# Physics-Informed Neural Networks and Verification 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**

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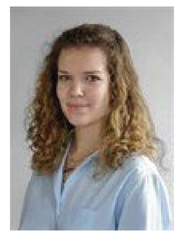
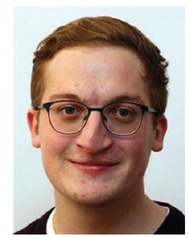


Elea Prat



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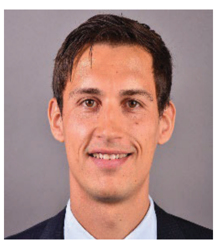

Florian Thams

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*Steven Low, Caltech*
*Guannan Qu, Caltech (now at CMU)*

# Machine Learning in Power Systems: Why?

- Machine learning "surrogate" models can deliver solutions **100-1'000 faster** than conventional models with acceptable accuracy

- ML models can be used to **screen very fast a very large number of scenarios**, in order to focus on the critical ones

- **Problem #1: Data is not enough**
  - Available data might be scarce or might not cover all abnormal situations.
  - Potential solution: Learn from the physics → **Physics-Informed Machine Learning**

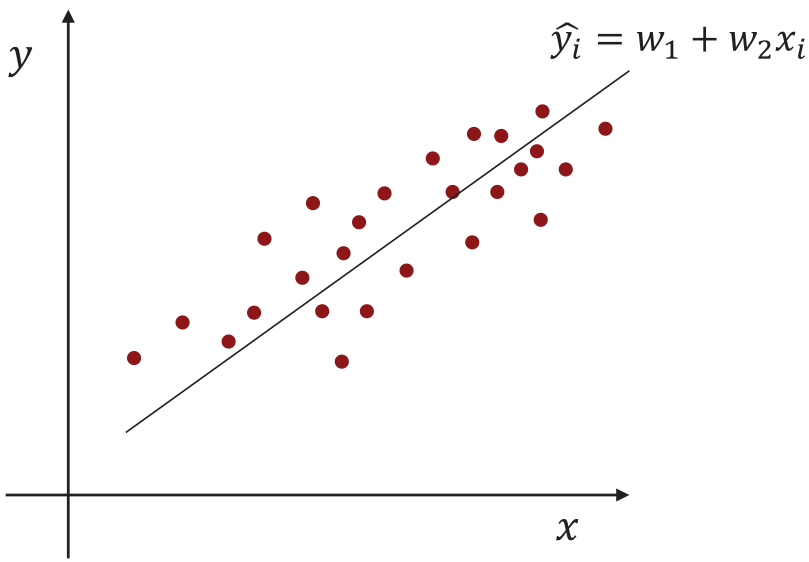
- **Problem #2: Can we trust the outputs of the ML models?**
  - Potential solution: **Trustworthy ML**

# Transient Stability Assessment with Physics-Informed Neural Networks

# Neural Networks: An advanced form of non-linear regression

$y_i$: actual/correct value

$\hat{y}_i$: estimated value




Loss function: Estimate best $w_1, w_2$ to fit the training data

$$\min_{w_1, w_2} \quad \| y_i - \hat{y}_i \|$$

s.t.

$$\hat{y}_i = w_1 + w_2 x_i \qquad \forall i$$

**Traditional training of neural networks required no information about the underlying physical model. Just data!**

# Physics-Informed Neural Networks for Power Systems

"Original" Loss function

"Physics-Informed" term

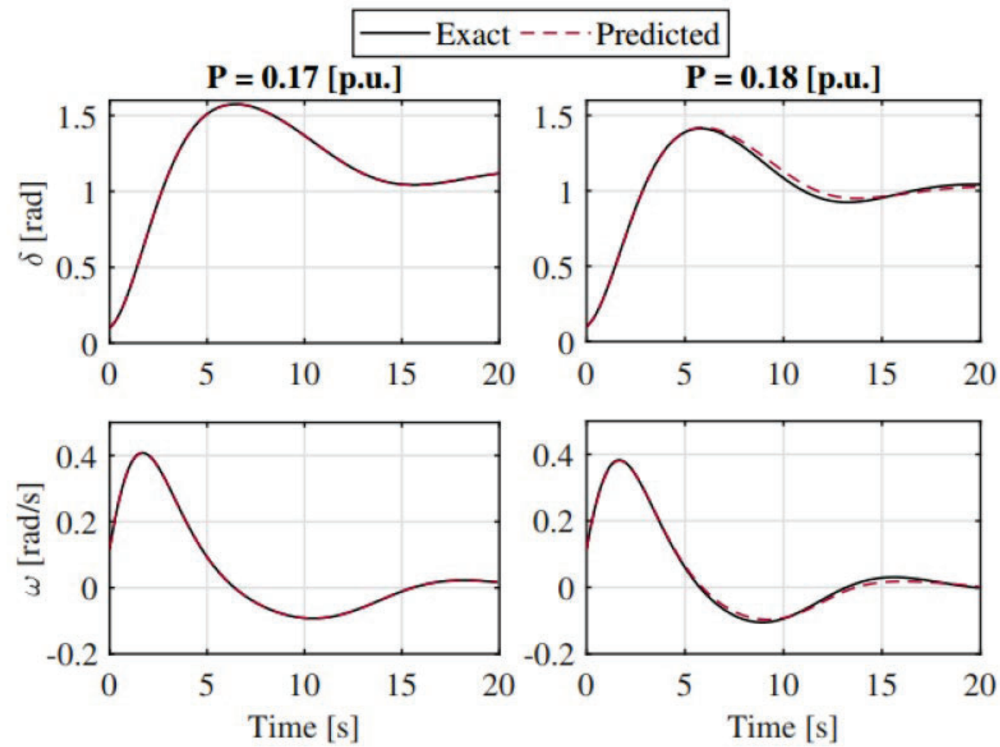
$$\boxed{\min_{\mathbf{W},\mathbf{b}} \quad \frac{1}{|N_\delta|}\sum_{i\in N_\delta}|\hat{\delta}-\delta^i|^2} + \boxed{\frac{1}{|N_f|}\sum_{i\in N_f}|f(\hat{\delta})|^2} \tag{6a}$$

