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US National Academy of Engineering
European Council of Academies of Applied Sciences, Technologies, & Engineering

Trustworthy AI to Remove Barriers for Machine Learning in Power Systems

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Digital Transformation of the Energy Sector

- Millions of new controllable devices (e.g. converters)
- Thousands of new injection points
- Millions of sensors

How can we manage the grid?

And what to do with all the data?

AI can help.

- IEA: digitalization can help to lower maintenance costs of electricity grids by 5% = **80 billion EUR**

- Strong interest by System Operators

Strong interest by Electric Power System Operators

- **Machine Learning for (short-term) Load Forecasting**
  - ANNSTLF (EPRI, 1990s) and other tools
- **Machine Learning for detecting anomalies and predictive maintenance**
  - Detect or predict failures in transformers, transmission lines, etc.
- **Learning to run a power network (initial development/concept phase)**
  - RTE (France) and others
  - Vision: Neural Networks to manage the power grid in real-time → similar to self-driving cars

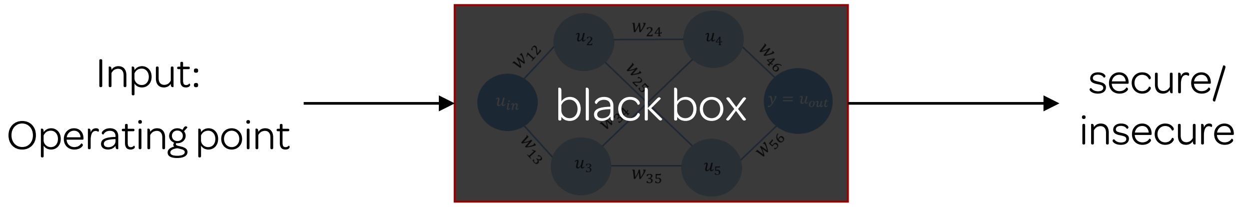
Neural Networks for Power System Resilience

1. **Extremely fast → can assess 100x-1'000x more of critical scenarios**
   - computation within only a **few milliseconds** (100x – 1000x faster than conventional methods)
     - Predict fast and act faster → drastically increase power system resilience

2. Good alternative if we do not have full knowledge of the actual system
   - Handle **very complex systems**
   - **Infer** from incomplete data

But: Would an Operator ever trust AI in the Control Room?

ML Barriers for Power systems

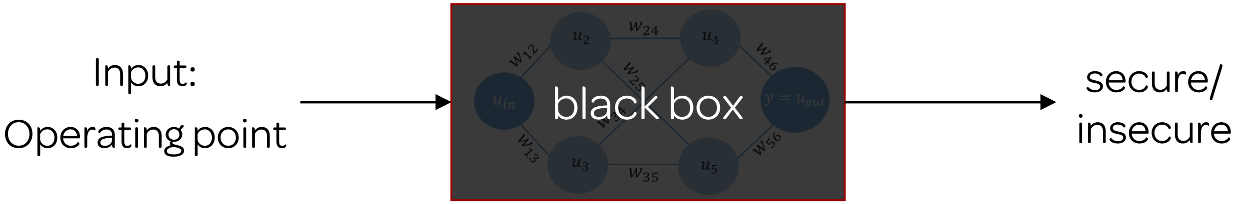


1. Why would we use a "**black box**" to decide about **a safety-critical application**?

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

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

ML Barriers for Power systems



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Neural Network verification: guarantees for the NN performance!

Integrate the physical models in NN verification

→ **worst-case guarantees** for regression NNs

Neural Network Verification

for Power Systems

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

V. Tjeng, K. Y. Xiao, and R. Tedrake, "Evaluating robustness of neural networks with mixed integer programming," in International Conference on Learning Representations (ICLR 2019), 2019

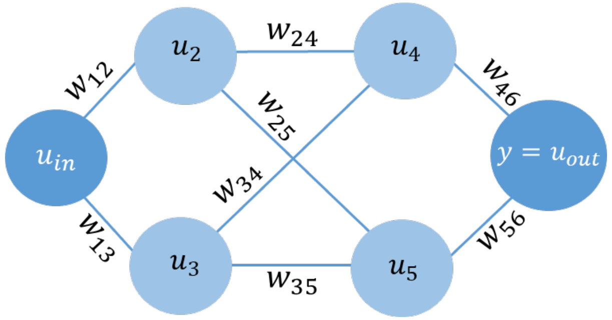
Guiding Application:
Security Assessment with Neural Networks

