AI4OPT Seminar Series
GeorgiaTech, Fall 2022

Machine Learning for Power Systems: Is it time to trust it?

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Working for a sustainable future

Management

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Kenneth Thomsen

Wind Energy Systems (WES)

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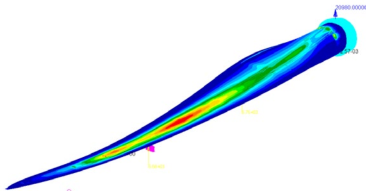
Cathy Suo

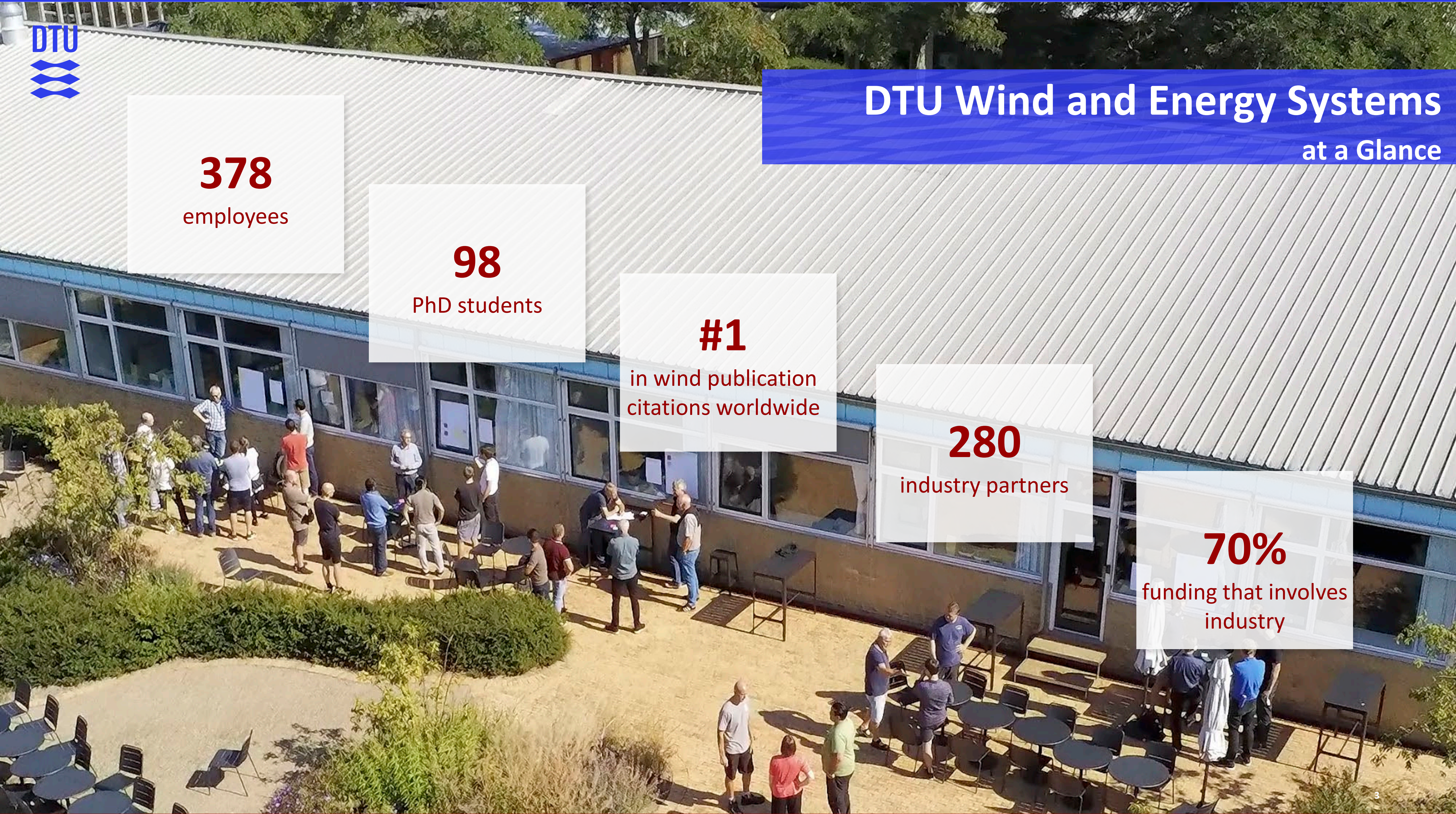
Power and Energy Systems (PES)