$$s.t. \qquad \hat{\delta} = NN(t, P_m, \mathbf{W}, \mathbf{b}) \tag{6b}$$

$$\dot{\hat{\delta}} = \frac{\partial\hat{\delta}}{\partial t}, \qquad \ddot{\hat{\delta}} = \frac{\partial\dot{\hat{\delta}}}{\partial t} \tag{6c}$$

$$\boxed{f(\hat{\delta}) = M\ddot{\hat{\delta}} + D\dot{\hat{\delta}} + A\sin\hat{\delta} - P_m} \tag{6d}$$

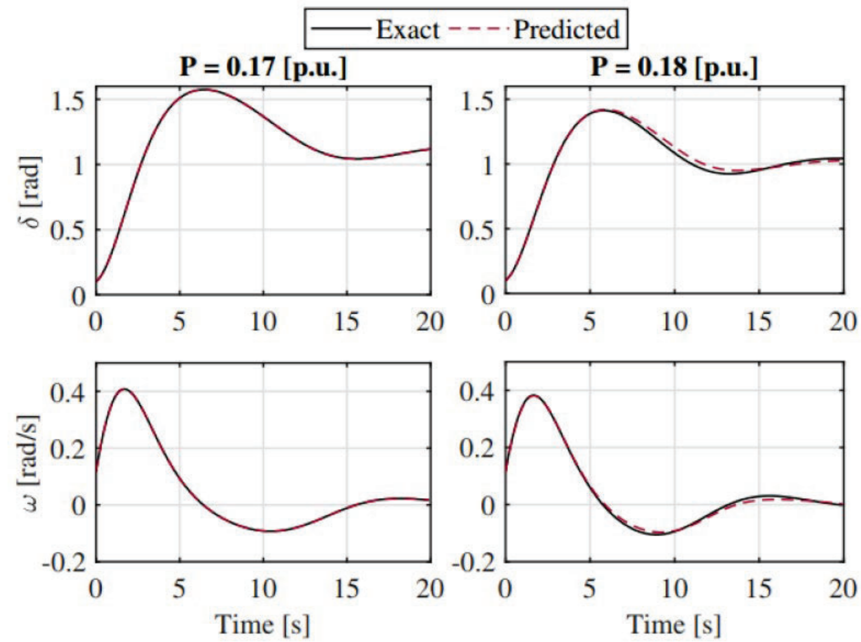
Swing equation




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

# Physics-Informed Neural Networks for Power Systems

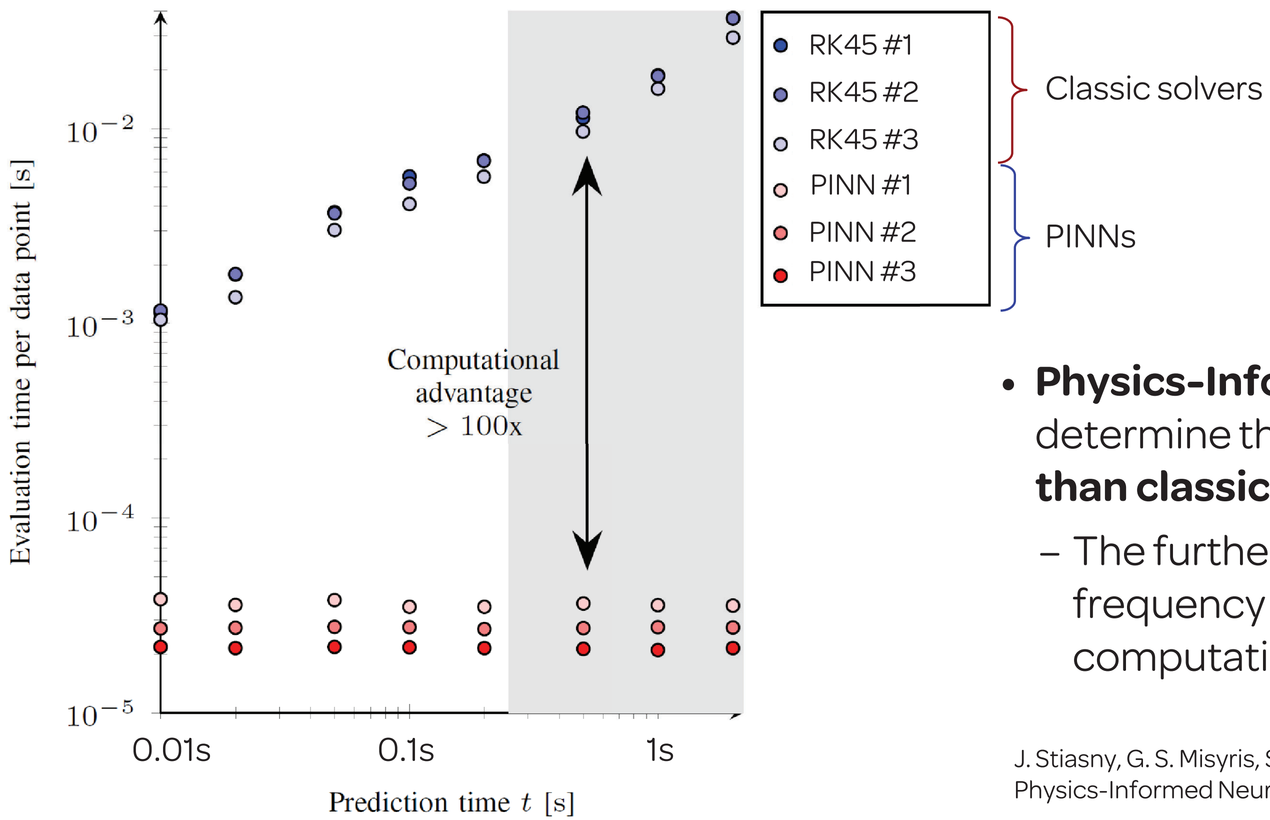
- Physics-Informed Neural Networks (PINN) could potentially replace solvers for systems of differential-algebraic equations in the long-term
