(Physics-Informed) Graph Neural Networks for Power Systems

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This work would not have been possible without the hard work of several people! Many thanks to…


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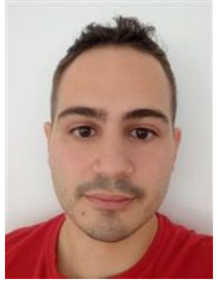
Rahul Nellikkath


Sam Chevalier


Lejla Halilbasic


Elea Prat


Ilgiz Murzakhanov


Petros Ellinas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European Research Council

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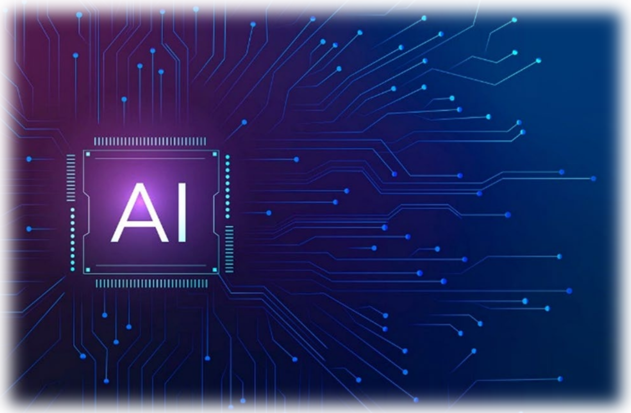
Outline

1. Trustworthy AI for Power Systems

2. Physics Informed Neural Networks

3. Physics-Informed Graph Neural Networks for N-k Contingency Analysis



AI and Energy: two of the Sectors with the highest growth potential

AI is already creating value in Energy Systems

- Load Forecasting
- Weather Forecasting
- Predictive Maintenance
- Energy Trading (forecasting of prices or quantities)

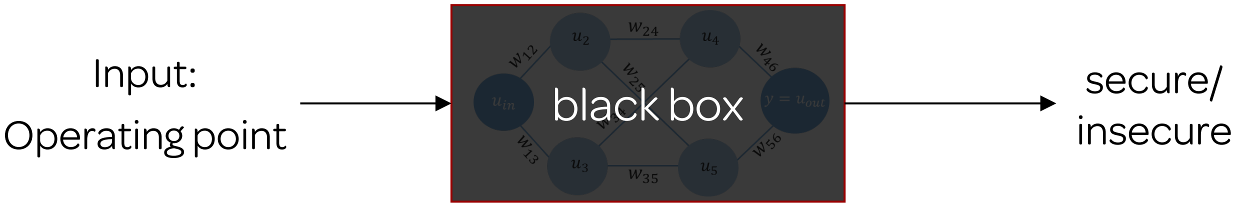
But AI can do a lot more things

1. Process massive amounts of texts (e.g. regulations, manuals, procedures, etc)
2. Virtual assistant: Helping maintenance technicians with step-by-step instructions
3. Support for decision making

And many more

But: Would you ever trust AI to run your electricity network?

Machine Learning (ML) Barriers for Power systems

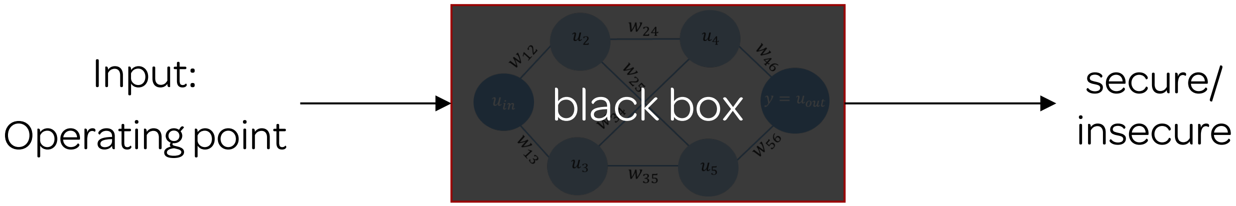


1. Why would we use a "**black box**" to decide about **a safety-critical application**?

2. Neural Networks performance metric is "Accuracy". **Accuracy is** a **purely statistical** performance metric. Who guarantees that the Neural Network can handle well previously unseen operating points?

3. Good AI Tools need good data. Why would we depend on **discrete and incomplete data**, when we have developed **detailed physical models** over the past 100 years?

Machine Learning (ML) Barriers for Power systems



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Trustworthy AI

Neural Network verification: guarantees for the NN performance!

Physics-Informed Neural Networks: potential to deliver tools that are 10x-100x-1000x faster!

Power Systems are Safety-Critical Systems
We need Trustworthy AI

When you design an AI method for power systems, think about:

1. Interpretability, e.g. SHAP
2. Neural Network Verification
3. Physics Informed Neural Networks
4. Safe by Design, e.g. Safe Reinforcement Learning → you enforce constraints on the NN output so that it does not violate physical limits, e.g. generation limits, voltage limits, etc.

SHAP

Examples:

A. Venzke, S. Chatzivasileiadis. Verification of Neural Network Behaviour: Formal Guarantees for Power System Applications. In *IEEE Transactions on Smart Grid*, vol. 12, no. 1, pp. 383-397, Jan. 2021, https://arxiv.org/pdf/1910.01624.pdf

A. Venzke, G. Qu, S. Low, S. Chatzivasileiadis, Learning Optimal Power Flow: Worst-case Guarantees for Neural Networks. **Best Student Paper Award** at IEEE SmartGridComm 2020. https://arxiv.org/pdf/2006.11029.pdf

D. Tabas, B. Zhang, Computationally Efficient Safe Reinforcement Learning for Power Systems, American Control Conference, 2022, https://par.nsf.gov/servlets/purl/10355393

Physics-Informed Neural Networks for Power Systems

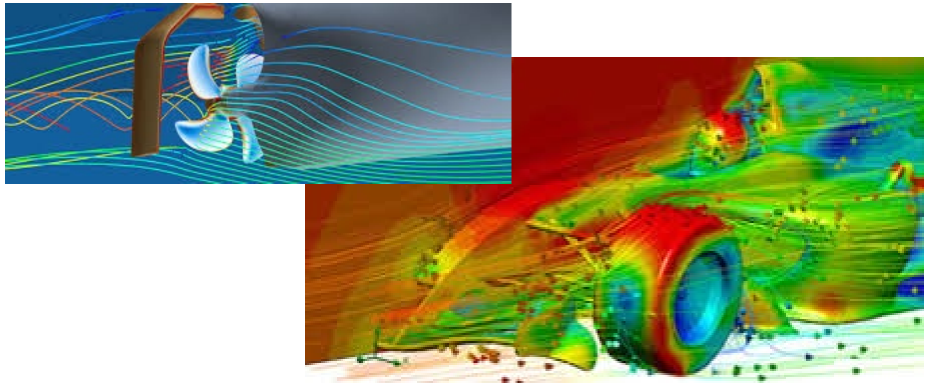
Physics-Informed Neural Networks (PINNs)

- **Why can Neural Networks be faster than conventional simulation tools?**
  – Conventional tools need to run iterative methods to approximate the solution of differential equations
  – For Neural Networks, it is a matrix multiplication (as long as they are accurate enough)

- **What is the benefit of PINNs over standard NNs?**
  – **PINNs do not need large amounts of training data.** They learn from the physical models included in training.
  – No need to spend (a lot of) time on generating data or depend on incomplete data

10x-100x-1'000x faster solution, depending on the application

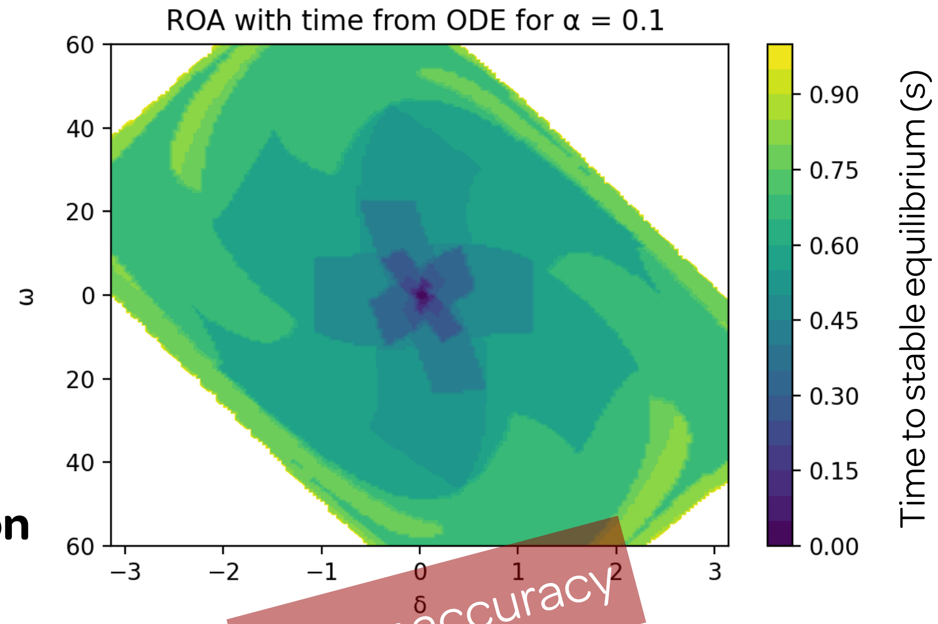
Seem to be achieving significant speedups for partial differential equations (e.g. computational fluid dynamics)



Simulations for Wind Farms:

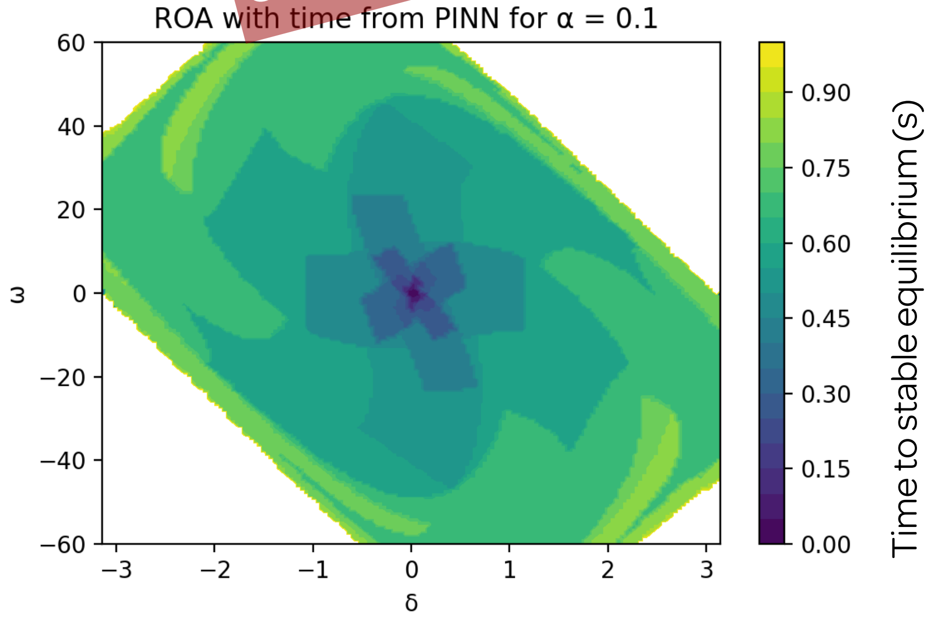
Estimating the Region of Attraction of a Wind Farm Controller

Conven-tional simulation



Similar accuracy

PINN



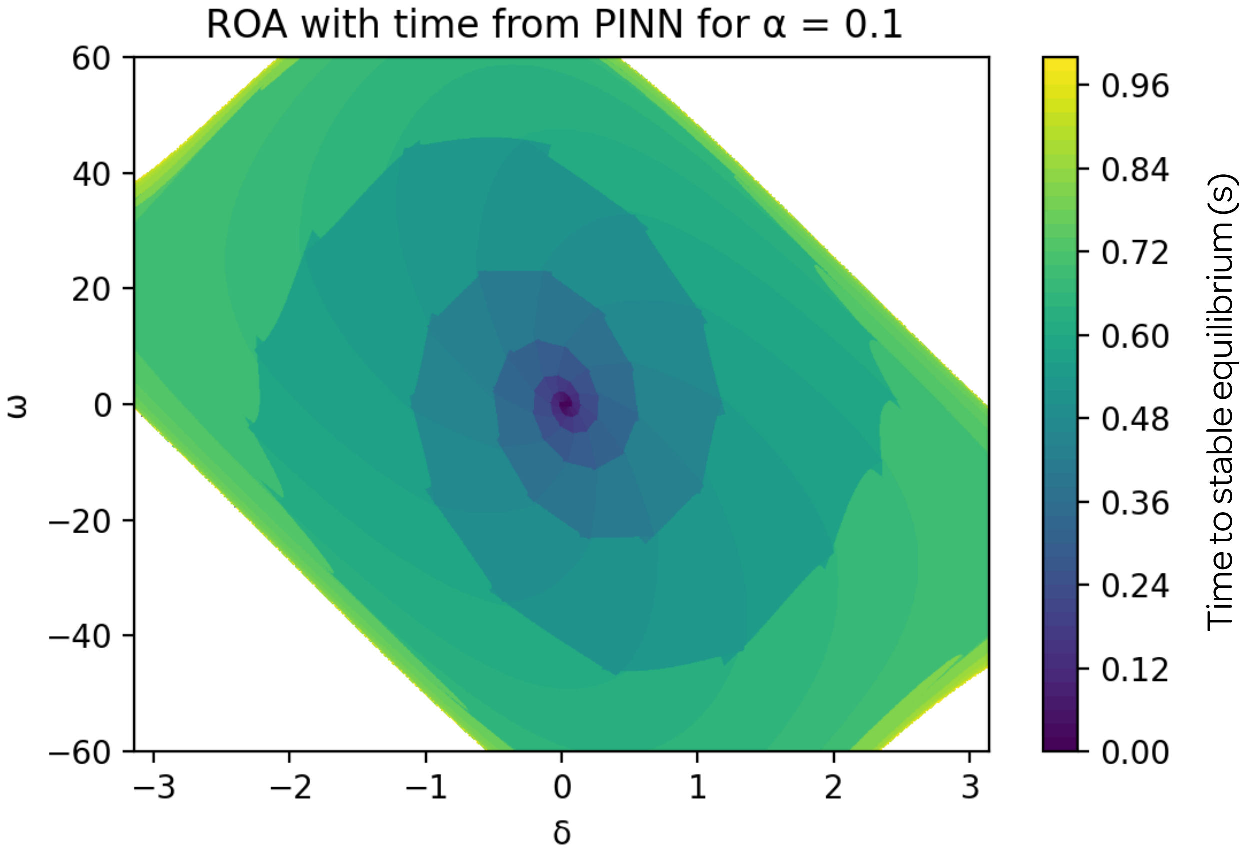
- Collaboration with Ørsted
  - Estimating the region of attraction of controllers is an important part of the wind farm design process
- Goal: Determine the best set of controller parameters (controller tuning)
- Training PINNs with GPUs
  - collaboration with NVIDIA

R. Nellikkath, A. Venzke, M. K. Bakhshizadeh, I. Murzakhanov, S. Chatzivasileiadis, Physics–Informed Neural Networks for Phase Locked Loop Transient Stability Assessment [https://arxiv.org/abs/2303.12116]

Simulations for Wind Farms:

Estimating the Region of Attraction of a Wind Farm Controller

5 million points with PINN



- Evaluation of 5 million points
- EMT: ~2 days @ DTU HPC
- PINNs: 90 minutes for training and 30 minutes for evaluation

25x – 100x faster

- Added benefit: once trained, PINN can run on a laptop

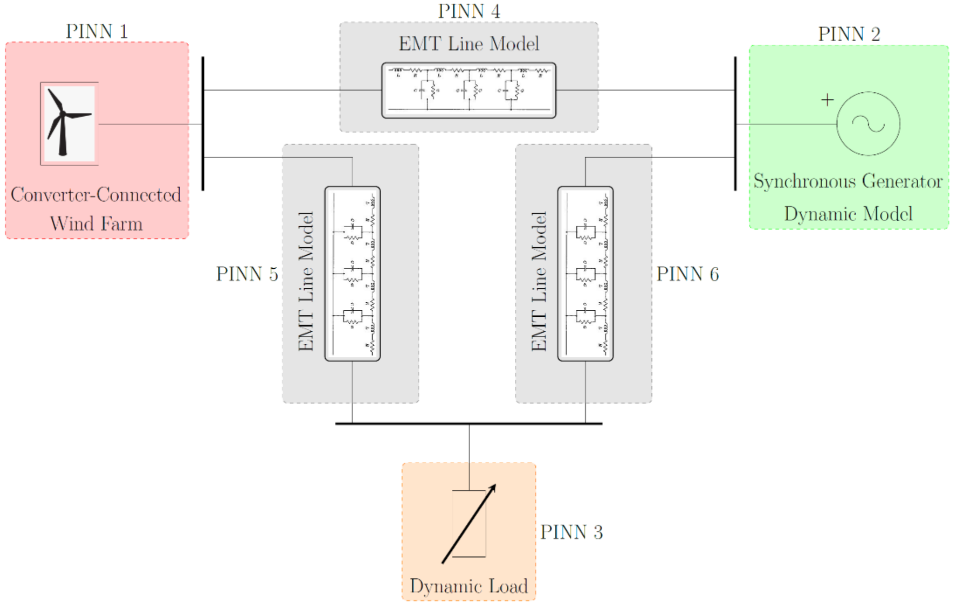
R. Nellikkath, A. Venzke, M. K. Bakhshizadeh, I. Murzakhanov, S. Chatzivasileiadis, Physics-Informed Neural Networks for Phase Locked Loop Transient Stability Assessment [https://arxiv.org/abs/2303.12116]

Physics-Informed Neural Networks for Power Systems: Vision

1. **PINNSim: A modular power system time-domain simulator**
   – A library of component models implemented with Neural Networks
   – "Drag'n'drop" to create your system

2. **Integrate/interface PINNSim with conventional power system simulation tools**

- A completely new way of simulation which can be 10x-100x faster.
  – What does this mean? Instead of assessing 100 scenarios leading to a blackout within 1 hour, I can now assess 10,000 scenarios



Very first version of **PINNSim** simulation engine:

J. Stiasny, B. Zhang, S. Chatzivasileiadis, PINNSim: A Simulator for Power System Dynamics based on Physics-Informed Neural Networks, PSCC 2024. https://arxiv.org/abs/2303.10256

First effort to **integrate PINNs with conventional simulation** solvers:

I. Ventura-Nadal, J. Stiasny, S. Chatzivasileiadis, Integrating Physics-Informed Neural Networks into Power System Dynamic Simulations, https://arxiv.org/pdf/2404.13325

(Physics-Informed) Graph Neural Networks for Fast N-k Contingency Assessment

Agnes Nakiganda, Spyros Chatzivasileiadis, **Graph Neural Networks for Fast Contingency Analysis of Power Systems**, 2025. Online https://arxiv.org/abs/2310.04213

European Research Council
Established by the European Commission

Agnes Nakiganda

Postdoc

Imperial College (formerly with DTU)

Agnes Nakiganda, Spyros Chatzivasileiadis, **Graph Neural Networks for Fast Contingency Analysis of Power Systems**, 2025. Online https://arxiv.org/abs/2310.04213

European Research Council
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What is the goal?

- Train a Graph Neural Network to estimate voltages and line flows of N-k contingencies
- Training only on base topology (N-0) and all N-1 cases
- Estimate line flows and voltages for all N-2 cases and N-3 cases
  - **No N-2 and N-3 cases were used for training**
  - N-2 and N-3 were used only for testing
- Why GNN? Because it captures topology

Why?