Head of Division
Jacob Østergaard



DTU Wind and Energy Systems

at a Glance



378
employees

98
PhD students

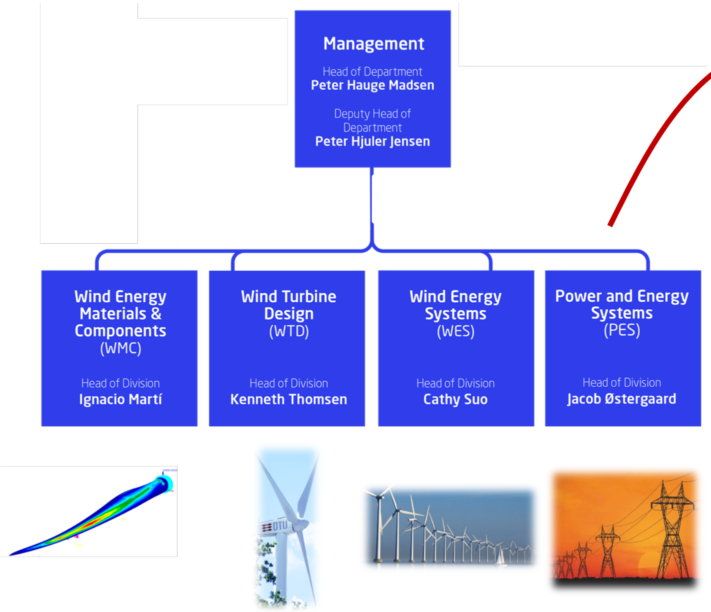
#1
in wind publication citations worldwide

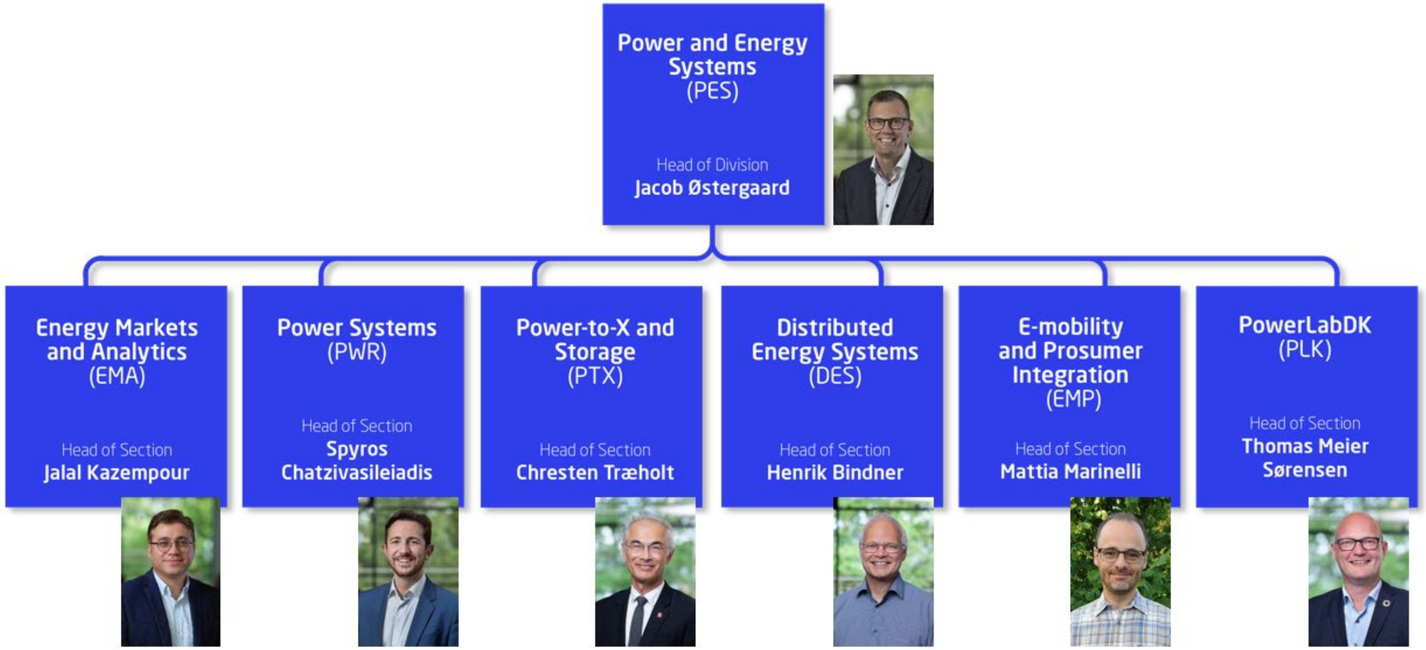
280
industry partners

70%
funding that involves industry

Department of Wind and Energy Systems

Working for a sustainable future





~100 people working on power systems

Electric Power Systems

PWR Section: 28+3 members; 20 nationalities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Hjörtur Jóhannsson


Nikos Cutululis


Tonny W. Rasmussen


Oscar Saborio-Romano


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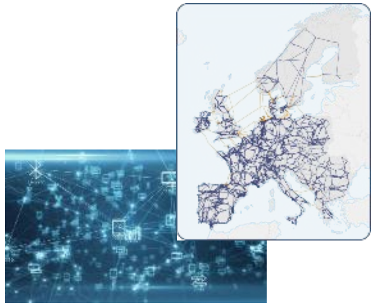
Ilgiz Murzakhanov