Approaches proposed up to now

Database of secure/insecure operating points

Any combination of **static/dynamic security** criteria
(e.g. N-1 & Small-signal stability)

1. Split the database in a training set and a test set



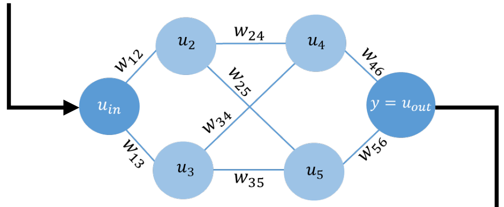
2. Train a neural network

3. Test the neural network

4. Is accuracy high enough?

5. Use the NN

Input:
Operating point



secure/
insecure

NN Output:

Binary classification:
secure/insecure

Extremely fast: up to 100x-1'000x faster

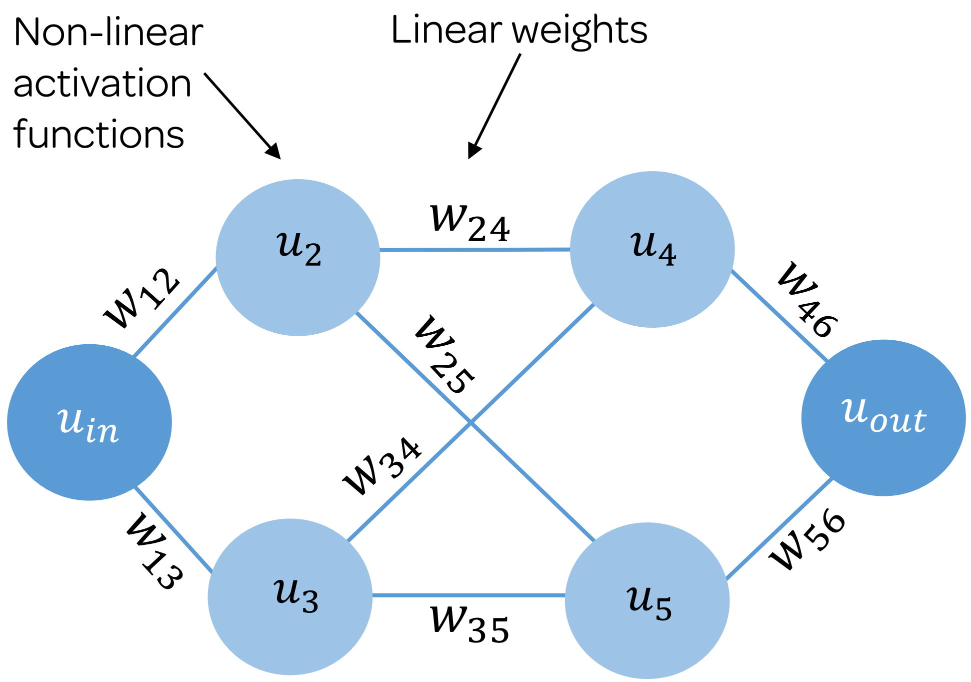
Neural Network Verification: HOW?

1. **Exact transformation:** Convert the neural network to a **set of linear equations with binaries**
   - The Neural Network can be included in a mixed-integer linear program

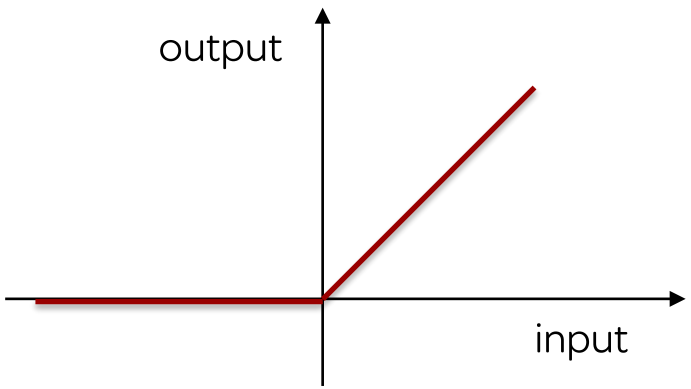
2. Formulate an **optimization** problem (MILP) and solve it → certificate for NN behavior