TABLE I
CHARACTERISTICS OF THE TEST NETWORKS

Network	6-Bus	24-bus	57-bus	118-bus
Nodes	6	24	57	118
Branches	11	33	63	173
Transformers	0	5	17	13
Generators	2	10	6	53
Loads	3	17	42	99
Eligible N−1 topologies	11	32	62	166
Eligible N−2 topologies	55	505	1'928	14'408
Eligible N−3 topologies	165	4'885	37'765	793'206

- 118-bus → >700'000 N-3 contingencies *for a single generation and demand scenario*
- Assume 19 generators with a high and low generation scenario
- Assume a high and a low demand profile (all loads vary uniformly)
- Total: 1,000,000 scenarios x 700,000 contingencies → we need to assess over 700 billion scenarios…!

What will we talk about?

- **2 Different Graph-Aware Neural Networks**
  - Guided Droupout
  - Edge-Varying Graph Neural Network
- **With and without a Physics-Informed** Loss Term and equations
  - The first to define and investigate a Physics-Informed Guided Dropout Neural Network
  - Among the first to work with Physics-Informed Graph Neural Networks

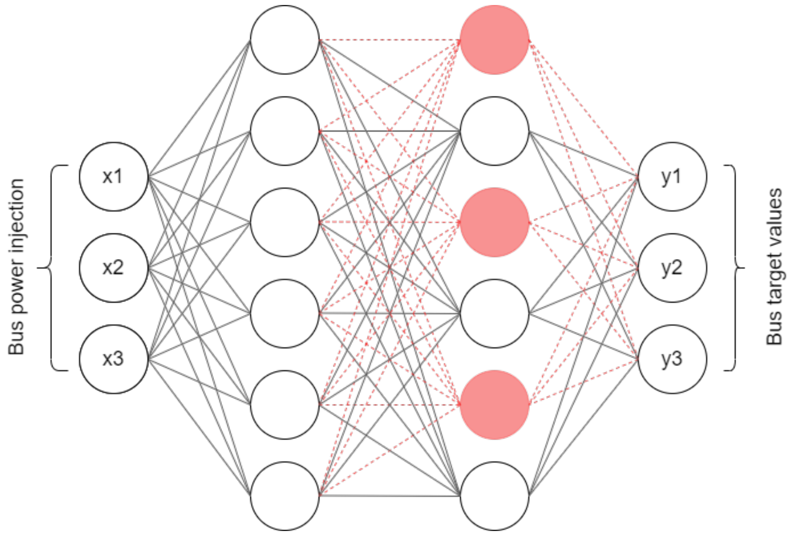
1. Investigate the performance of **4 different Graph-Aware Neural Networks**
   1. **Guided Dropout** without Physics-Informed
   2. **Guided Dropout** with Physics-Informed
   3. Edge-Varying **Graph Neural Network** without Physics-Informed
   4. Edge-Varying **Graph Neural Network** with Physics Informed
2. **Compare** their performance with **DC Power Flow** which is considered a standard tool to assess fast N-k contingencies
3. **Assess** their performance in terms of **time**

Guided-Dropout Neural Network

Ref: B. Donnot, I. Guyon, M. Schoenauer, A. Marot, and P. Panciatici, "Fast power system security analysis with Guided dropout," 2018

Base Case N-0

Conditional Neurons are out



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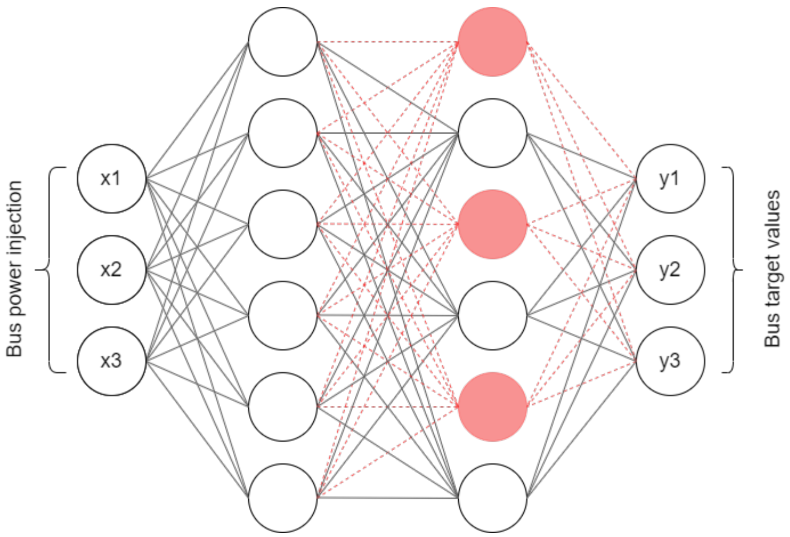
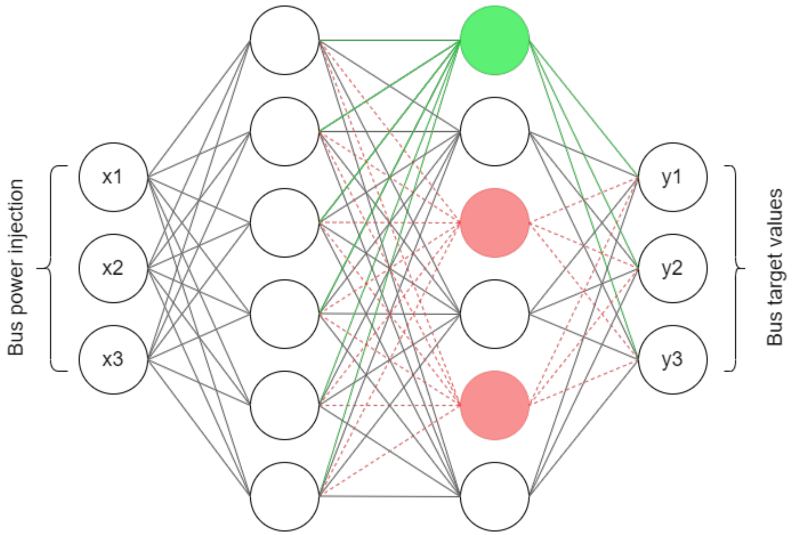


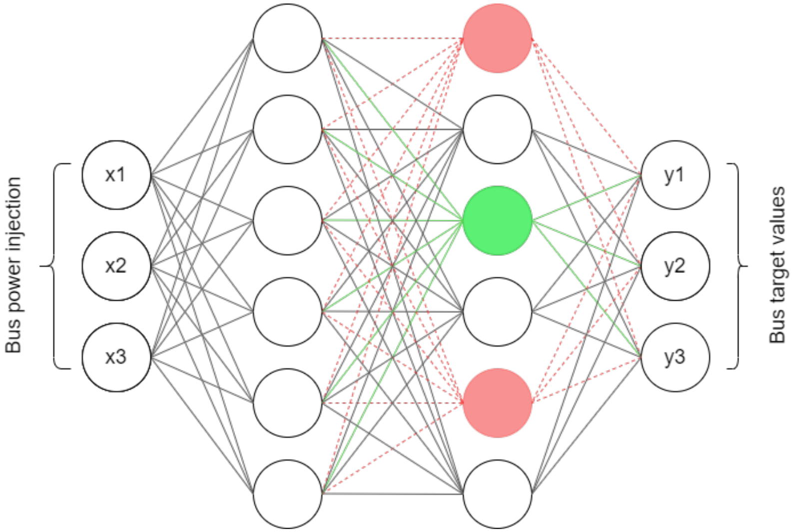
N-1; Line 1 out

Conditional Neuron 1 is <u>in</u>



N-1; Line 2 out

Conditional Neuron 2 is <u>in</u>



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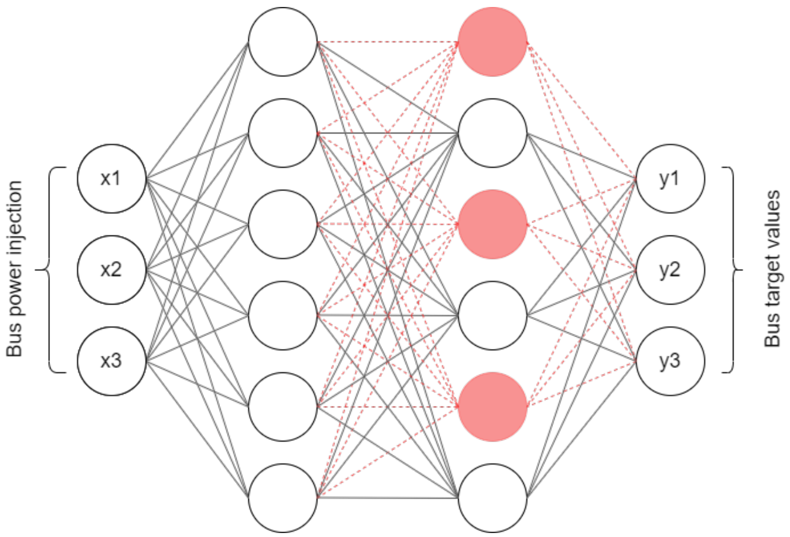

