Machine learning for power systems: present and future

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Machine learning is not a calculation. It is an estimation.

- Machine learning will **never be as accurate** as a model that fully describes a system or process.
  - Why: ML does not calculate a function. It estimates its result.

- Then, **why** shall we apply Machine Learning?
  1. **extremely fast**
  2. good alternative if we do not have full knowledge of the actual model
     - Handle **very complex systems**
     - **Infer** from incomplete data

- **Data is key**

https://en.wikipedia.org/wiki/Garbage_in,_garbage_out

ML Opportunities and Barriers for Power systems

- ML can work well for forecasting/predicting
  - Weather/wind/PV or load forecasting, prediction of electricity prices, prediction of failures

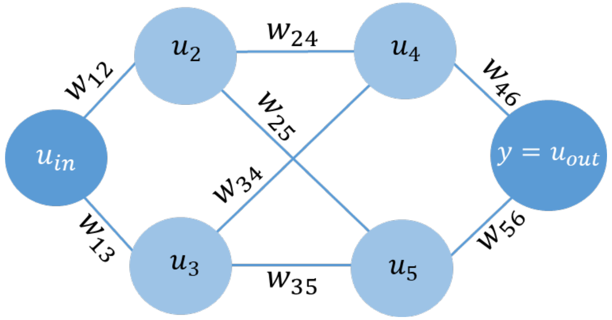
Barriers

1. Why would we use a “black box” to decide about **a safety-critical application**?
   - Example #1: ML for security assessment
   - Example #2: ML for any type of power system optimization/optimal power flow
2. Accuracy is a purely statistical ML performance metric. Who guarantees that the Neural Network can handle well previously unseen operating points?
3. Why would we depend on **incomplete data**, when we have developed **detailed physical models** over the past 100 years?

Security Assessment with Neural Networks

Database of secure/insecure operating points

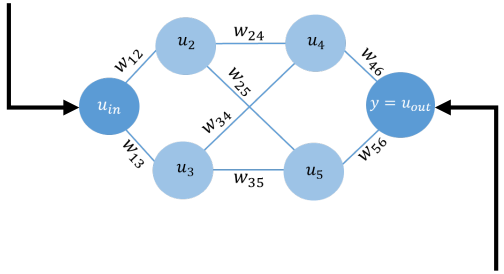
Any combination of **static/dynamic security** criteria (e.g. N-1 & Small-signal stability)



5. Use the NN

Input:

Operating point



Output

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?

NN Output:

Binary classification: **secure/insecure**

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

Why accuracy is not enough? (or “Data is key”)

- Example: Power System Security Assessment; Classify SAFE or UNSAFE

Total operating points = 1000	Actually Safe (Total = 20)	Actually Unsafe (Total = 980)
Predicted safe	1	30
Predicted Unsafe	19	950

$$\text{Accuracy} = \frac{1+950}{1000} = 95\%$$

- 95% accurate but we have misclassified almost all truly safe points!

- **We need high-quality training databases, and**
- **We need Neural Network Verification** for safety-critical applications
  - Formal guarantees about the classification over *continuous* input regions
  - We no longer rely on statistical performance metrics
  - Systematic identification of adversarial examples

Neural Network Verification: HOW?