Alessandra Follo

Guests

Yan Xu


Simon Stock

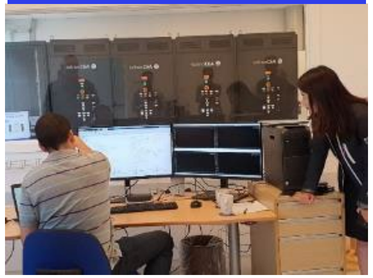


PowerLabDK

Energy System Simulation Lab

Digital Energy Lab

AC/DC Wind Power Lab



PWR: Advanced Methods and Tools for Power System Security and Control

Methods Going Beyond the State-of-the-art

1. **Trustworthy AI** for Power Systems
2. **Quantum** Computing
3. **Cyber Physical** Systems
4. **Energy Data** Spaces
5. Stability, Optimization, and Control of **Zero-Inertia Systems**

Advanced Tools

1. **World-Record** in Fast Real-time Security Assessment of Electric Power Systems
2. **Open-Source Models** of the Nordic and European Systems
3. **Digitalization tools** for e.g. grid black start
4. **Digital Twins** for Power Systems

Applications

1. **RTDS** infrastructure and **Hardware-in-the-Loop**
2. **Demonstration** in Bornholm
3. System-stability and operation including the **Bornholm and North Sea Energy Islands**

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

Andreas Venzke

Rahul Nellikkath

Sam Chevalier

Lejla Halilbasic

Elea Prat

Ilgiz Murzakhanov

Spyros Chatzivasileiadis

Florian Thams

Georgios Misyris

Jochen Stiasny

Brynjar Sævarsson

And to our collaborators:

Dan Molzahn, Georgia Tech

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

Panagiotis Papadopoulos, Robert Hamilton, Tabia Ahmad, Univ. Strathclyde

Machine learning: Why shall we apply it in power systems?

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. Can handle **very complex systems** and **infer** from incomplete data
   - Excellent potential to create accurate **surrogate models**
     - Accelerate simulations; and offer good approximations of previously intractable systems

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

This talk: Two Challenges and One Opportunity

- **Challenge #1:** Machine Learning is extremely dependent on high-quality data.

- **Challenge #2:** Has the Neural Network been trained to generalize well? Can we trust it?

- **Opportunity:** "AI for Optimization". Use trustworthy Machine Learning to capture (=approximate well) previously intractable constraints and embed them in any optimization problem
  - Example[1]: Instead of running 10,000 scenarios to determine the critical clearing time of a converter-based system, run a single optimization.

<u>Abbreviations I will use:</u>

- ML: Machine Learning
- NN: Neural Network

[1]G. S. Misyris, J. Stiasny, S. Chatzivasileiadis, Capturing Power System Dynamics by Physics-Informed Neural Networks and Optimization. *IEEE Conference on Decision and Control (CDC), 2021*. [.pdf]

Challenge #1: ML extremely dependent on high-quality data

Facts	Consequence
1. **All data are not the same** For a NN that assesses if a system is stable, training data close to the stability boundary contain much more information than training data far away from it.	Statistical sampling is not enough

Challenge #1: ML extremely dependent on high-quality data

Facts

1. **All data are not the same**
   For a NN that assesses if a system is stable, training data close to the stability boundary contain much more information than training data far away from it.

2. **Training data must follow the same statistical properties as real data**
   Do we have enough historical data about e.g. outages? Is this possible?

Consequence

Statistical sampling is not enough

1. For power systems: We have so many physical models. Add them!

2. We cannot trust "Neural Network Accuracy" as a performance metric

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Challenge #1: ML extremely dependent on high-quality data	2. **Training data must follow the same statistical properties as real data** Do we have enough historical data about e.g. outages? Is this possible?	1. For power systems: We have so many physical models. Add them! 2. We cannot trust "Neural Network Accuracy" as a performance metric
Challenge #2: Has NN been trained to generalize well?	3. **NN training is an extremely complex optimization procedure** Prone to overfitting/underfitting	Can we trust it?