  - **Probable power system application: Extremely fast screening of critical contingencies**
- In our example: PINN 87 times faster than ODE solver
- Can **directly estimate** the rotor angle at **any** time instant




Code is available on GitHub: https://github.com/jbesty

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

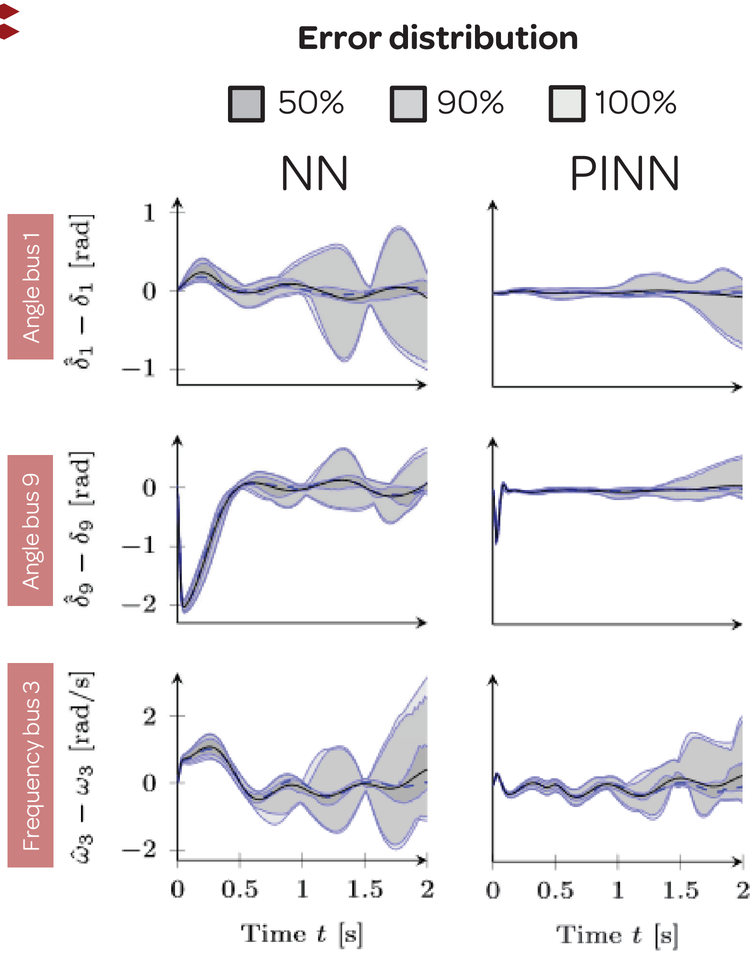
# Computation time: Classical numerical solvers vs. Physics-Informed NNs




- **Physics-Informed Neural Networks** can determine the outputs more than **100x faster than classical numerical solvers**
  – The further we look in time, e.g. what is the frequency at t=1s, the larger the computational advantage is