1. 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

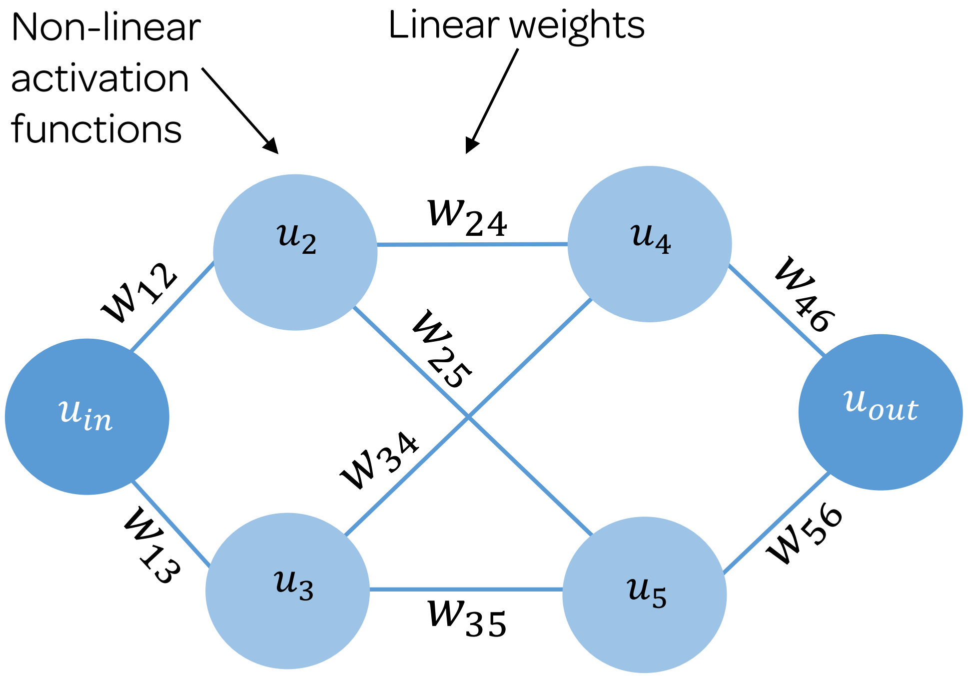
<u>Two types of optimization problems:</u>

A. Certify that in a region around a given input x_{ref} the neural network maintains the same classification → guarantee that all input points (continuous range) in the neighborhood will be classified the same

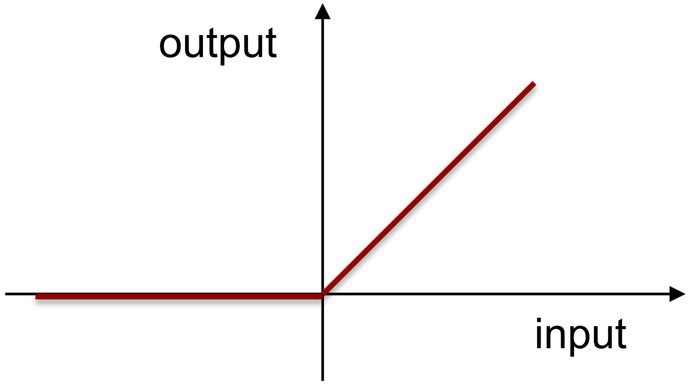
B. Find the minimum distance from x_{ref} that the classification changes (possibility of adversarial examples)

A. Venzke, S. Chatzivasileiadis. Verification of Neural Network Behaviour: Formal Guarantees for Power System Applications. *Accepted to IEEE Trans. Smartgrid*, 2020. https://arxiv.org/pdf/1910.01624.pdf

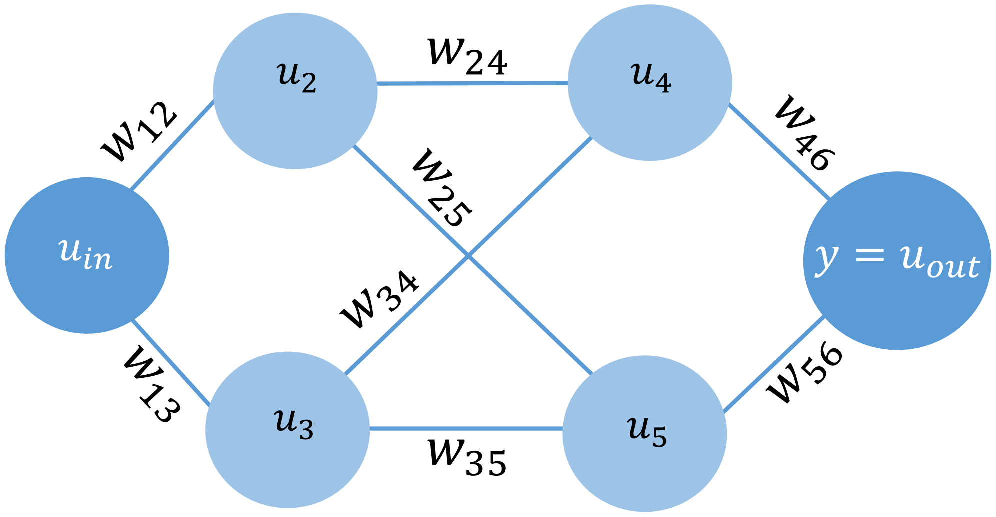
From Neural Networks to Mixed-Integer Linear Programming