Facts

Solution

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Statisti … ough

Sampling beyond Statistics

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DTU

Facts

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Physics-Informed NNs

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DTU

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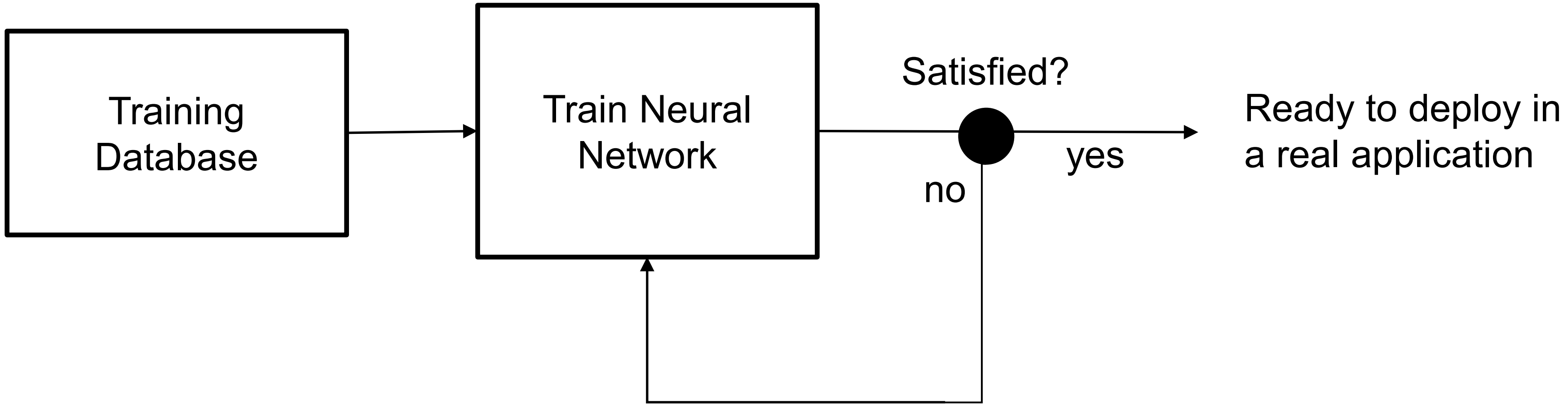
Neural Network Verification

Closing the Loop: A Framework for Trustworthy Machine Learning in Power Systems

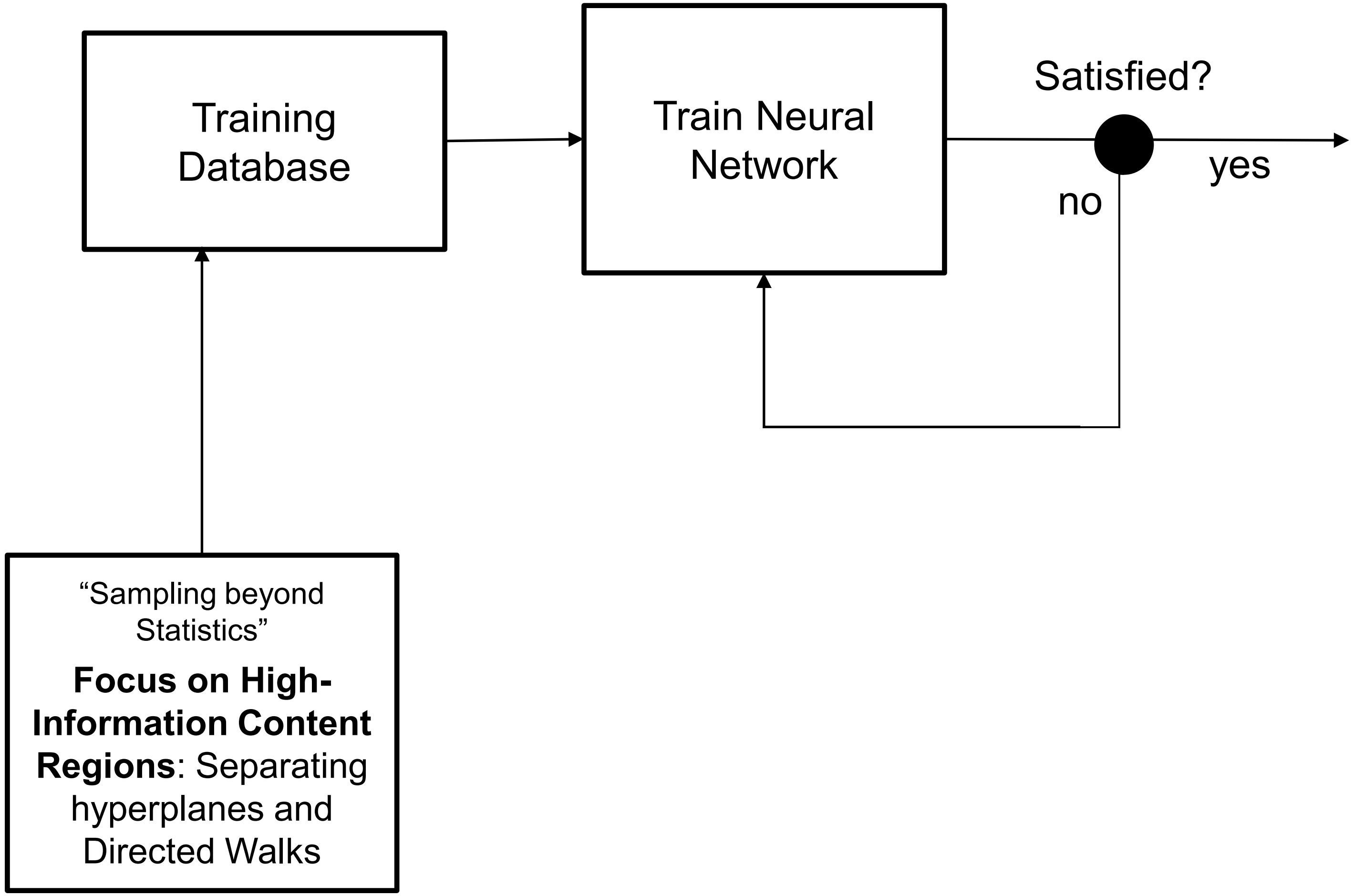
J. Stiasny, S. Chevalier, R. Nellikkath, B. Sævarsson, S. Chatzivasileiadis. Closing the Loop: A Framework for Trustworthy Machine Learning in Power Systems. Accepted to *2022 iREP Symposium - Bulk Power System Dynamics and Control - XI (iREP)*. Banff, Canada. July 2022. [paper | code]