N-1; Line 1 out

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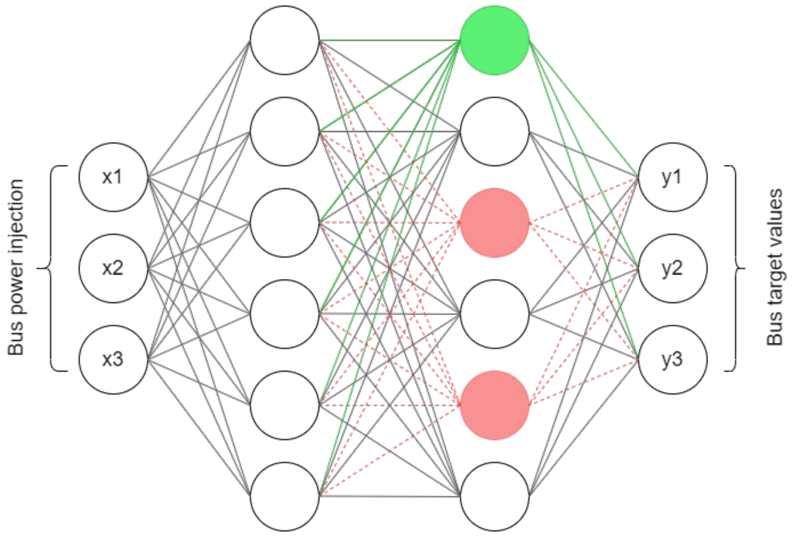
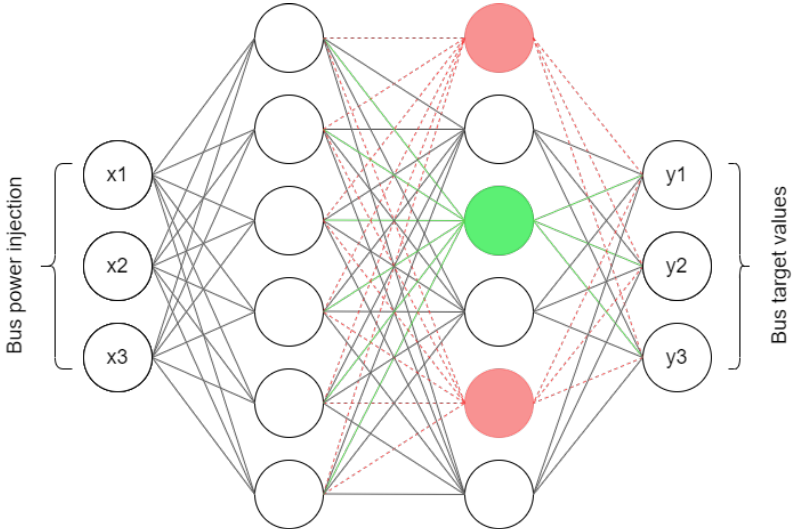


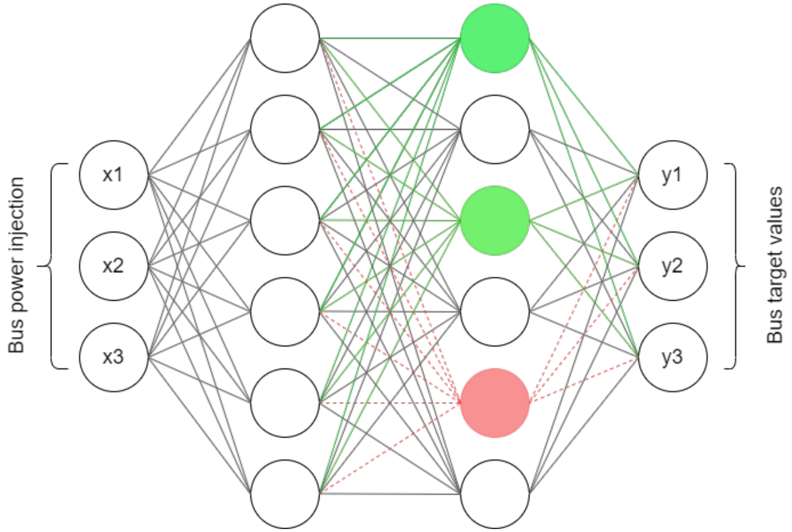
N-1; Line 2 out

Conditional Neuron 2 is <u>in</u>



N-2; Lines 1 and 2 are out

Conditional Neurons 1 and 2 are <u>in</u>



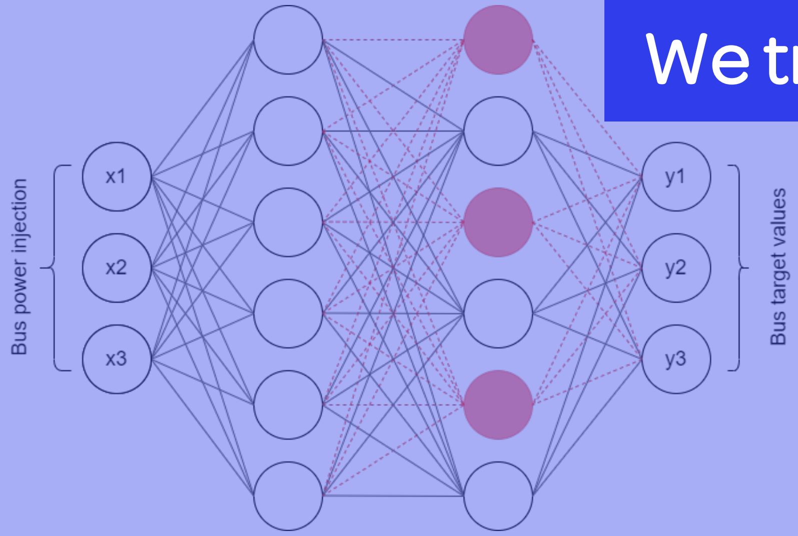
Guided-Dropout Neural Network

Ref: B. Donnot, I. Guyon, M. Schoenauer, A. Marot, and P. Panciatici, "Fast power system security analysis with Guided dropout," 2018

We train for this

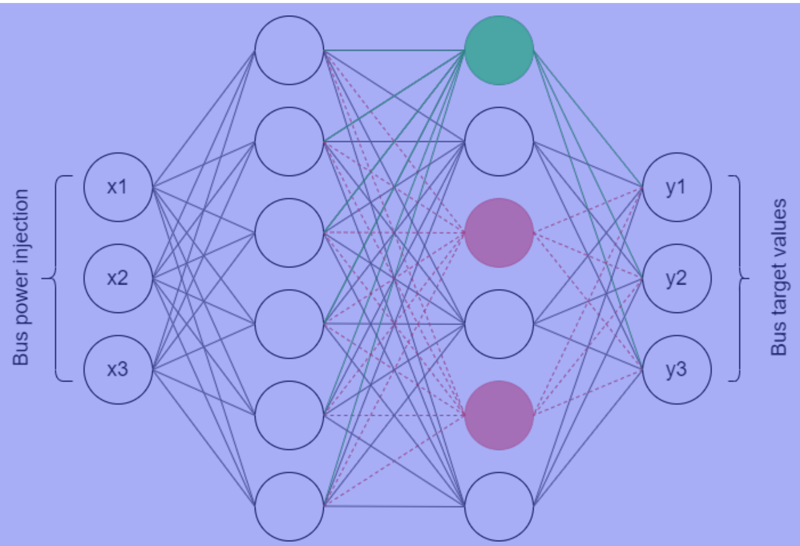
Base Case N-0

Conditional Neurons are <u>out</u>



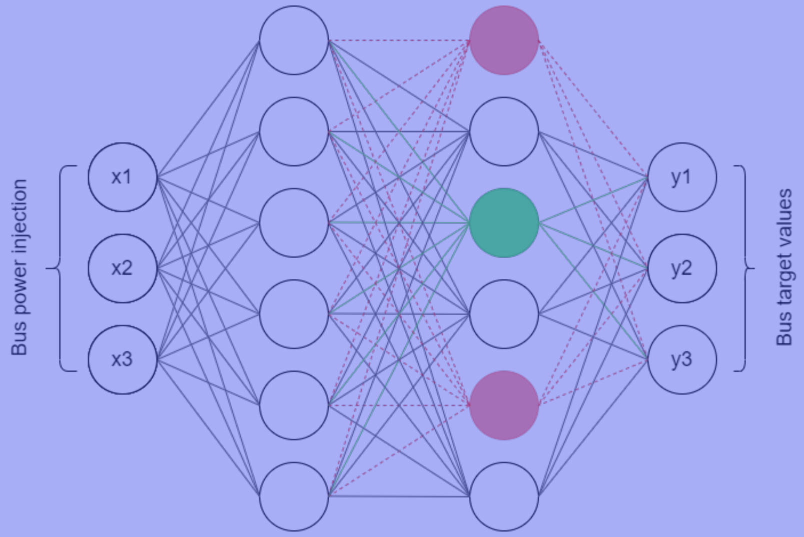
N-1; Line 1 out

Conditional Neuron 1 is <u>in</u>



N-1; Line 2 out

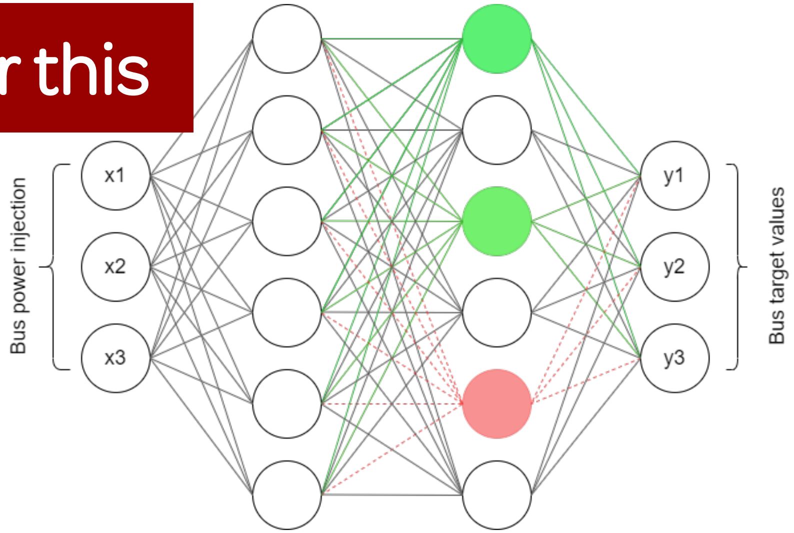
Conditional Neuron 2 is <u>in</u>



We test for this

N-2; Lines 1 and 2 are out

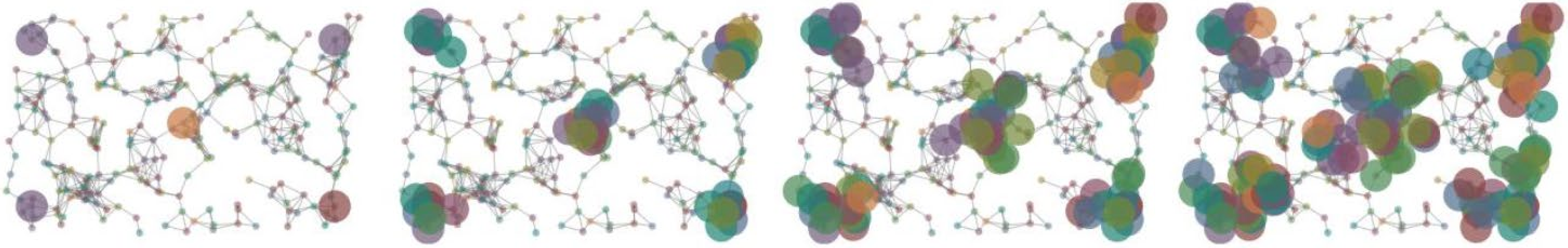
Conditional Neurons 1 and 2 are <u>in</u>