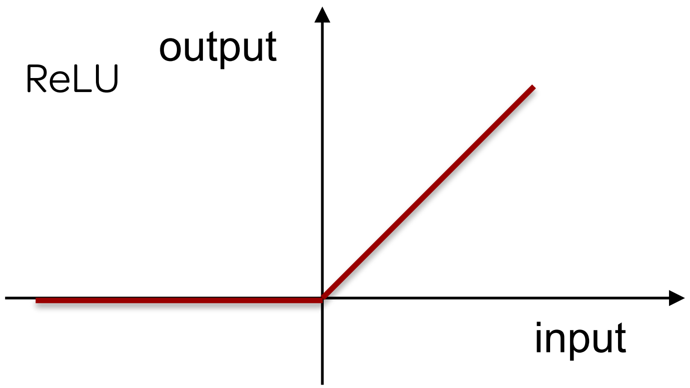
- Most usual activation function: ReLU
- ReLU: Rectifier Linear Unit



From Neural Networks to Mixed-Integer Linear Programming

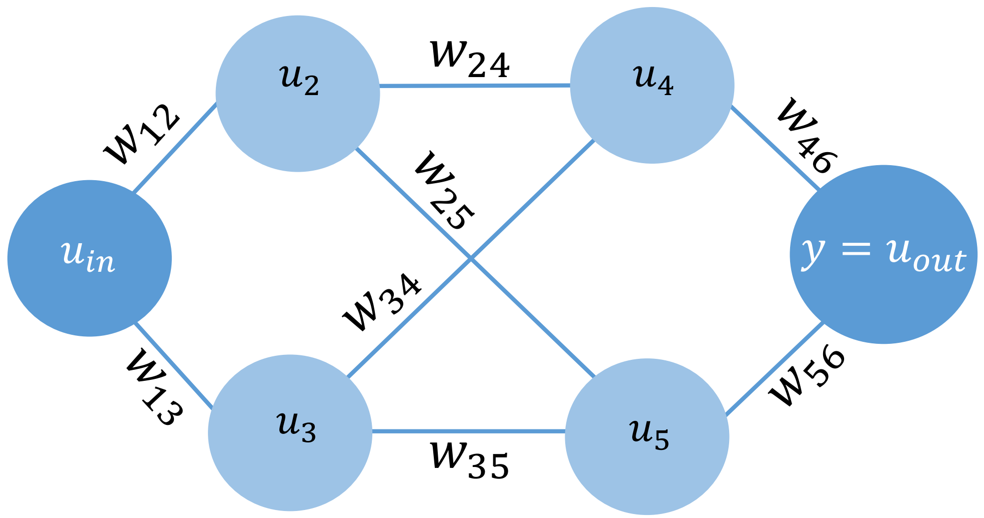


- Linear weights
- On every node: a non-linear activation function
  - ReLU: $\boldsymbol{u_j = \max(0, w_{ij}u_i + b_i)}$
- But ReLU can be transformed to a piecewise linear function with binaries



MILP

From Neural Networks to Mixed-Integer Linear Programming



- Input: Active power gen. setpoints

$$\mathbf{x} = [p_{g1}, p_{gi}, \ldots, p_{gN}]^T$$

- Output
  - Binary classification: safe/unsafe
  - Output vector y with two elements:

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

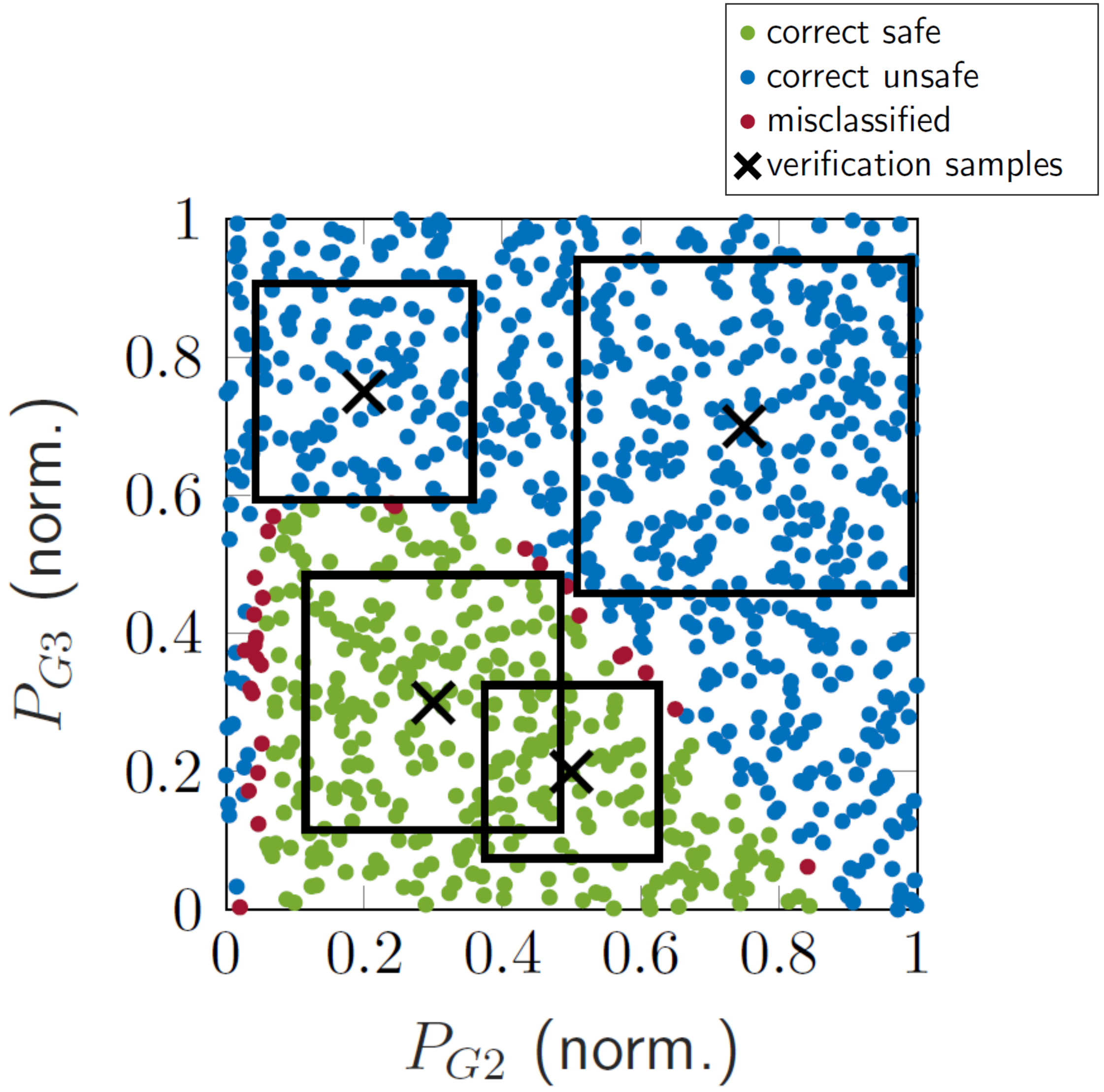
- $\boxed{y_1 \geq y_2\text{: safe}}$
- $y_1 < y_2$: unsafe

Certify the output for a continuous range of inputs

- We assume a given input x_{ref} with classification y: $y_1 > y_2$

1. For distance ϵ evaluate if input x exists with different classification y_2

$$\max_{x,y} \quad \mathbf{y_2} - \mathbf{y_1}$$
$$\text{s.t.} \quad y = NN(x)$$
$$|\mathbf{x} - \mathbf{x}_{\text{ref}}|_\infty \leq \epsilon$$