3. Assess if the neural network output complies with the ground truth

From Neural Networks to Mixed-Integer Linear Programming



- Most usual activation function: ReLU
- **ReLU:** Rectifier Linear Unit



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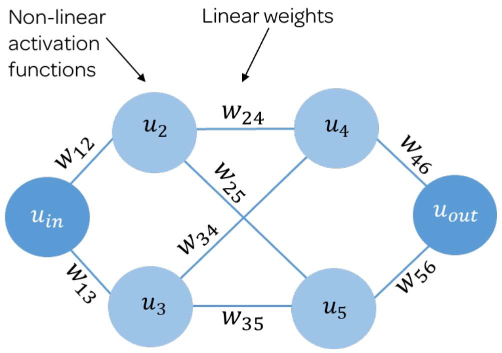
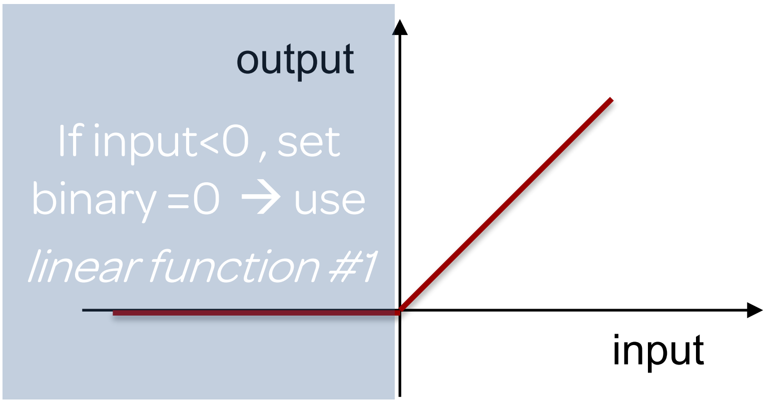
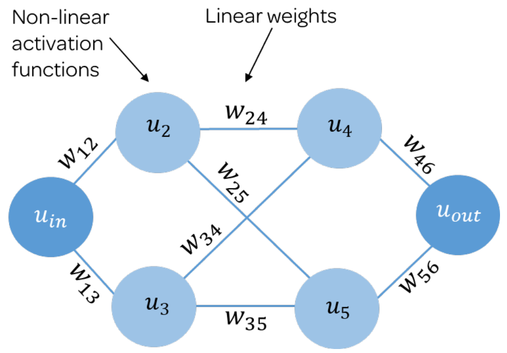


1. But **ReLU** can be transformed to a **piecewise linear function with binaries**



From Neural Networks to Mixed-Integer Linear Programming



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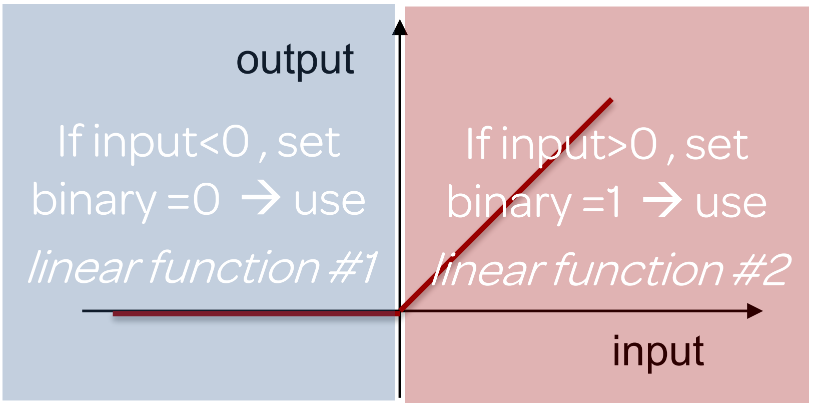

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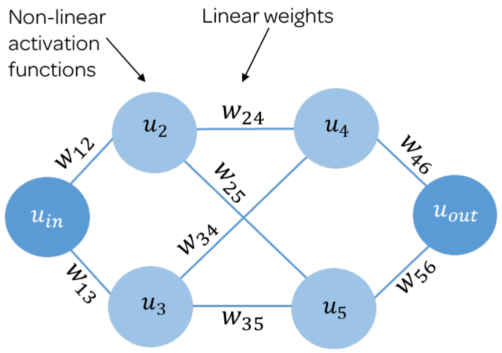

