will use Autoencoder training the classified 8 groups data for 8 topologies. In this way, no matter what the real-time PMU data has been detected, the network trained by Autoencoder will automatically identify the current grid topology. Thus, this method could be implemented to report the error location in the grid when some faults happened.

Framework:

The proposed framework for online power system topology identification is illustrated in Figure 5. The PMUs data is first used for offline training of the pre-built Autoencoder model. The trained model is then used for online identification of the power distribution network topology.

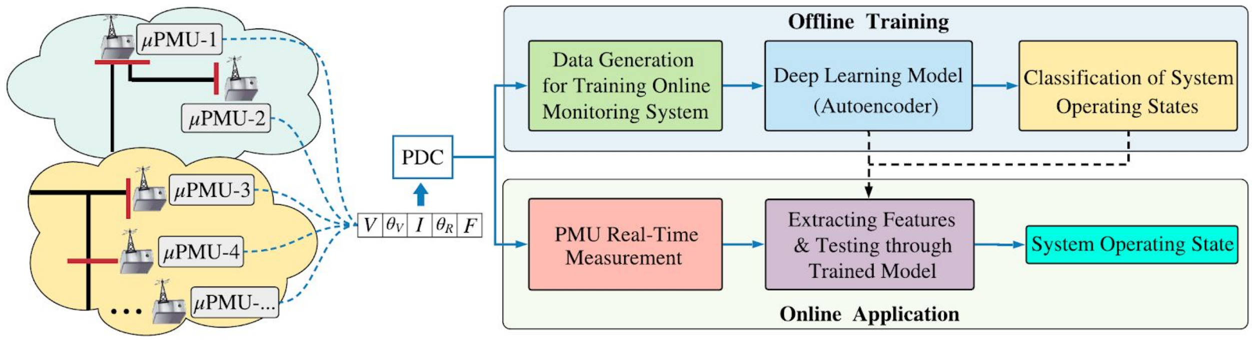

Fig. 5. The proposed framework for power system online topology identification

Validation:

- Use the full observation data (the PMU data without missing values or added noise) to test the accuracy of the network identification and estimation result.
- Use the interfered data (the PMU data with missing values or added noise or both) to test the accuracy.
- The metric used for this project is the accuracy.
- Use the training set with interfered data to train a network and see if it could achieve a high accuracy on estimation.

Schedule:

Table 1. Rough Schedule for Project

Date	Assignment	Note
11/10/2020	Submit the Group Proposal	
11/17/2020	Build the new model	Autoencoder
11/24/2020	Test the model using full observation data and modify the parameters	To do some optimization process increasing accuracy
12/01/2020	Test the model under numerical case experiments	Check the accuracy among different scenarios
12/08/2020	Write the report and do the presentation	Upload to Github

References:

[1] Li, Yifu. *Date-Driven Topology Identification in Power Distribution Systems with Machine Learning*. Diss. The George Washington University, 2020.

[2] “34-bus feeder case,” IEEE PES, [Online] Available at: https://site.ieee.org/pes-testfeeders/resources

[3] Sharma, A. (2018, July 20). *Autoencoder as a Classifier using Fashion-MNIST Dataset*. Datacamp, [Online] Available at: https://www.datacamp.com/community/tutorials/autoencoder-classifier-python