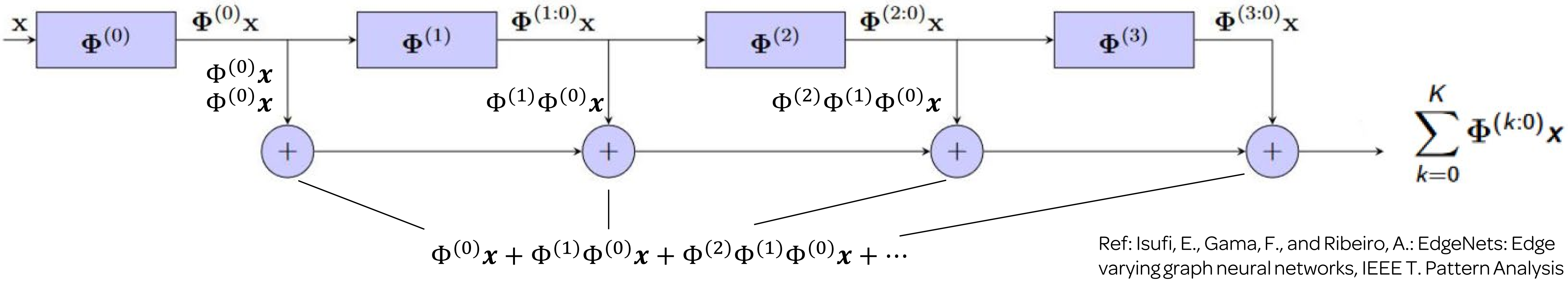


Graph Neural Networks

- $\Phi^{(k)}$ encodes the NN weights based on the graph adjacency matrix → Neurons are connected based on the topology of the network

As we increase the hops, we widen the neighborhood that influences a specific node



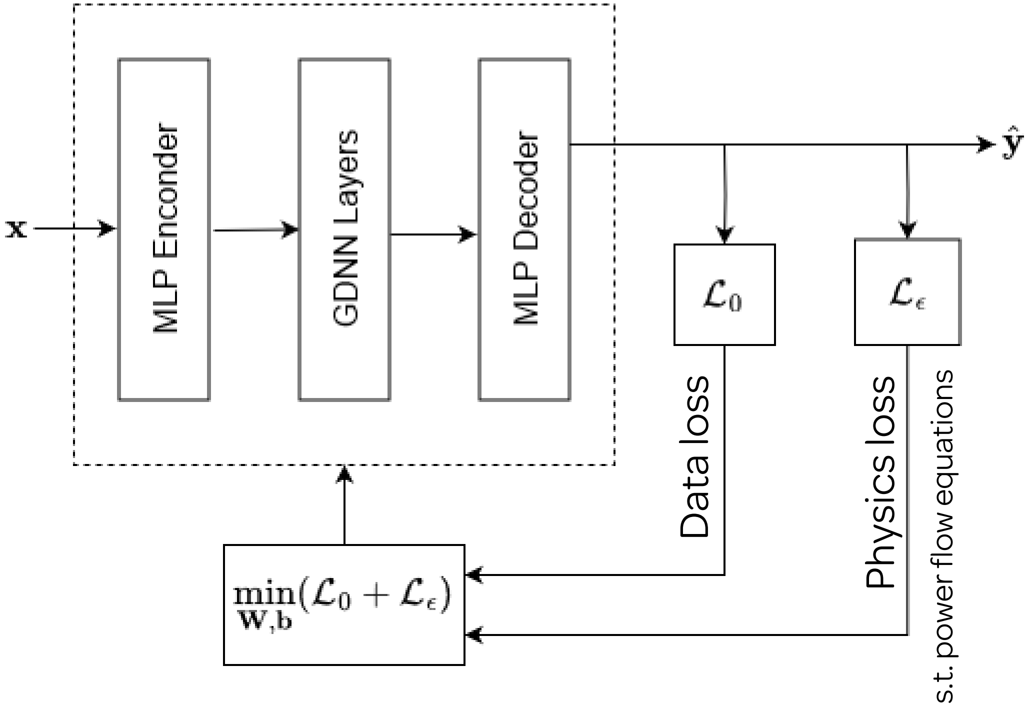


Ref: Isufi, E., Gama, F., and Ribeiro, A.: EdgeNets: Edge varying graph neural networks, IEEE T. Pattern Analysis