J. Stiasny, G. S. Misyris, S. Chatzivasileiadis, Transient Stability Analysis with Physics-Informed Neural Networks. https://arxiv.org/abs/2106.13638 [ code ]

# Accuracy:
# Standard Neural Networks (NN) vs Physics-Informed NNs (PINN)




- **PINNs result in lower errors** than standard neural networks
- The error increases as we look further into the future
- PINNs can deliver an excellent screening tool, i.e. to very quickly assess if critical scenarios are secure or not.
  - To determine the exact numerical values, classic solvers are still very valuable

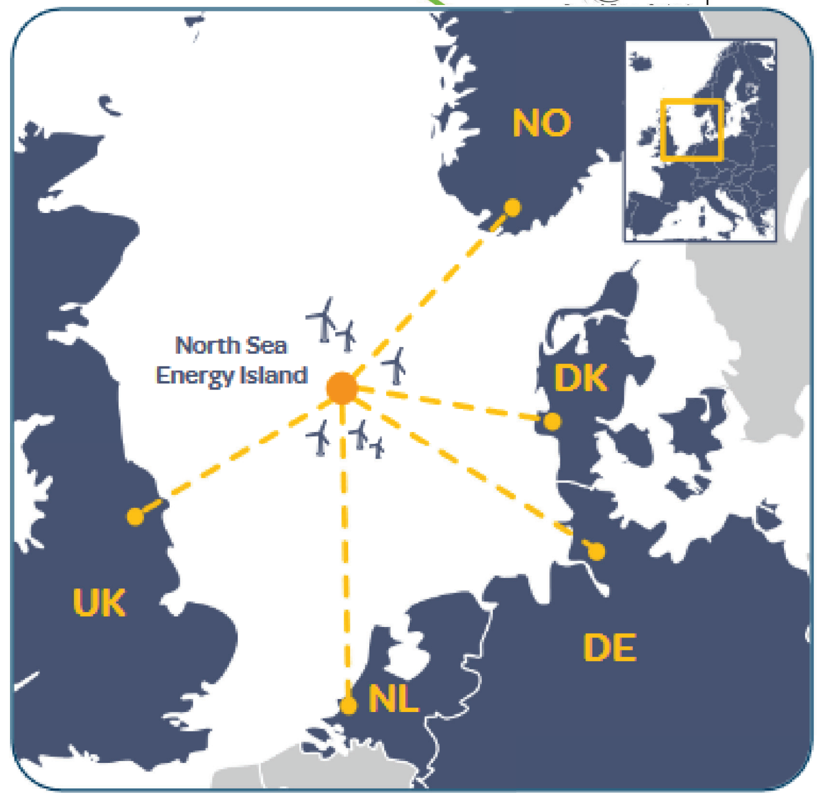
J. Stiasny, G. S. Misyris, S. Chatzivasileiadis, Transient Stability Analysis with Physics-Informed Neural Networks. https://arxiv.org/abs/2106.13638 [ code ]

# Small-signal stability assessment and tuning of controller gains with trustworthy neural networks

# An Example

- North Sea Wind Power Hub
- Wind Hub Operators offer **energy** **and** primary **frequency** control **and** primary **voltage** control
  - Can determine both P and Q, **and**
  - $K_{p,f}$ **and** $K_v$ (freq. droop and voltage droop)
- What are the permissible combinations of P,Q, $K_{p,f}$, and $K_v$ that satisfy:
  - Small-signal Stability (e.g. ζ>3%), **for all**
  - N-1 contingencies

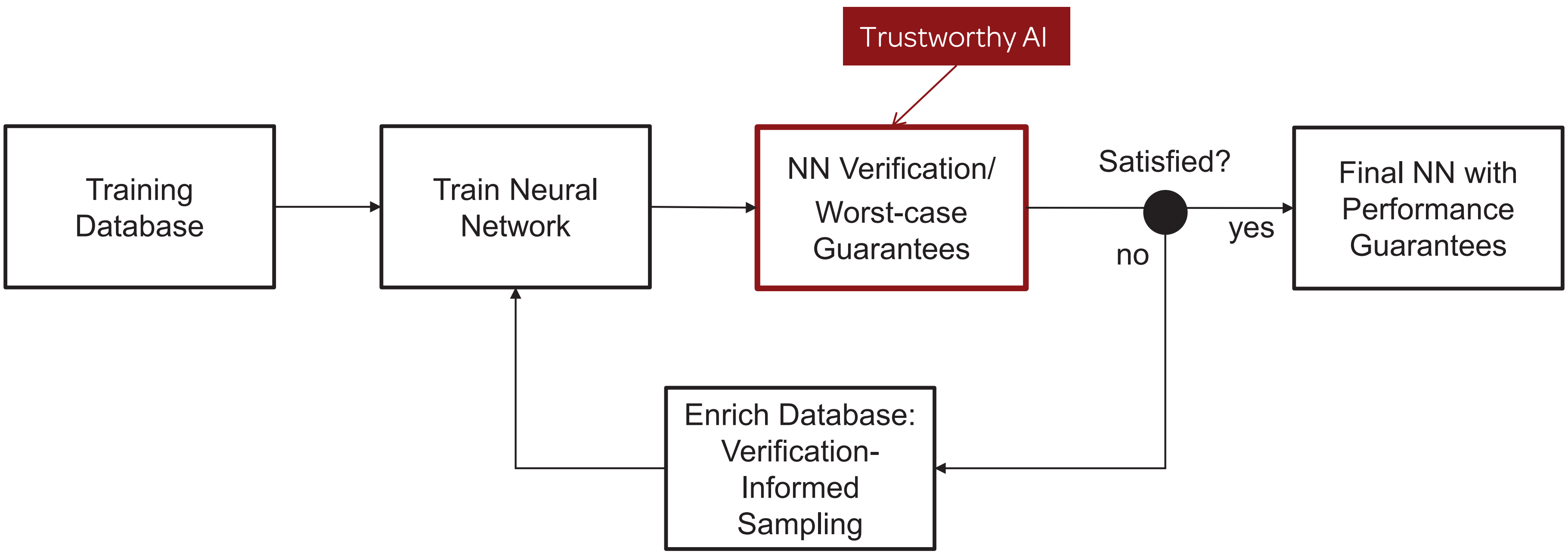
**Problem extremely difficult to solve: infinite combinations**