Closing the Loop: Trustworthy ML for Power Systems

Conventional Neural Network Training for Power System Applications



Closing the Loop: Trustworthy ML for Power Systems



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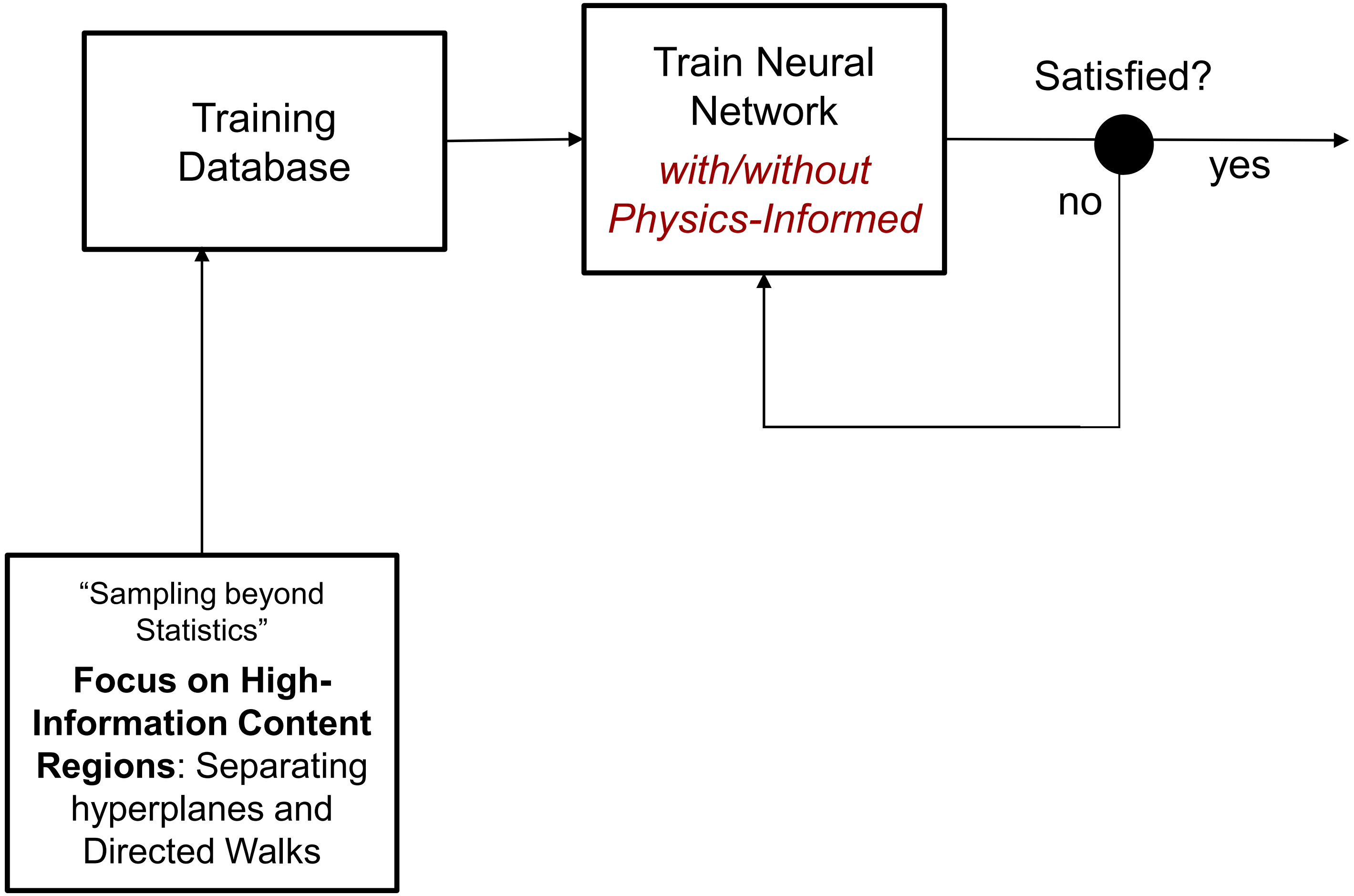

