

# W Distribution grid management G with graph neural networks



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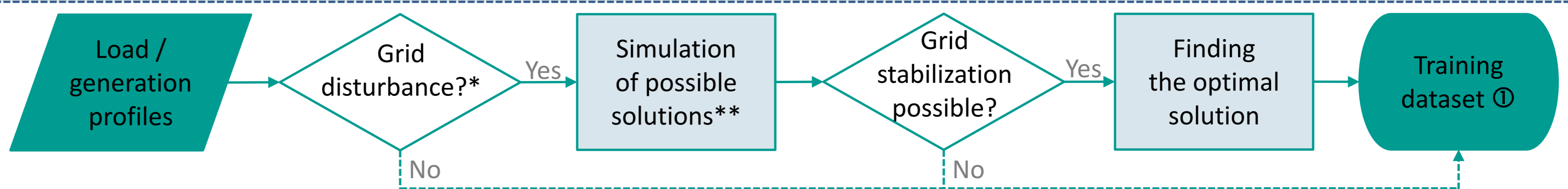
## INTRO

The expansion of renewable energies leads to a need for active grid operation management in the distribution grid. Conventional methods are too slow to react to short term disturbances.

**OUR IDEA:** A grid optimization tool based on graph neural networks (GNNs) to support distribution system operators.

**GOAL:** Reduction of grid expansion and avoidance of supply bottlenecks through intelligent use of the existing grid infrastructure.

## TRAINING DATA



\* **Disturbances:** Overloads of lines and transformer stations and voltage deviations above 3%

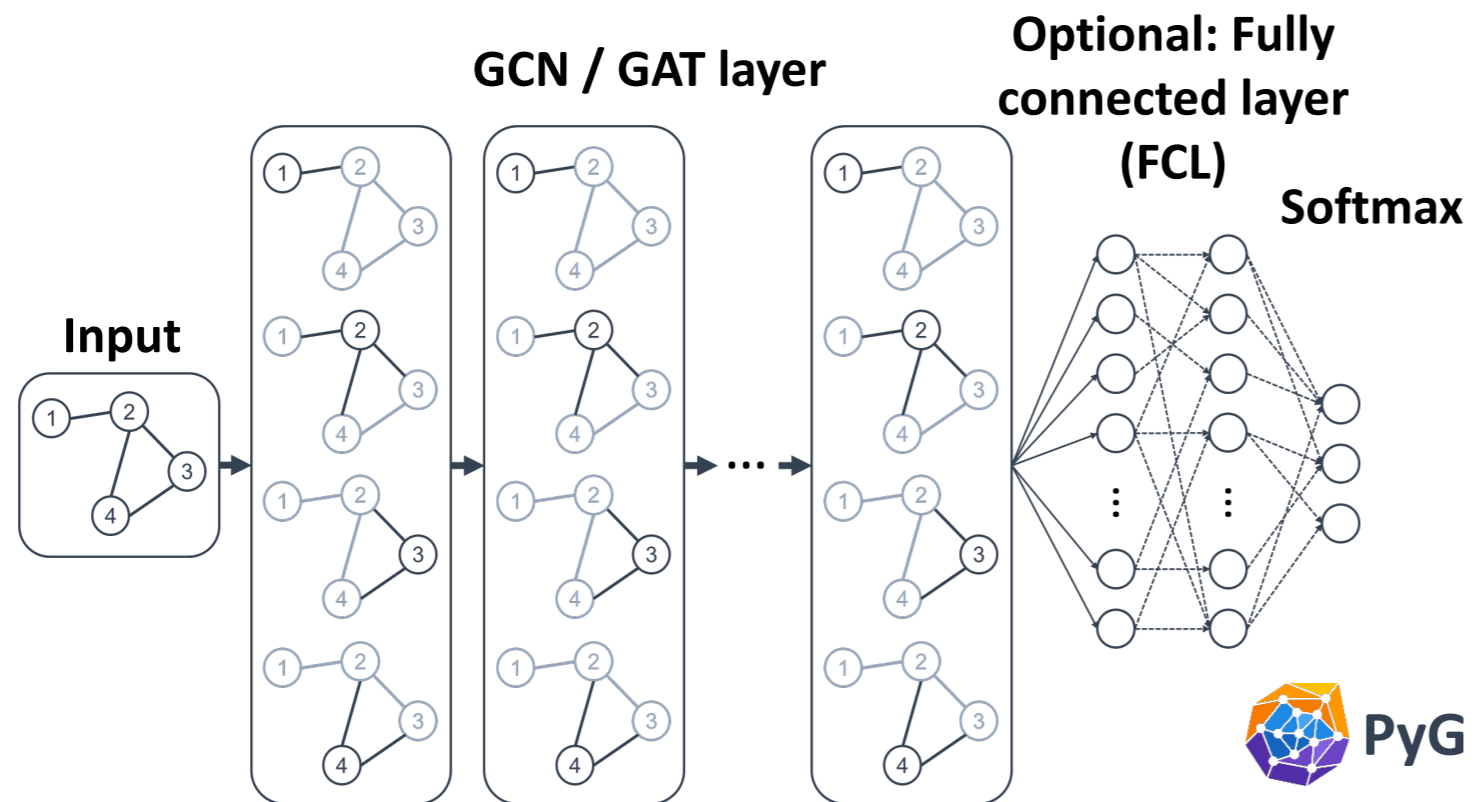
\*\* **Possible Solutions:** Different grid states with varying positions of the transformer tap changers and remote-controlled line switches