J. Stiasny, S. Chevalier, R. Nellikkath, B. Sævarsson, S. Chatzivasileiadis. **Closing the Loop: A Framework for Trustworthy Machine Learning in Power Systems.** Accepted to *2022 iREP Symposium - Bulk Power System Dynamics and Control - XI (iREP).* Banff, Canada. 2022. [ paper | code ]

# Step 1:
# Learn the permissible region of P,Q, $K_{p,f}$, and $K_v$

Goal: satisfy small-signal stability margin for all N-1 contingencies



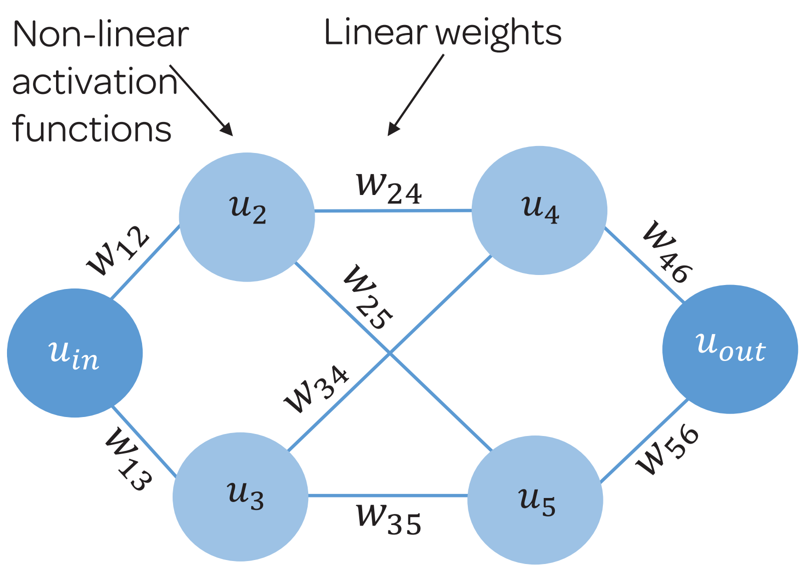
# Neural Network Verification: HOW?

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

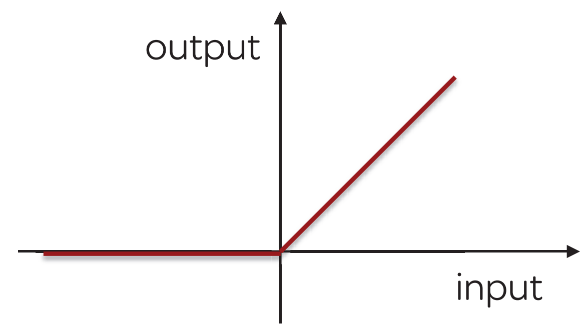
2. Formulate an **optimization** problem (MILP) and solve it → certificate for NN behavior

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

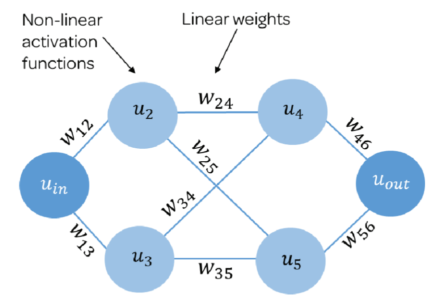
# From Neural Networks to Mixed-Integer Linear Programming