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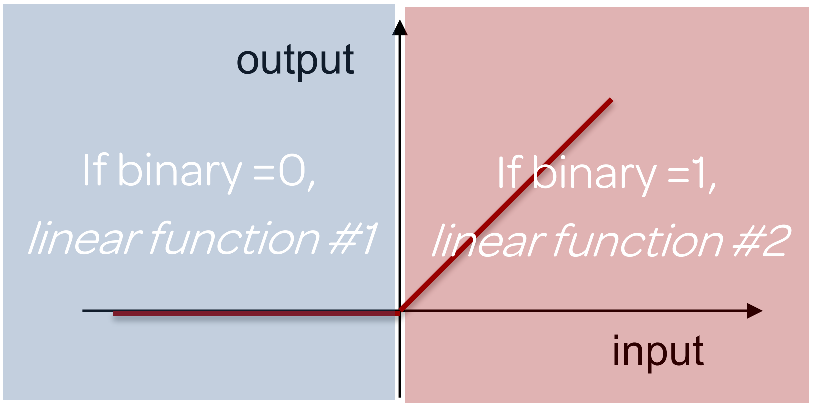
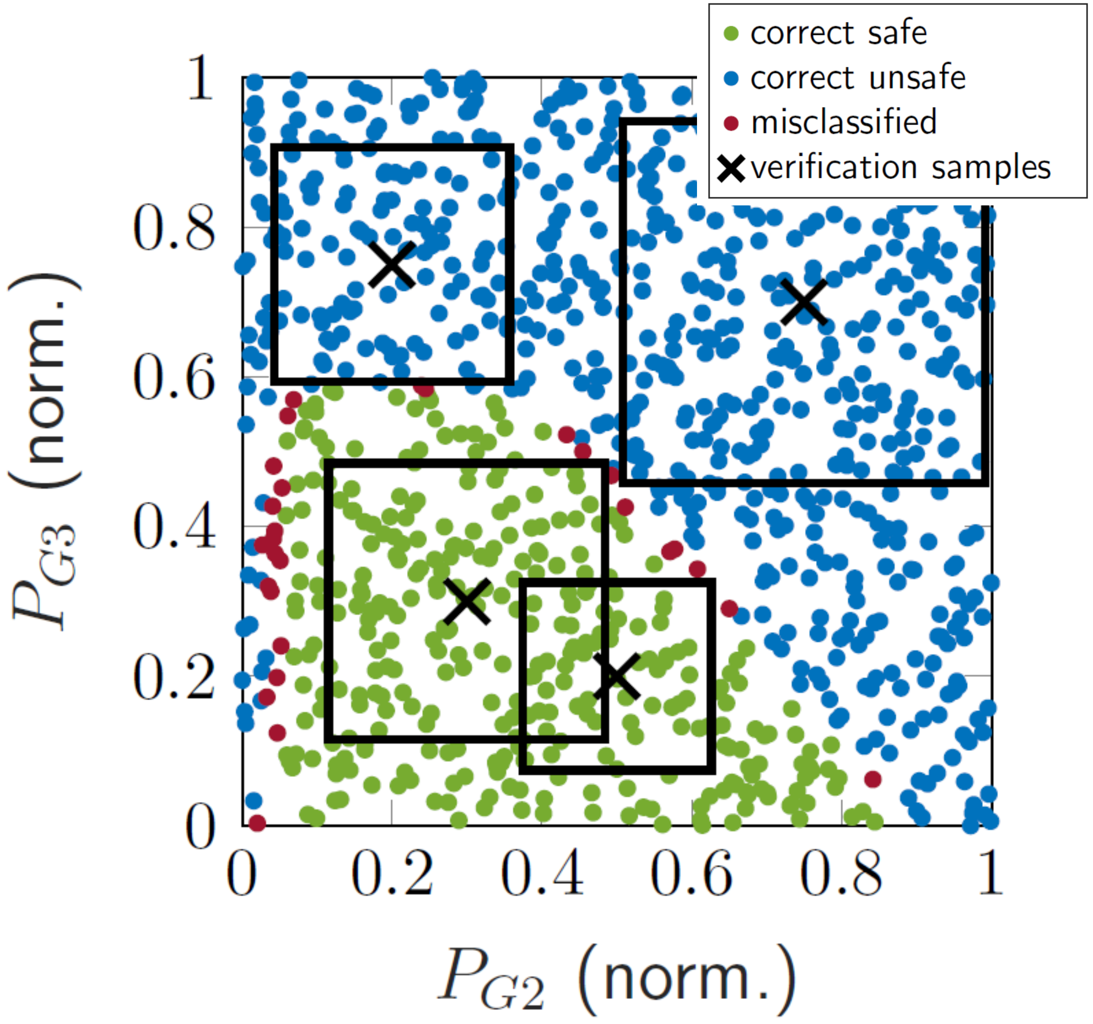