## GNN-MODEL & INPUT

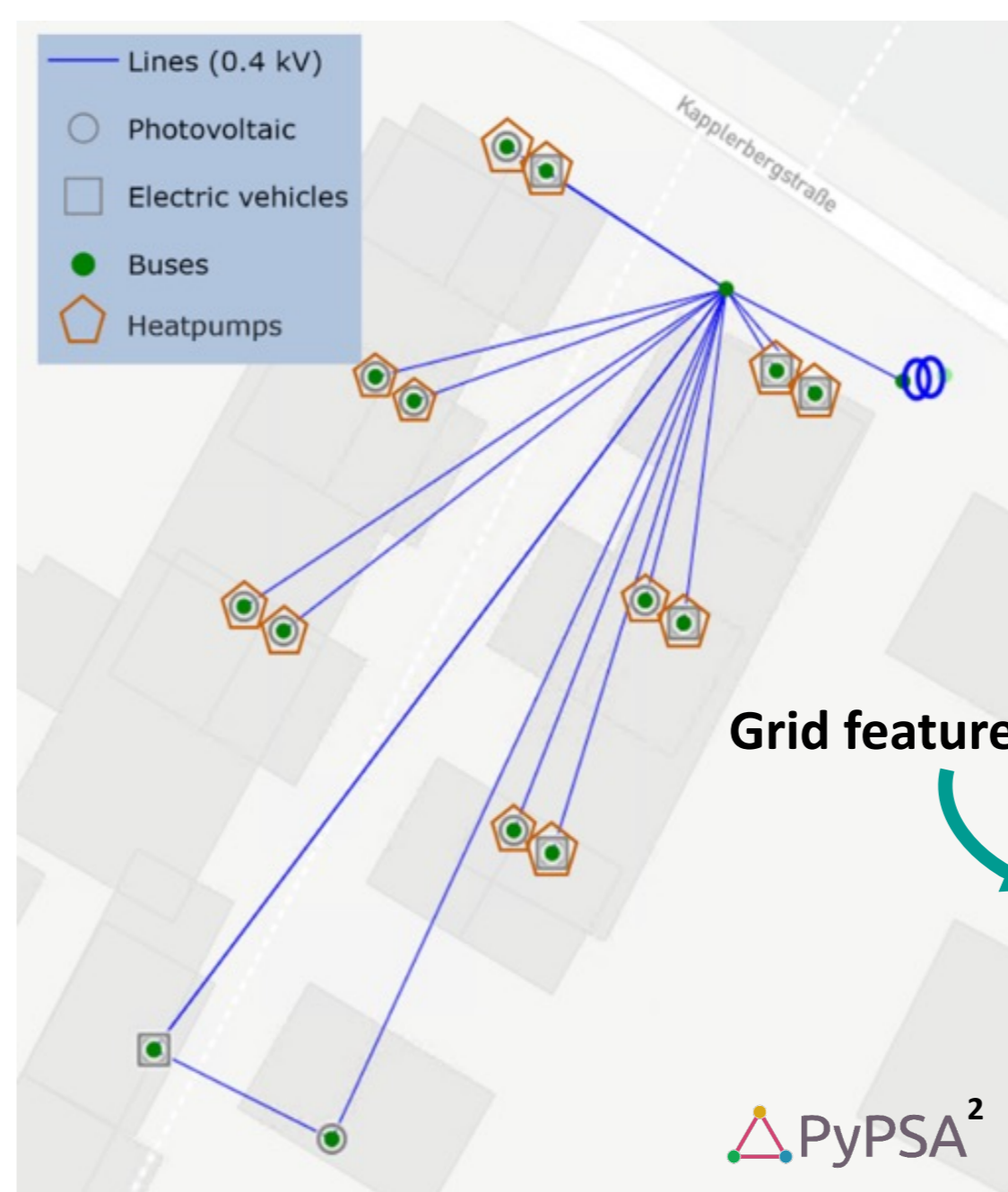
### Graph Convolutional Network (GCN) & Graph Attention Network (GAT)

- Model architecture is independent of the size of the input grid and permutation invariant
- Topology of the network is used for training
- Trained GNN can also be applied to new topologies

#### Model Architecture



### Input: training dataset ① and grid features ②



#### Training dataset ①

Node features	Loads [MW]
	Generations [MW]
	Storage units [MW]
Targets	Solution vector

#### Edge index: Adjacency matrix

0	1	...	1
1	0	...	0
...	...	...	...
1	0	...	0

#### Edge features

- Line length [km]
- Primary line constants ( $x, r, g, b$ )
- Ratio of per unit voltages at each bus for tap changed (tap ratio)

## RESULTS & CONCLUSION

Model	Training Loss	Validation Loss	Test Accuracy	F1 Score			
				Klassen	0	1	2
GCN	0.191	0.152	92.2 %	GCN	0.895	0.947	0.928
<b>GAT</b>	0.099	<b>0.079</b>	<b>94.4 %</b>	<b>GAT</b>	<b>0.923</b>	0.961	0.951
GCN-FCL	0.238	0.164	93.0 %	GAT-FCL	0.912	0.938	<b>0.961</b>
<b>GAT-FCL</b>	<b>0.097</b>	0.108	93.6 %	GCN-FCL	0.905	<b>0.965</b>	0.923

Best overall performance!

### CONCLUSION

GNNs are well-suited for controlling a distribution grid and enable optimal use of existing grid infrastructure

### OUTLOOK

- Integrating the curtailment of generation and consumption
- Test at the Digital Grid Lab (Fraunhofer ISE)

## REFERENCES

<sup>1</sup> M. Fey, J. E. Lenssen, Fast Graph Representation Learning with PyTorch Geometric, 2019, ICLR 2019 (RLGM Workshop), <https://doi.org/10.48550/arXiv.1903.02428>

<sup>2</sup> T. Brown, J. Hörsch, D. Schlachtberger, PyPSA: Python for Power System Analysis, 2018, Journal of Open Research Software, 6(1), <https://doi.org/10.5334/jors.188>

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