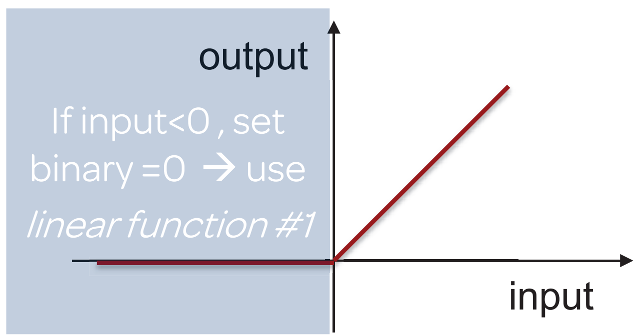

- Most usual activation function: ReLU
- **ReLU:** Rectifier Linear Unit



# From Neural Networks to Mixed-Integer Linear Programming




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



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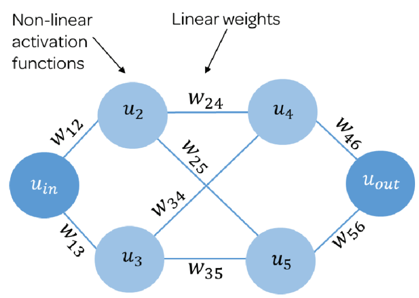


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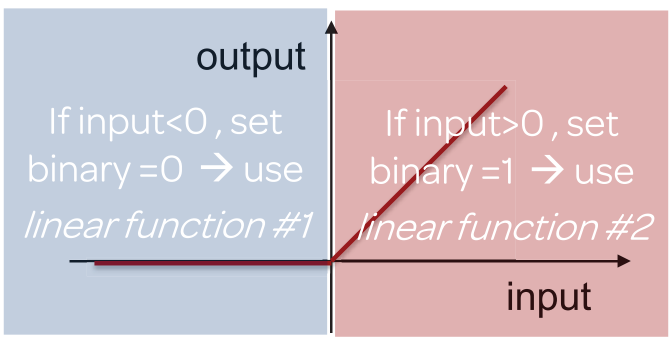

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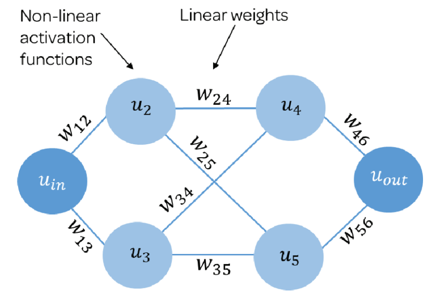


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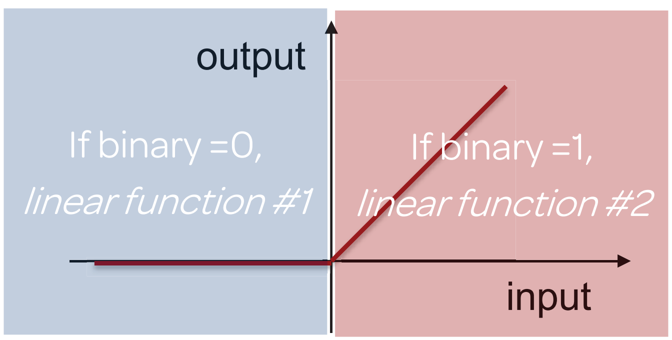
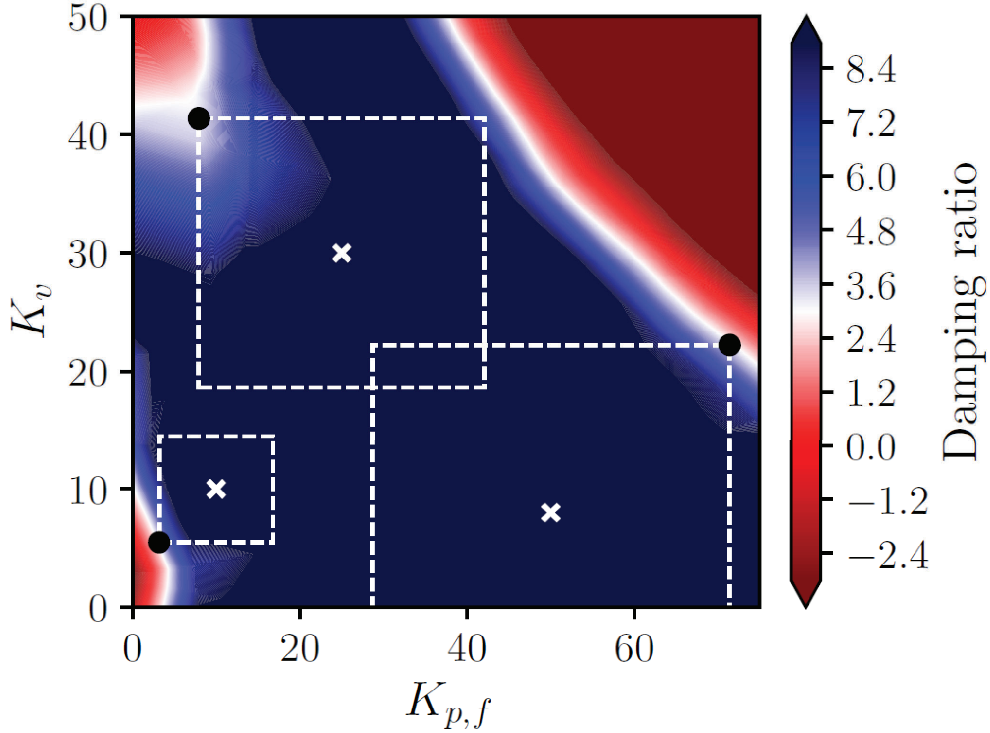