2. I can encode all operations of a Neural Network to a system of linear equations with continuous and binary variables

3. I can **integrate** all information encoded in a **neural network inside an optimization program**

Certify the output for a continuous range of inputs



1. We assume a given input x_{ref} with classification "safe"

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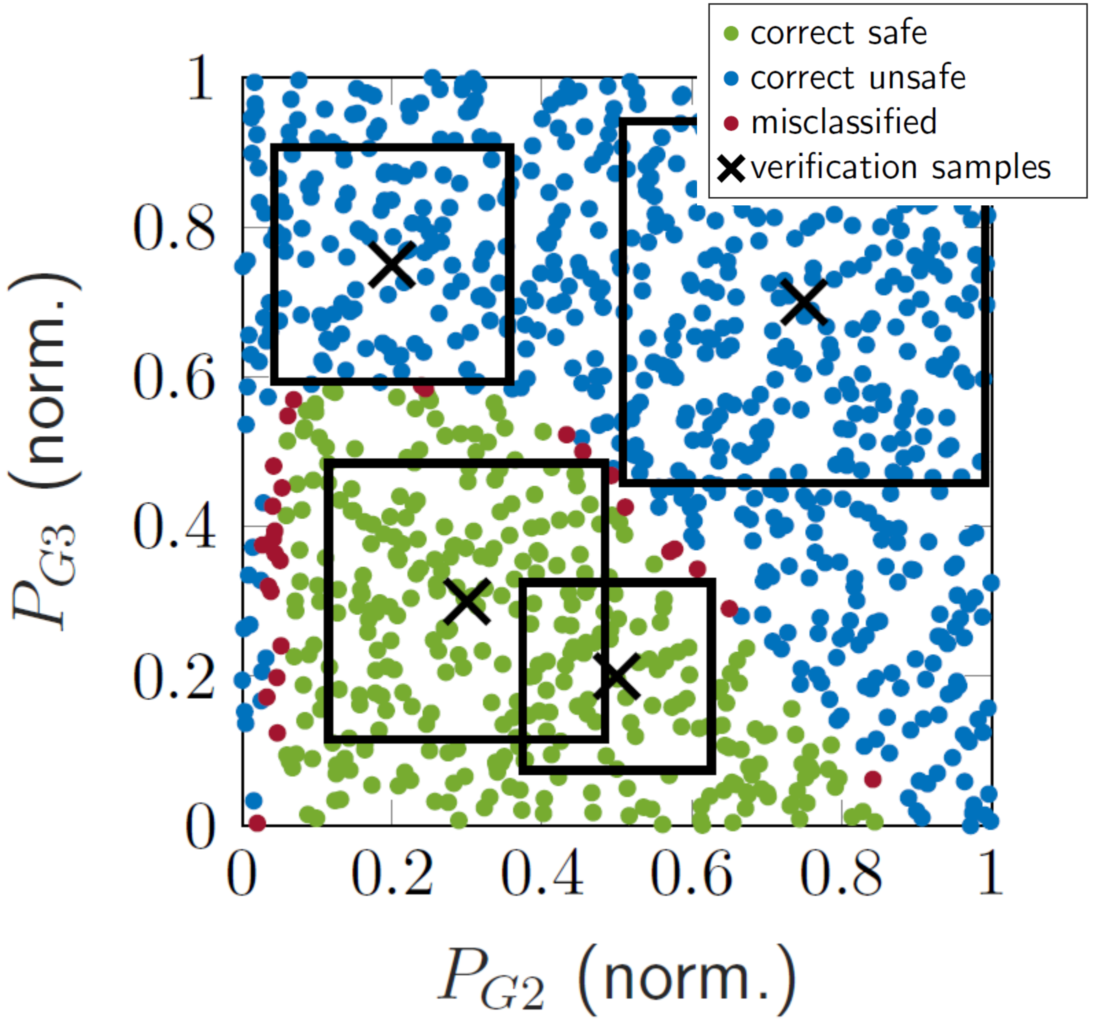