Physics Informed Graph-Aware Neural Networks

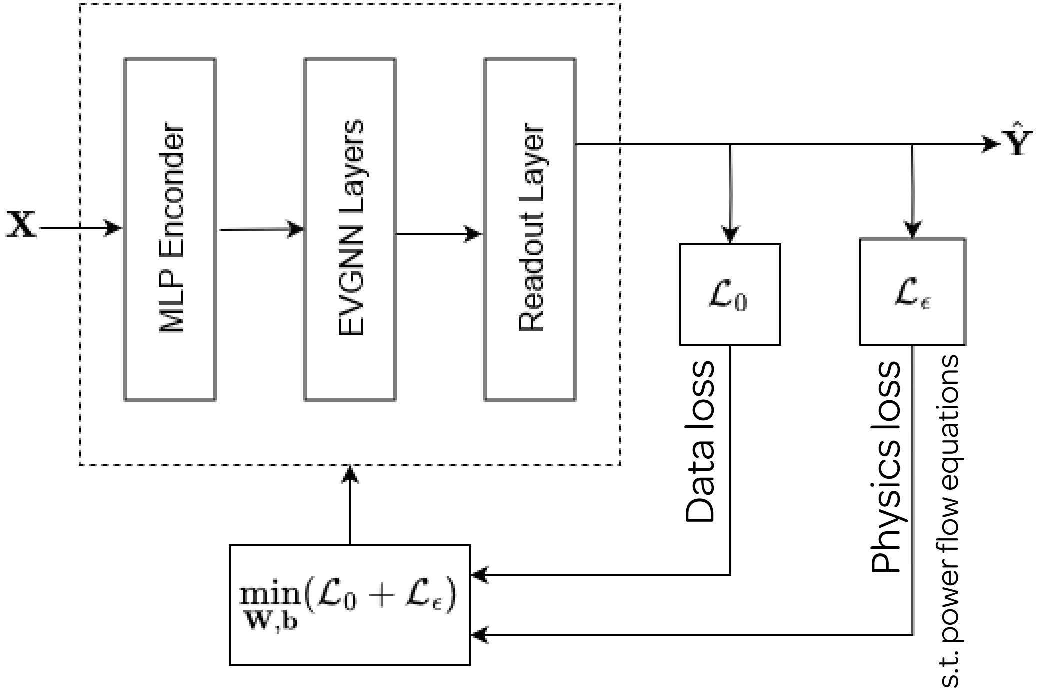
PI-GDNN

Physics-Informed Guided Dropout



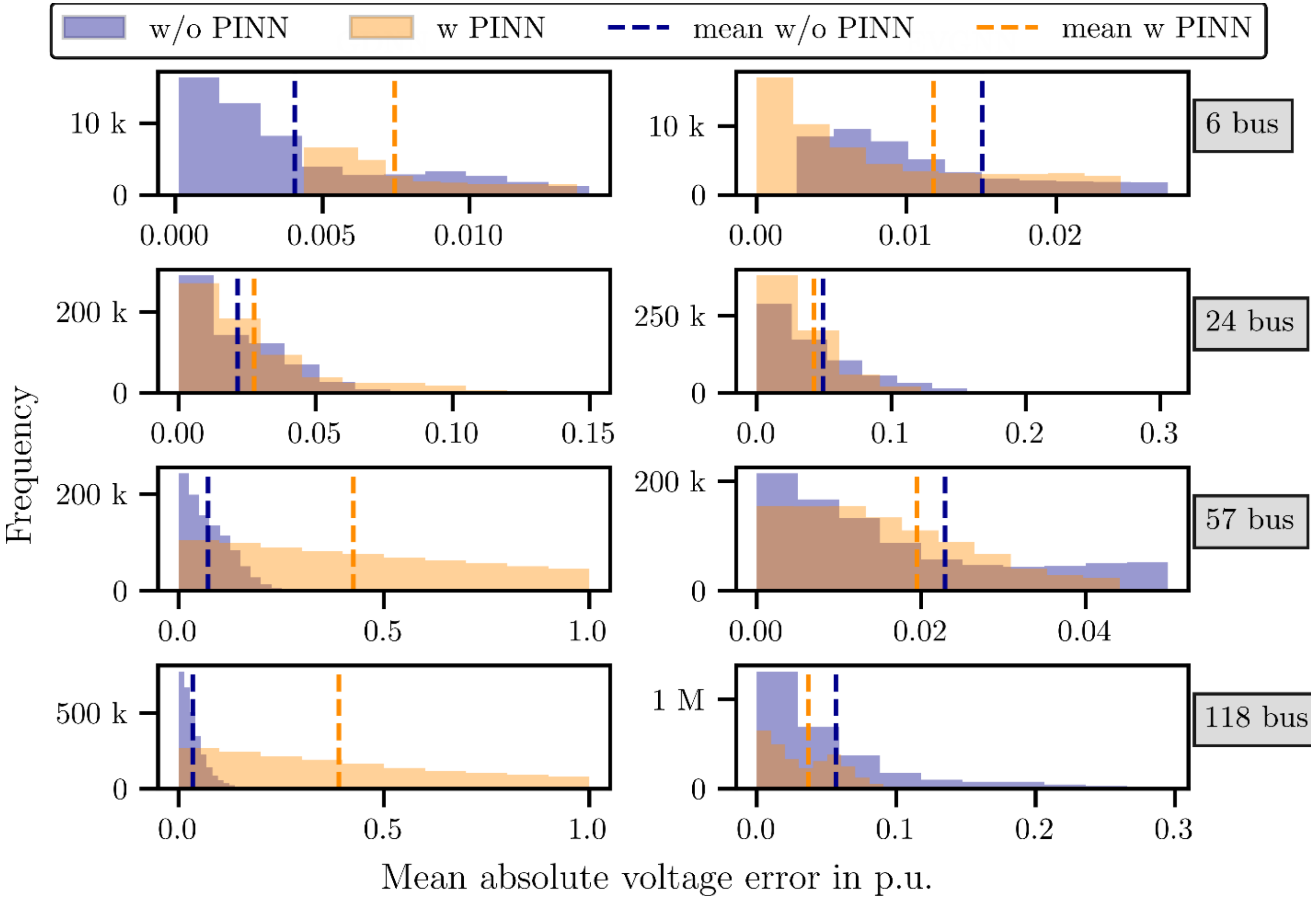
PI-EVGNN

Physics-Informed Graph Neural Network



Physics-Informed NNs do not always perform better

Guided Dropout | Graph Neural Networks

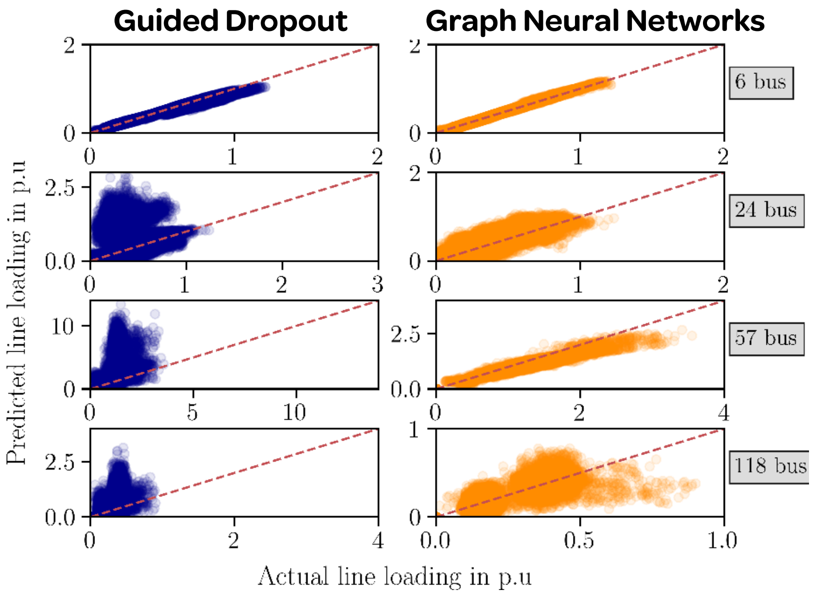


PINNs vs non-PINNs

- **Physics-Informed Graph Neural Networks perform better** than non-Physics-Informed
- **Non-Physics-Informed Guided Dropout perform better** than Physics-Informed Guided Dropout
- For the rest of our comparisons, we limit ourselves to 2 models:
  - GDNN
  - PI-EVGNN

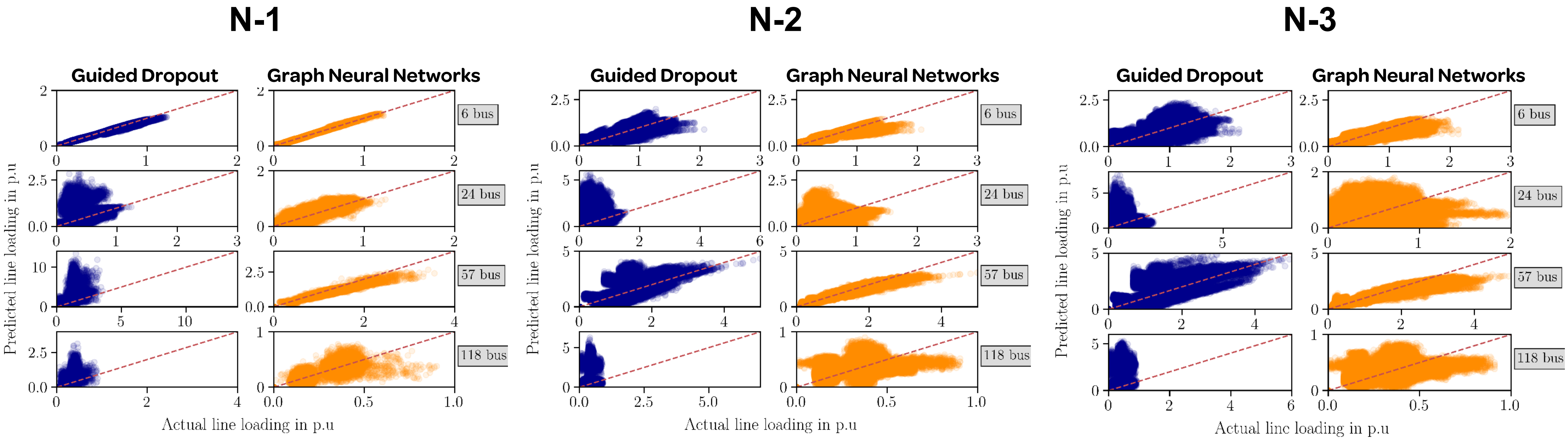
GNNs for Regression: Estimating the line flows

N-1



GNNs for Regression: Estimating the line flows

No training on N-2 and N-3, only testing!

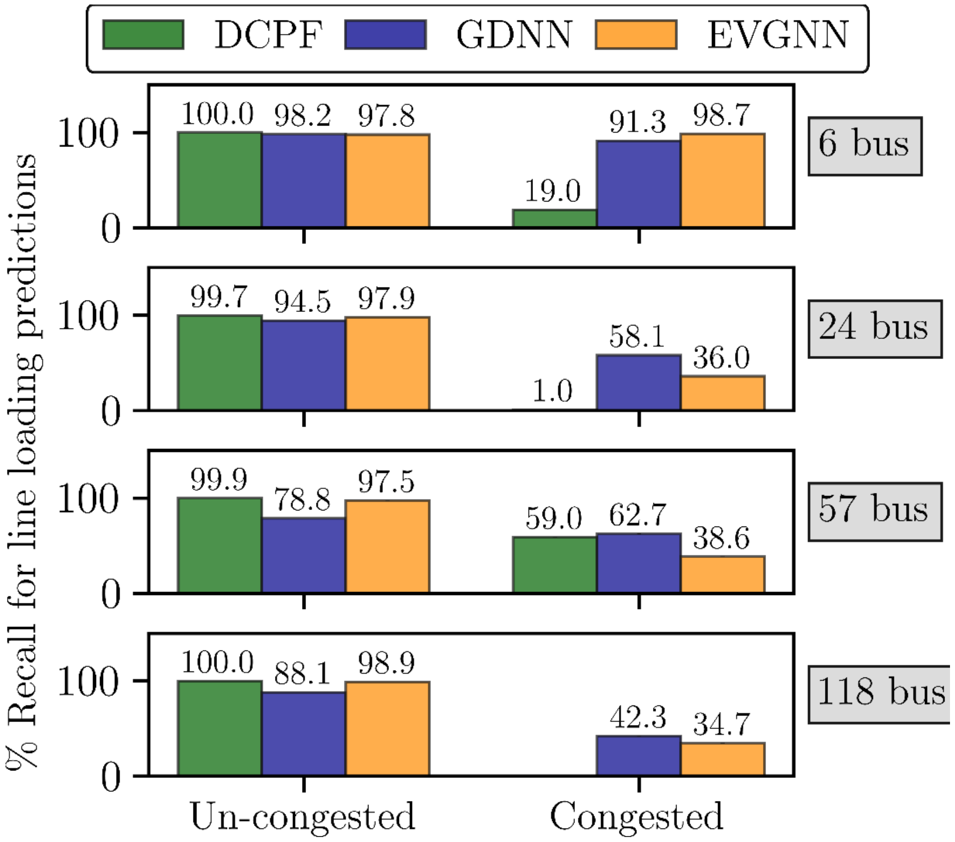


- Estimating the bus voltages had in general a **better** performance from the line flows

More info here: Agnes Nakiganda, Spyros Chatzivasileiadis, **Graph Neural Networks for Fast Contingency Analysis of Power Systems**, 2025.
Online https://arxiv.org/abs/2310.04213