2. I can encode all operations of a Neural Network to a system of linear equations with continuous and binary variables

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"

A. Venzke, S. Chatzivasileiadis. Verification of Neural Network Behaviour: Formal Guarantees for Power System Applications. *IEEE Transactions on Smart Grid*, Jan. 2021. https://arxiv.org/pdf/1910.01624.pdf

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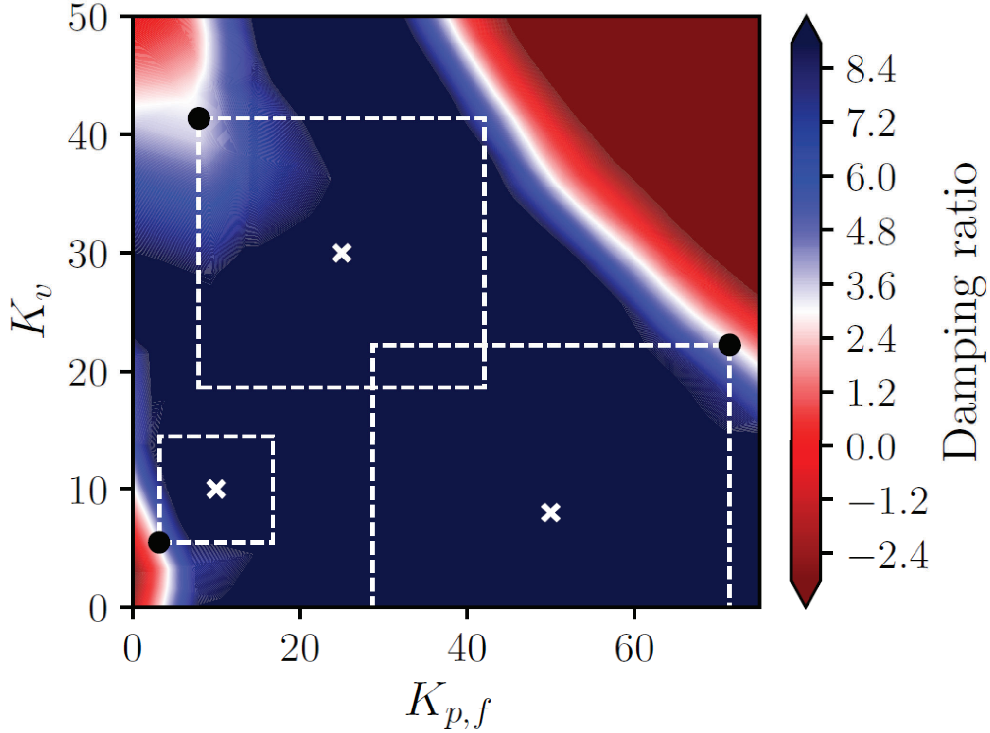


1. We assume a given input $x_{ref}$ with classification "safe"

2. Solve optimization problem: **Find the minimum distance for which the classification changes**?

3. **Outcome:**
   a) **I can certify** that my neural network will classify the whole continuous region as "safe"
   b) I have either identified the classification **boundary or a misclassified point →** sample around it and **enrich** the training database