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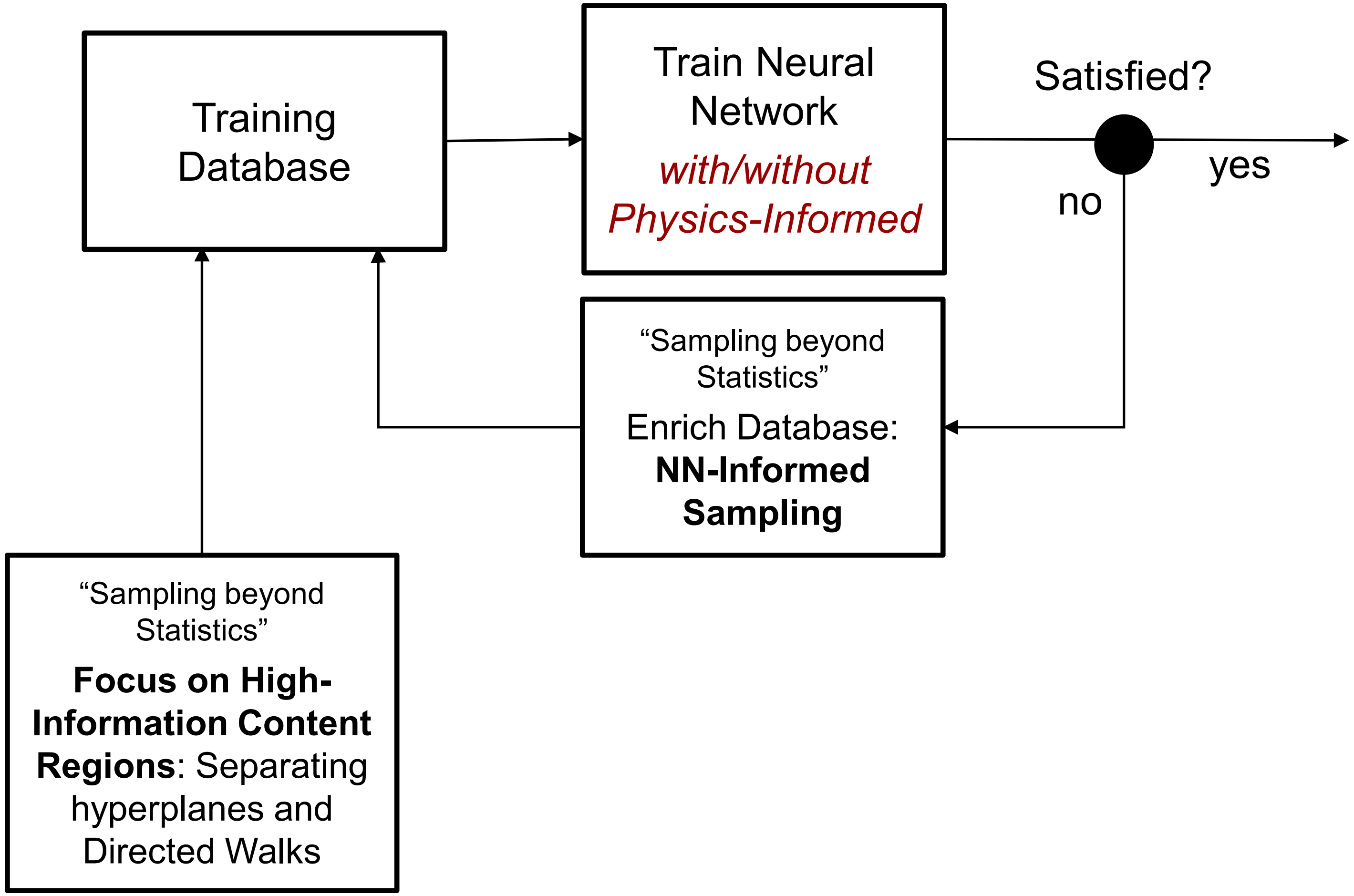