GNNs vs DC Power Flow: Estimating Line Overloadings

N-1

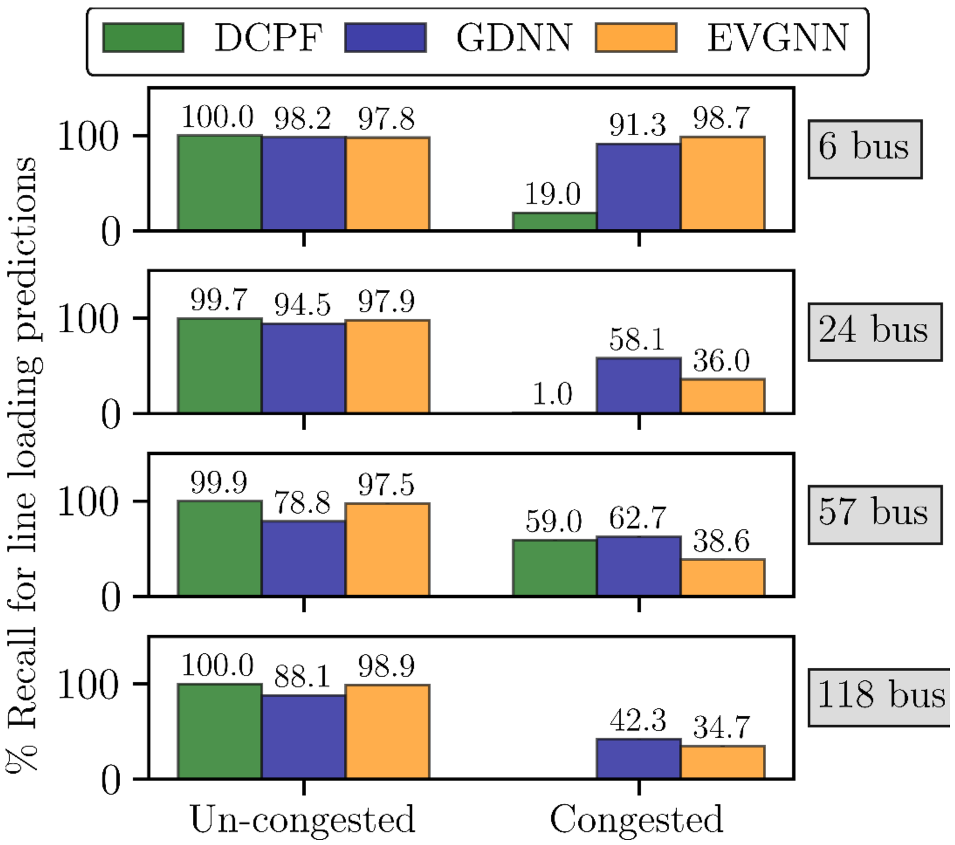


Metric: Recall (True Positive Rate) ; Recall=100%: NN has classified correctly all data points belonging to a class

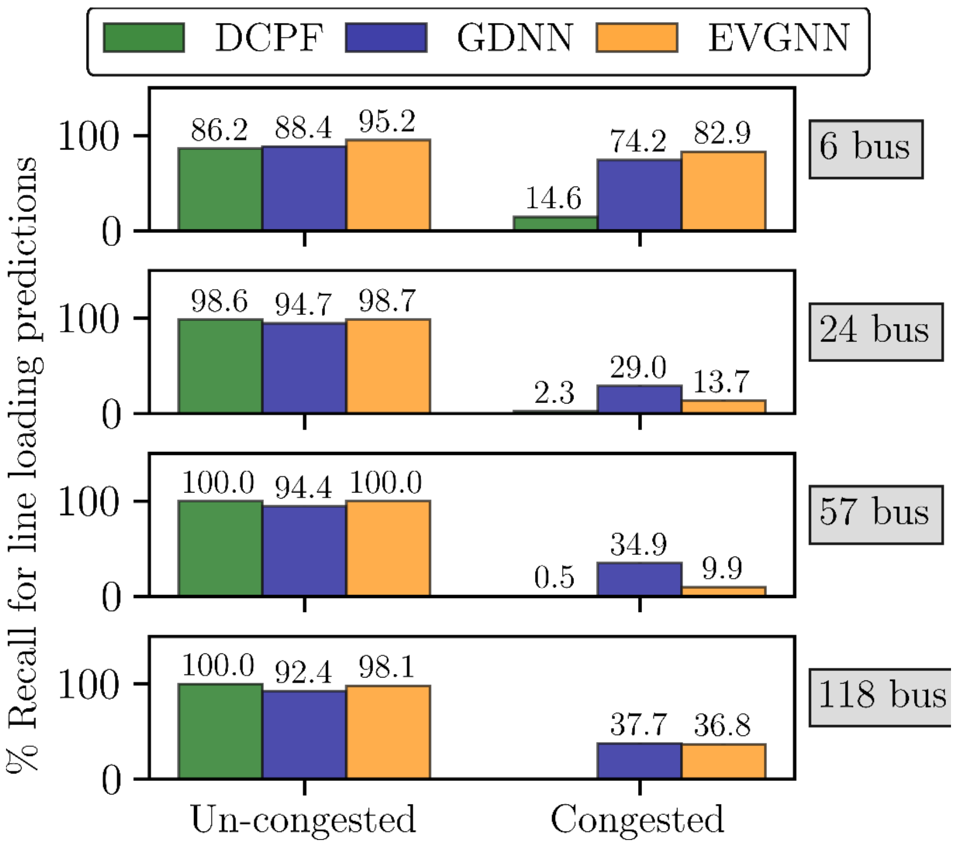
GNNs vs DC Power Flow: Estimating Line Overloadings

No training on N-2 and N-3, only testing!

N-1



N-3

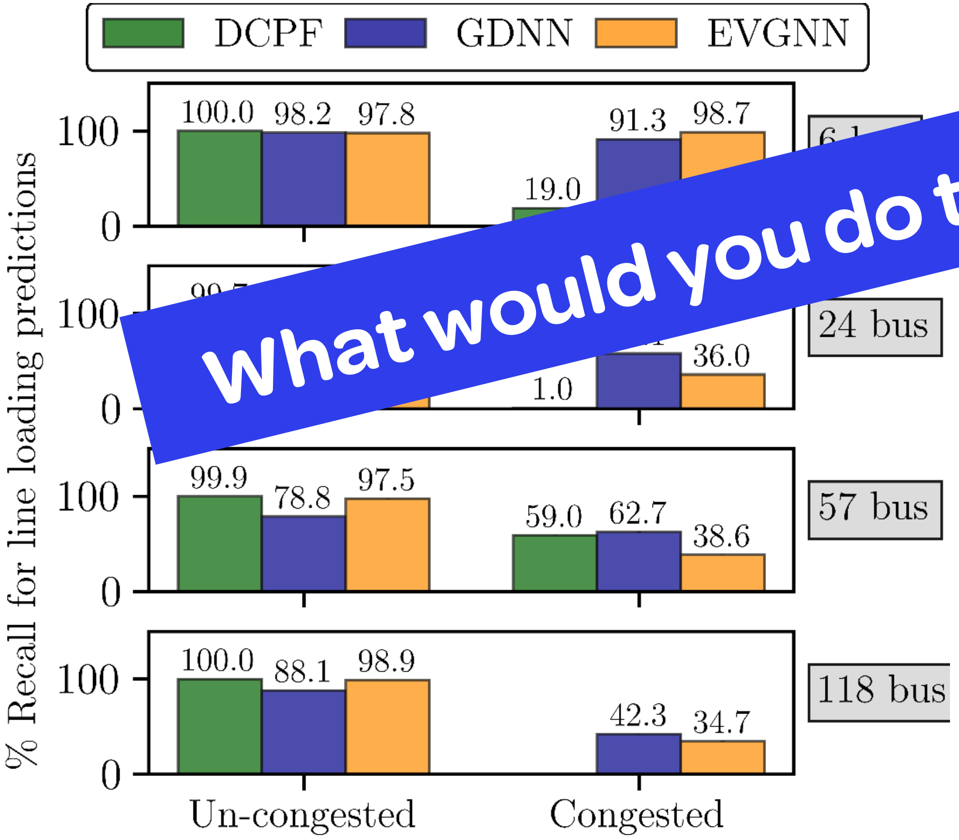


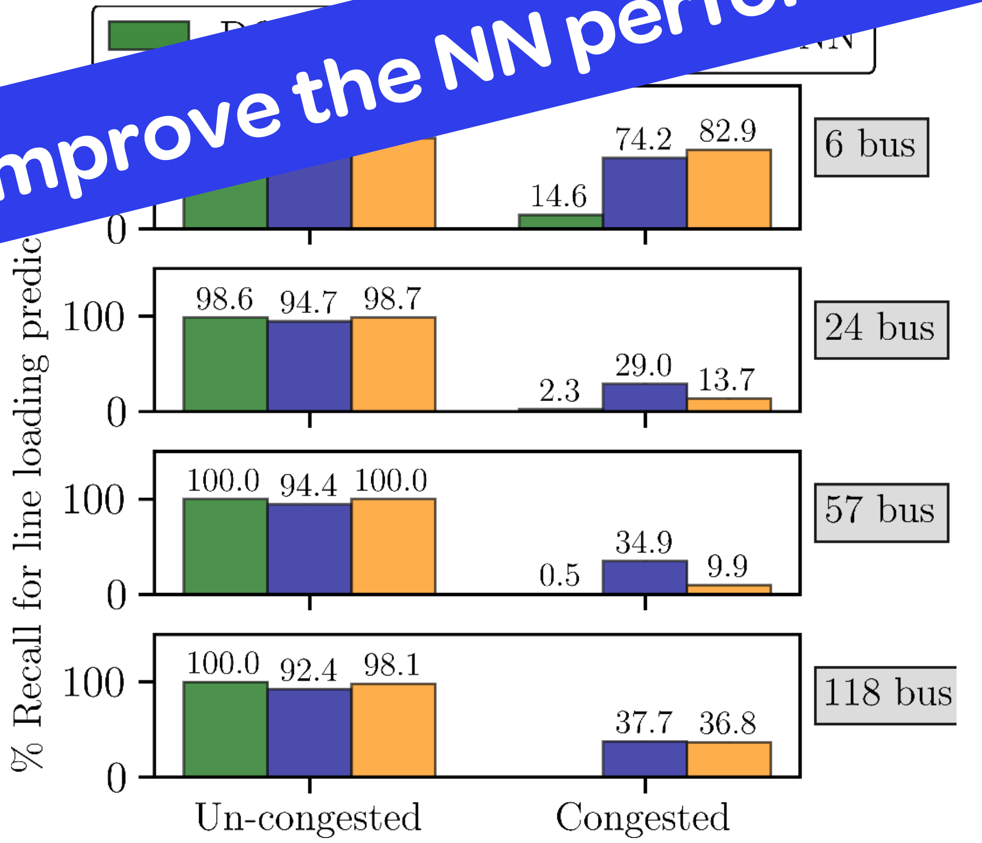
- DC Power Flow performs the worst: cannot estimate any line congestion
- Both Guided Dropout and Graph NN perform better, but not much better

Metric: Recall (True Positive Rate) ; Recall=100%: NN has classified correctly all data points belonging to a class

No training on N-2 and N-3, only testing!

What would you do to improve the NN performance?





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Metric: Recall (True Positive Rate) ; Recall=100%: NN has classified correctly all data points belonging to a class

What would you do to improve the NN performance?