1. We assume a given input x_{ref} with classification "safe"
2. Solve optimization problem: **Does classification change for *any* input within distance ε from $\mathbf{x_{ref}}$**?
3. If not, then **I can certify** that my neural network will classify the whole continuous region as "safe"
4. I can repeat this for other regions and different classifications

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Provable Worst-case Guarantees

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

R. Nellikkath, S. Chatzivasileiadis, Physics-Informed Neural Networks for Minimising Worst-Case Violations in DC Optimal Power Flow. In IEEE SmartGridComm 2021, Aachen, Germany, October 2021.

R. Nellikkath, S. Chatzivasileiadis. Physics-Informed Neural Networks for AC Optimal Power Flow. 2021.

Neural Networks for Power System Optimization

- **Several different objectives, while ensuring a <u>safe</u> system operation**
  - Minimize total generation cost, losses
  - Enhance resilience, etc.

- **Here**: find the **minimum** total generation **cost** while you **do not violate** any system constraints

- **Input**:
  - Varying load demand at different nodes
  - Generator Costs

- **Application:** Neural Networks can accelerate this procedure by 100-1000 times

Minimize Total Generation Cost

Subject to:

Total supply = Total load demand

Transmission line limits

Generator limits

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Several recent approaches in literature

- Demonstrate up to **100x speedup**
- But **no performance guarantees** → *Does the Neural Network decision lead to any violations?*

Provable Worst Case Guarantees for Neural Networks

- We developed an **Optimization Algorithm** that determines the worst-case violations of any neural network applied to such problems

- We **integrate**:
  - Neural network equations
  - **Physical equations**

- **Provable worst-case guarantees** of neural network performance

Minimize Total Generation Cost

Subject to:

Total supply = Total load demand

Transmission line limits

Generator limits

Worst violation over the **whole training dataset** (training+test set)

Our algorithm: **provable** worst-case guarantee over the **whole input domain**

	Empirical lower bound		Exact worst-case guarantee	
Test cases	ν_{g} (MW)	ν_{line} (MW)	ν_{g} (MW)	ν_{line} (MW)
case9				
case30				
case39				
case57				
case118				
case162				
case300				

ν_{g} Maximum violation of generator limits

ν_{line} Maximum violation of line limits

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Test cases	ν_{g} (MW)	ν_{line} (MW)	ν_{g} (MW)	ν_{line} (MW)
case9	2.5	1.8	2.8	1.9
case30	1.7	0.6	3.6	3.1
case39	51.9	37.2	270.6	120.0
case57	4.2	0.0	23.7	0.0
case118	149.4	15.6	997.8	510.8
case162	228.0	180.0	1563.3	974.1
case300	474.5	692.7	3658.5	3449.3

ν_{g} Maximum violation of generator limits

ν_{line} Maximum violation of line limits

Over the whole input domain **violations can be much larger** (here ~7x) compared to what has been estimated empirically on the dataset

Worst violation over the **whole training dataset** (training+test set)

New algorithm: **provable** worst-case guarantee over the **whole input domain**

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We can now provide **guarantees that no NN output will violate the line limits** over the whole input domain

Wrap-up

- Trustworthy AI is necessary for safety-critical applications

- Neural network verification can remove barriers for neural network applications in power systems

- In this talk, we discussed:
  1. Verification of Neural Networks for Power Systems
  2. Provable worst-case guarantees for Neural Networks

- Such methods can be used to build trust in machine learning methods that can enhance power system resilience

Thank you!

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R. Nellikkath, S. Chatzivasileiadis, Physics-Informed Neural Networks for Minimising Worst-Case Violations in DC Optimal Power Flow, IEEE SmartGridComm 2021. [.pdf | code]

Some code available at:

www.chatziva.com/downloads.html