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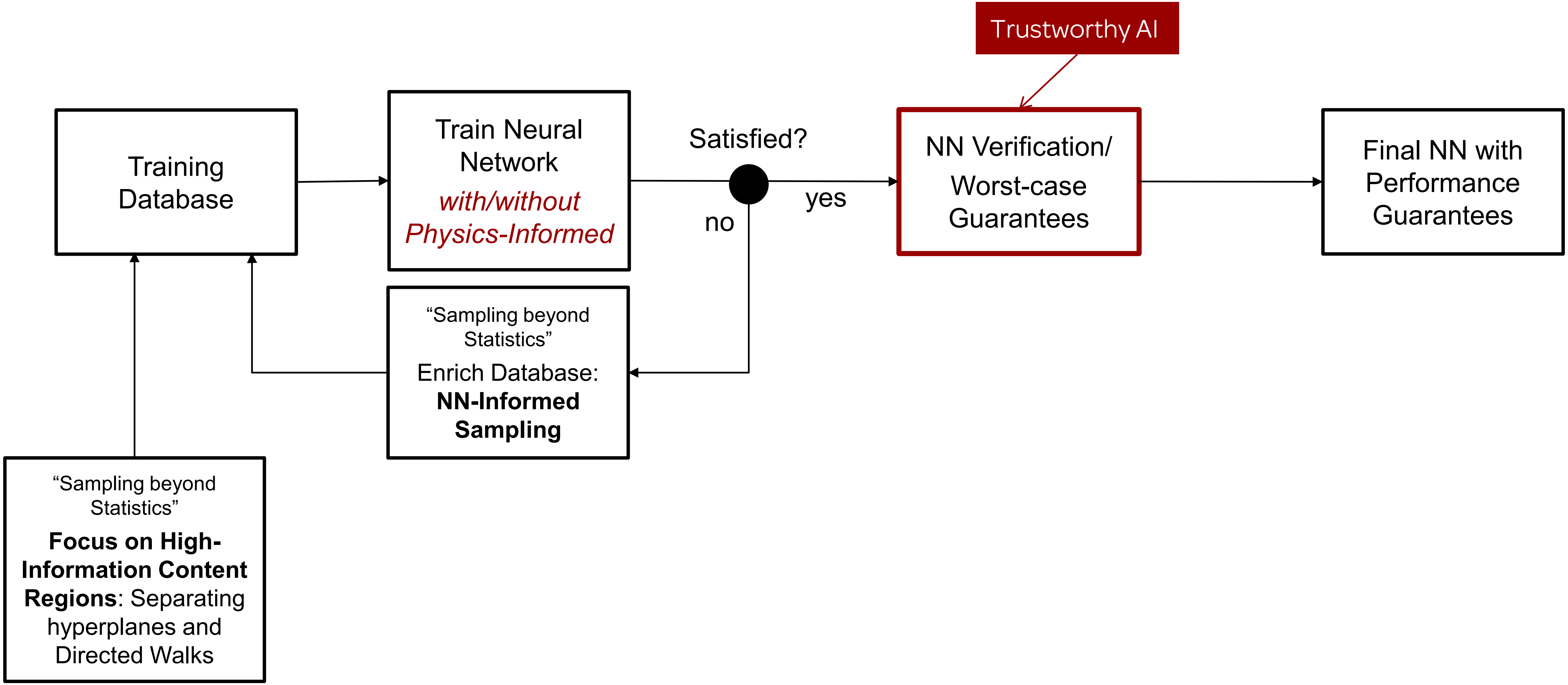

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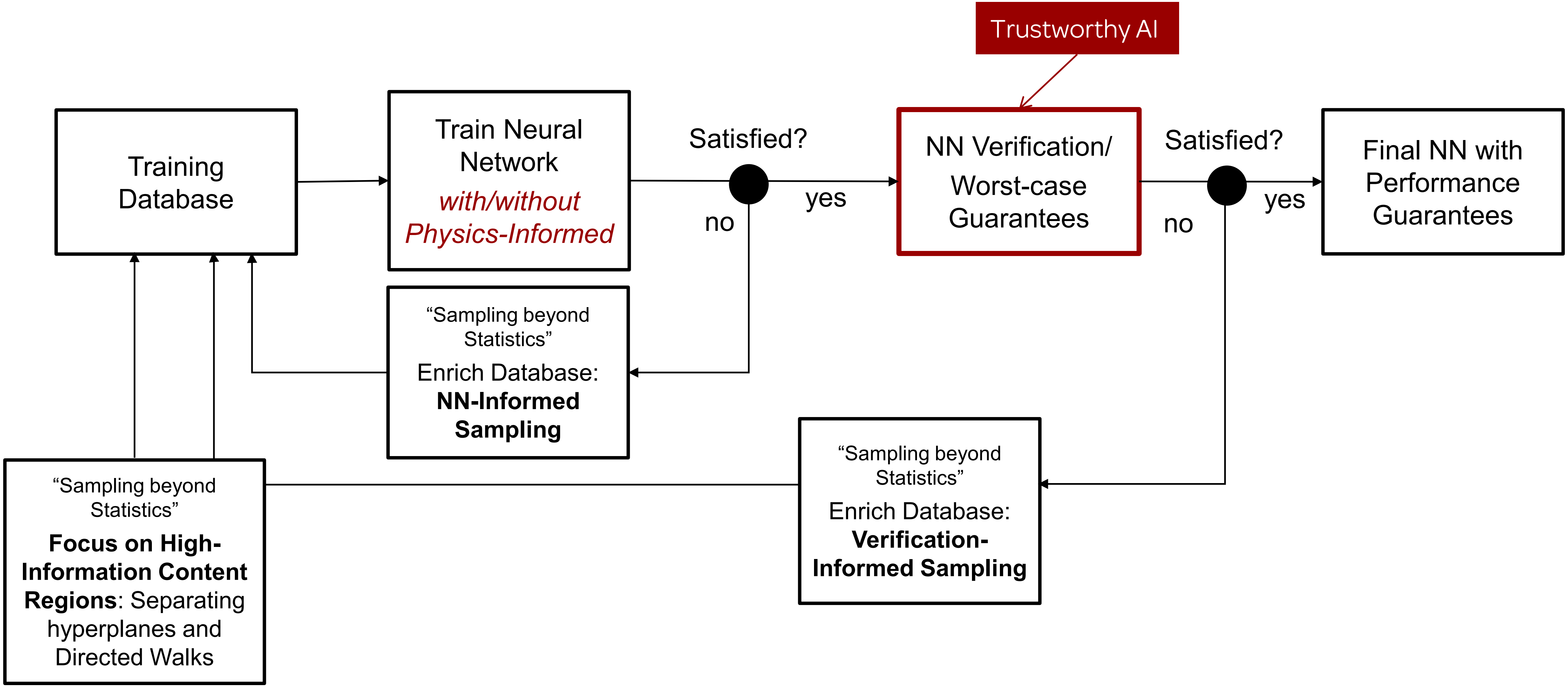