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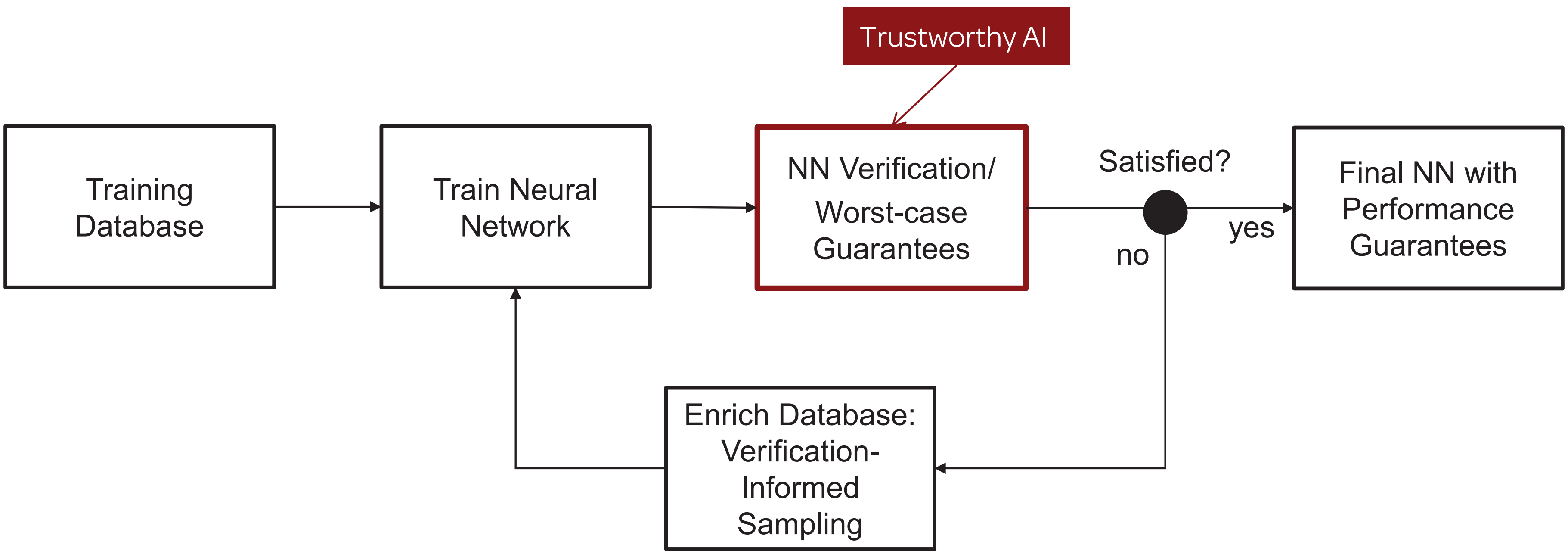
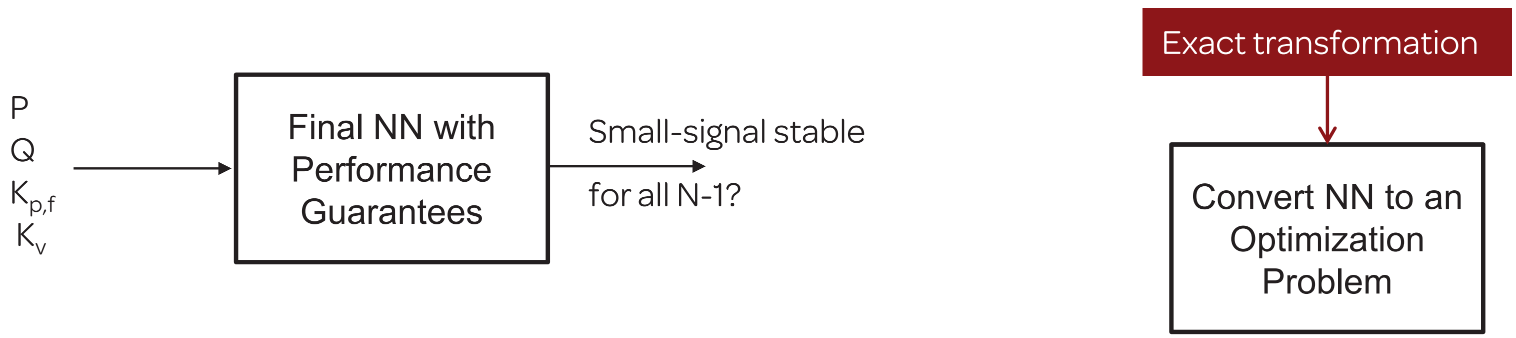
# Step 1:
# Learn the permissible region of P,Q, $K_{p,f}$, and $K_v$

Goal: satisfy small-signal stability margin for all N-1 contingencies



# Step 2:
# Convert Verified Neural Network to an Optimization Problem

Goal: satisfy small-signal stability margin for all N-1 contingencies




**Optimization Problem #1**

For given $P^*_{ref}$ , $Q^*_{ref}$, what is the maximum range of $K_{p,f}$ and $K_v$ around $K_{p,f,0}$ and $K_{v,0}$ that ensures small-signal stability for all N-1 contingencies?

**Optimization Problem #2**

For given $K^*_{p,f}$ and $K^*_v$, what is the maximum range of $P_{ref}$ and $Q_{ref}$ around $P_{ref,0}$ and $Q_{ref,0}$ that ensures small-signal stability for all N-1 contingencies?

# Wrap-up

- Physics-Informed Neural Networks use the underlying physical models to estimate solutions 100-1’000 faster than conventional models
  – useful for screening very fast large number of scenarios

- Trustworthy AI can help determine permissible ranges of operation that
  – would be very difficult to determine otherwise
  – with a predefined level of trust (worst-case guarantees)

# Thank you!

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- J. Stiasny, G. S. Misyris, S. Chatzivasileiadis, Transient Stability Analysis with Physics-Informed Neural Networks. https://arxiv.org/abs/2106.13638 [ code ]
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- 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.[ .pdf | slides | video ]
- 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

Article without any equations ☺

S. Chatzivasileiadis, A. Venzke, J. Stiasny and G. Misyris, **"Machine Learning in Power Systems: Is It Time to Trust It?,"** in *IEEE Power and Energy Magazine*, vol. 20, no. 3, pp. 32-41, May-June 2022 [ .pdf ]

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