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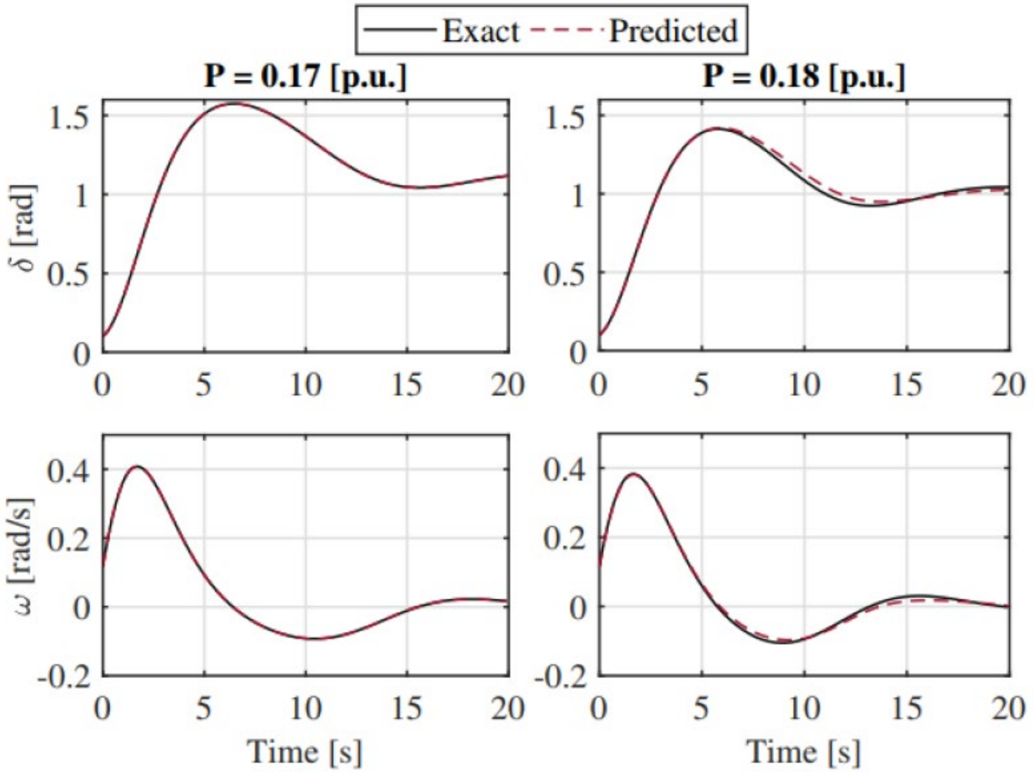
Why use incomplete datasets when we have detailed physical models?

- **Physics-Informed Neural Networks**
  1. Include the physical models inside the NN training → need for less data, probably smaller NN sizes
  2. **Extremely fast:** can potentially replace solvers for systems of differential-algebraic equations
  3. Turn **NN training** from supervised to **unsupervised learning**



Single Machine Infinite Bus Example: Physics-Informed NN is 87x faster than ODE solver

G. S. Misyris, A. Venzke, S. Chatzivasileiadis, Physics-Informed Neural Networks for Power Systems. Presented at the Best Paper Session of IEEE PES GM 2020. https://arxiv.org/pdf/1911.03737.pdf

Takeaways

1. **Extremely fast** (up to 1'000x faster): Revolutionize power system computation → replace non-linear and differential-algebraic solvers for e.g. OPF, sec. assessment, etc.

2. **Data is key:** Sampling beyond statistics
   - Use physical modeling (e.g. convex relaxations of OPF) to accelerate generation of high-quality data

3. We need **Verification of Neural Networks** for safety-critical applications

4. **Physics-Informed Machine Learning**: Use the already available models in the NN training

Did not have the time to talk about in this presentation:

5. **Interpretable AI**: we need to better understand how ML behaves to remove the barriers for its application in power systems

6. **From NN to MILP**: Decision Trees/Neural Networks can capture previously intractable constraints and convert them to a MILP

7. Before you apply ML/RL on power systems: Think! **ML/RL is an estimation, not a calculation!**
   - Given infinite time or data ML/RL will converge to the correct decision/optimal strategy. Do you have solid reasons why spending so many resources for ML/RL training will lead to a better performance than a Linear Program or Kalman filter? If not, then better stick to the conventional approach.

Thank you!

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Some datasets and code on Machine Learning for Power systems (e.g. Physics-Informed ML, NN verification, etc)

available at:

www.chatziva.com/downloads.html