- We need better databases!
- And better methods to generate these databases fast and with information-rich content!
- Some first efforts from our side:

F. Thams, A. Venzke, R. Eriksson, S. Chatzivasileiadis. Efficient Database Generation for Data-Driven Security Assessment of Power Systems. *IEEE Transactions on Power Systems*, vol 35, no. 1, pp. 30-41, Jan. 2020 [.pdf | Databases | IEEEXplore]

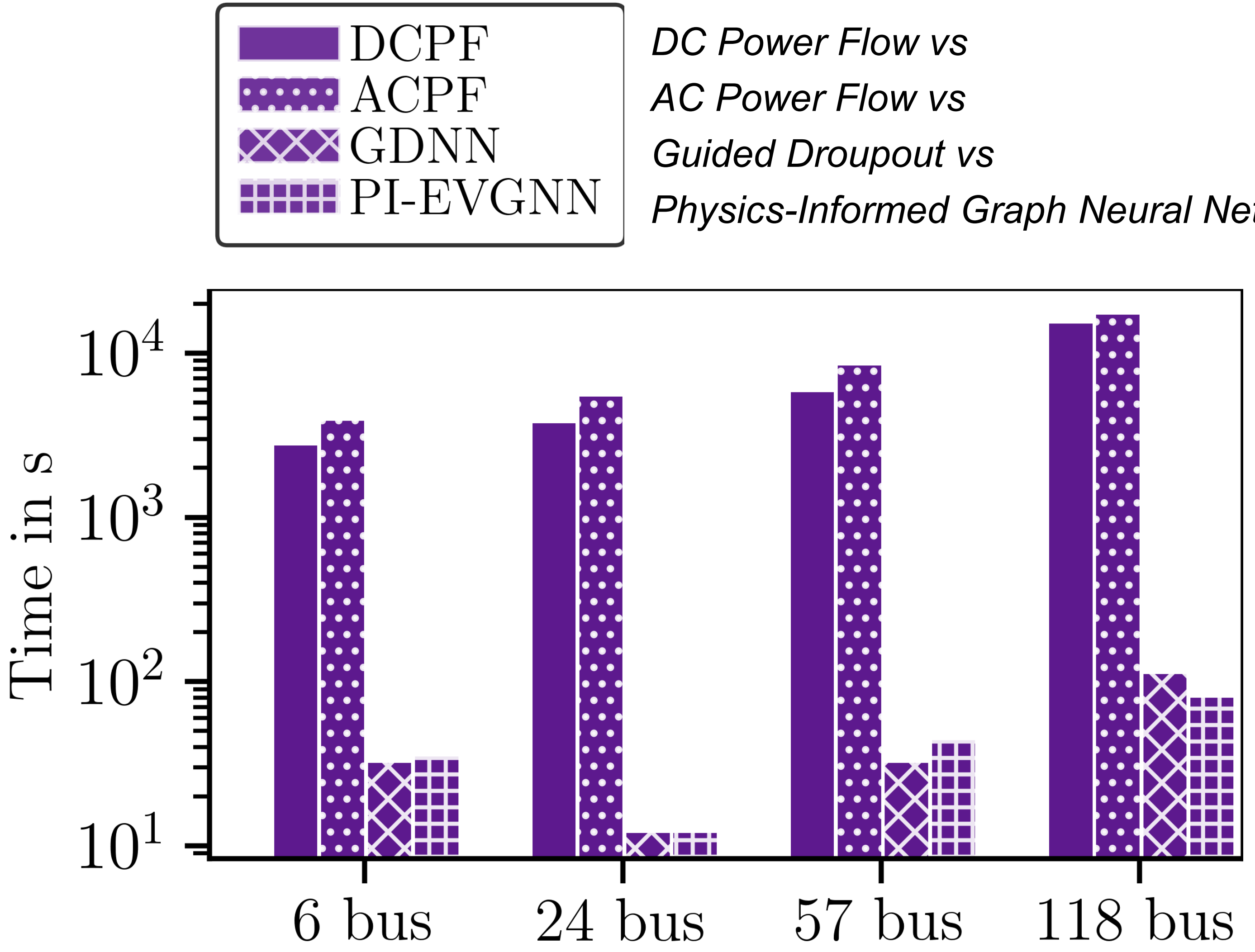
Bastien Giraud, Lola Charles, Agnes Marjorie Nakiganda, Johanna Vorwerk, Spyros Chatzivasileiadis, A Dataset Generation Toolbox for Dynamic Security Assessment: On the Role of the Security Boundary, IREP 2025, https://arxiv.org/abs/2501.09513

Open-source toolbox!

Which method you think is the fastest ?

Evaluation time

DC Power Flow vs
AC Power Flow vs
Guided Droupout vs
Physics-Informed Graph Neural Network



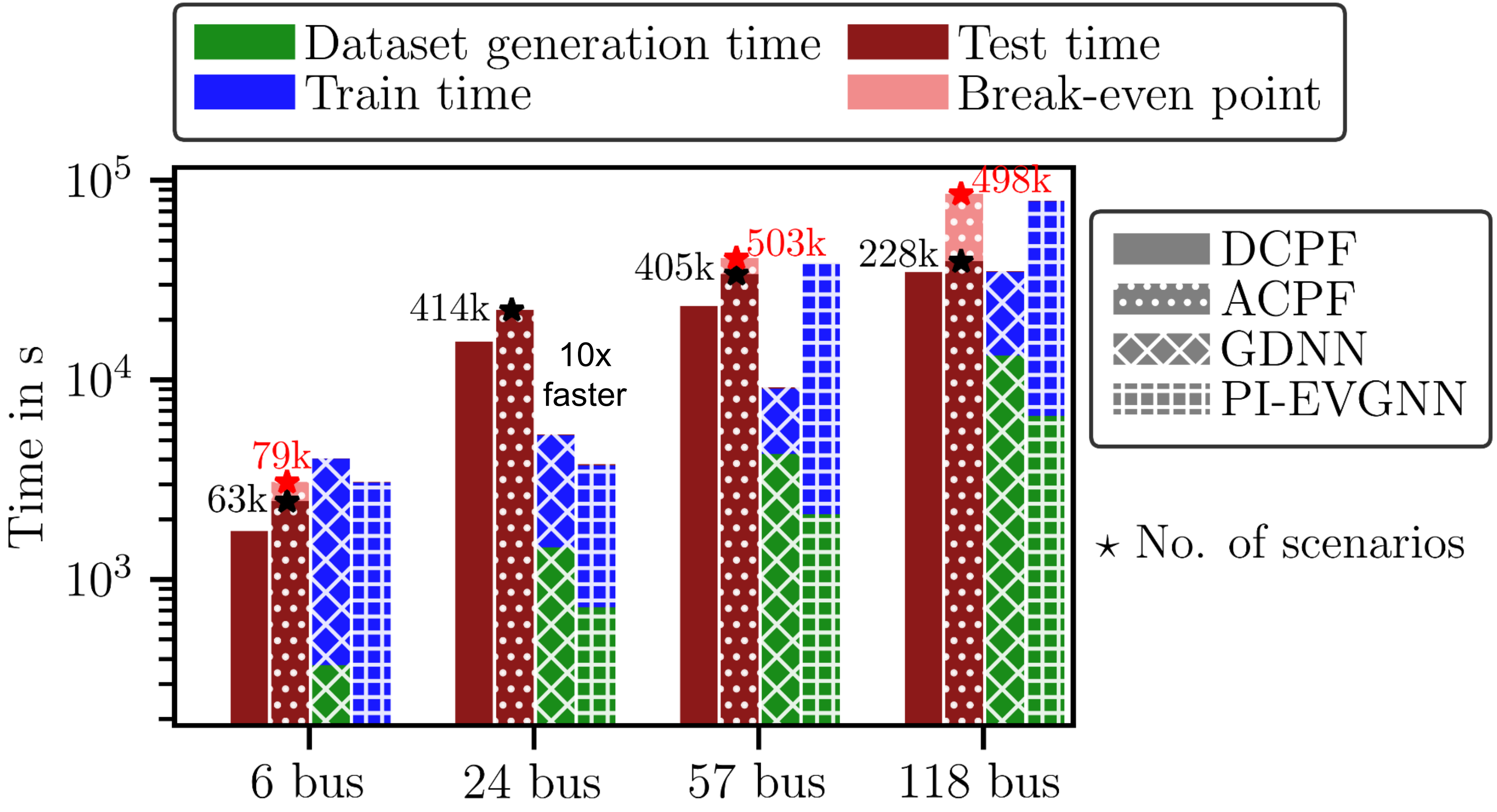
- Logarithmic Axis!

Neural Networks
100-400 times faster
than AC and DC
Power Flow

- NNs need **1.5 minutes** to assess 100,000 scenarios
- AC/DC Power Flow need **5 hours** to assess 100,000 scenarios

What happens if we include the training time?

Computation Time including NN training



- **Logarithmic Axis!! Bar length not proportional to time**
- For the larger systems, it appears that the break-even point is at approx. 500,000 scenarios
  - For more than 500,000 scenarios the NNs are faster
- Considering that we talked about 700 billion scenarios (118-bus, N-3 cases), then NNs appear very promising for screening

Conclusions

- Power systems need Trustworthy AI!

- Graph-Aware Neural Networks are a promising option to screen a vast number of N-k contingences (hundreds of millions)
  - Can capture topology changes
  - Can be 100x-400x faster in their evaluation (1.5 minutes instead of 5 hours for 100,000 scenarios)
  - Much better performance than DC Power Flow

- Including training time, the break-even point with conventional methods appears to be at over 500,000 scenarios (57-bus, 118-bus)
  - Considering that a moderate assessment of N-3 contingencies in the 118-bus system might require 700 billion scenarios, the break-even point is low

- **But:** The screening performance still needs to be improved. A lot of R&D potential in:
  - Efficient and information-rich database generation for NN training
  - Improved NN training, e.g. design of input and output vectors, NN structures
  - Inclusion of Physics-informed terms or not

Thank you!

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