Sampling beyond Statistics: Separating Hyperplanes and Directed Walks

- Historical data are often insufficient
- Need to generate our own data

- Here: generate data for N-1 security+small-signal stability
  - Assessing the stability of 100'000s of operating points is an extremely demanding task
  - Immense search space
  - How can I do it efficiently?

F. Thams, A. Venzke, R. Eriksson, and S. Chatzivasileiadis, "Efficient database generation for data-driven security assessment of power systems". ". IEEE Trans. Power Systems, vol. 35, no. 1, pp. 30-41, Jan. 2020. https://www.arxiv.org/abs/1806.0107.pdf

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Proposed approach:

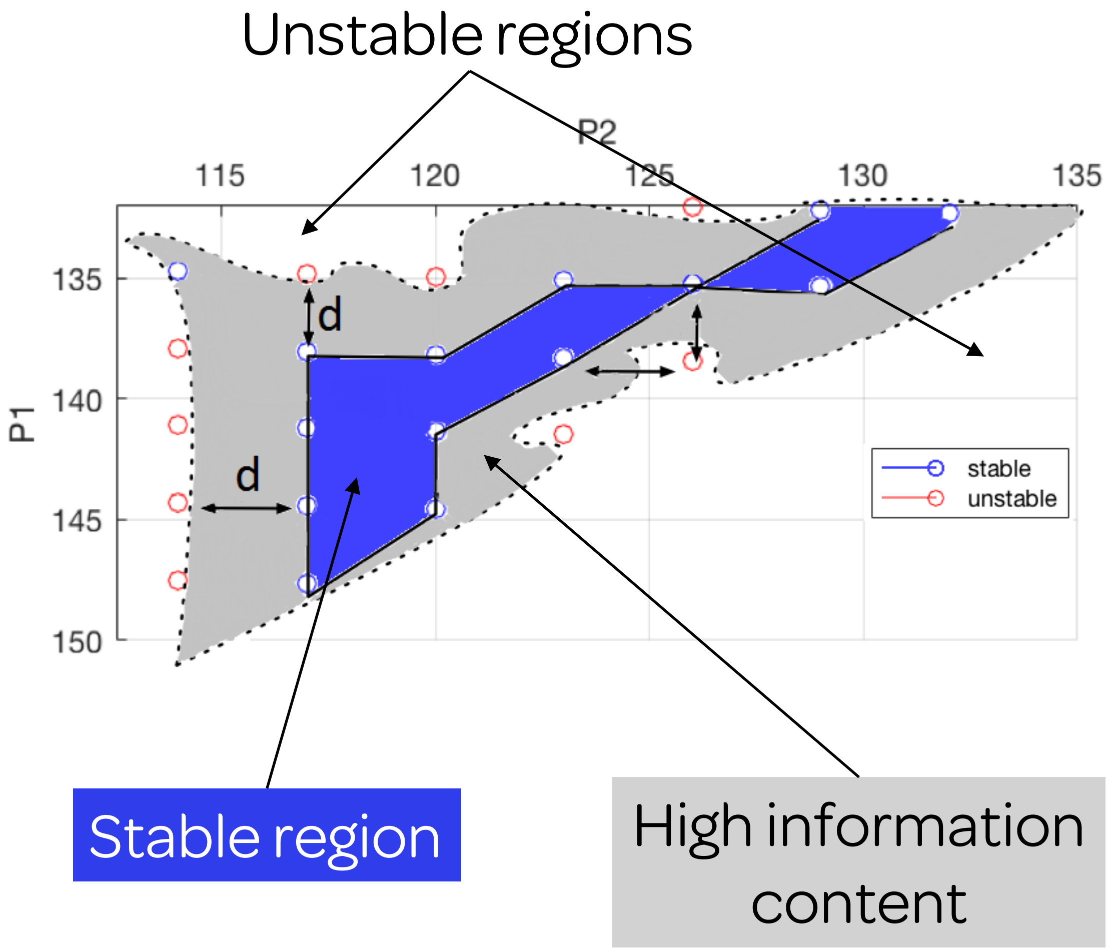
- Can accommodate numerous definitions of power system security (e.g. N-1, N-k, small-signal stability, voltage stability, transient stability, **or a combination** of them)
- **10-20 times faster** than existing state-of-the-art approaches
- Generated Databases for IEEE 14-bus and NESTA 162-bus system available!

  http://www.chatziva.com/downloads.html#databases

Sampling beyond Statistics: Efficient Database Generation

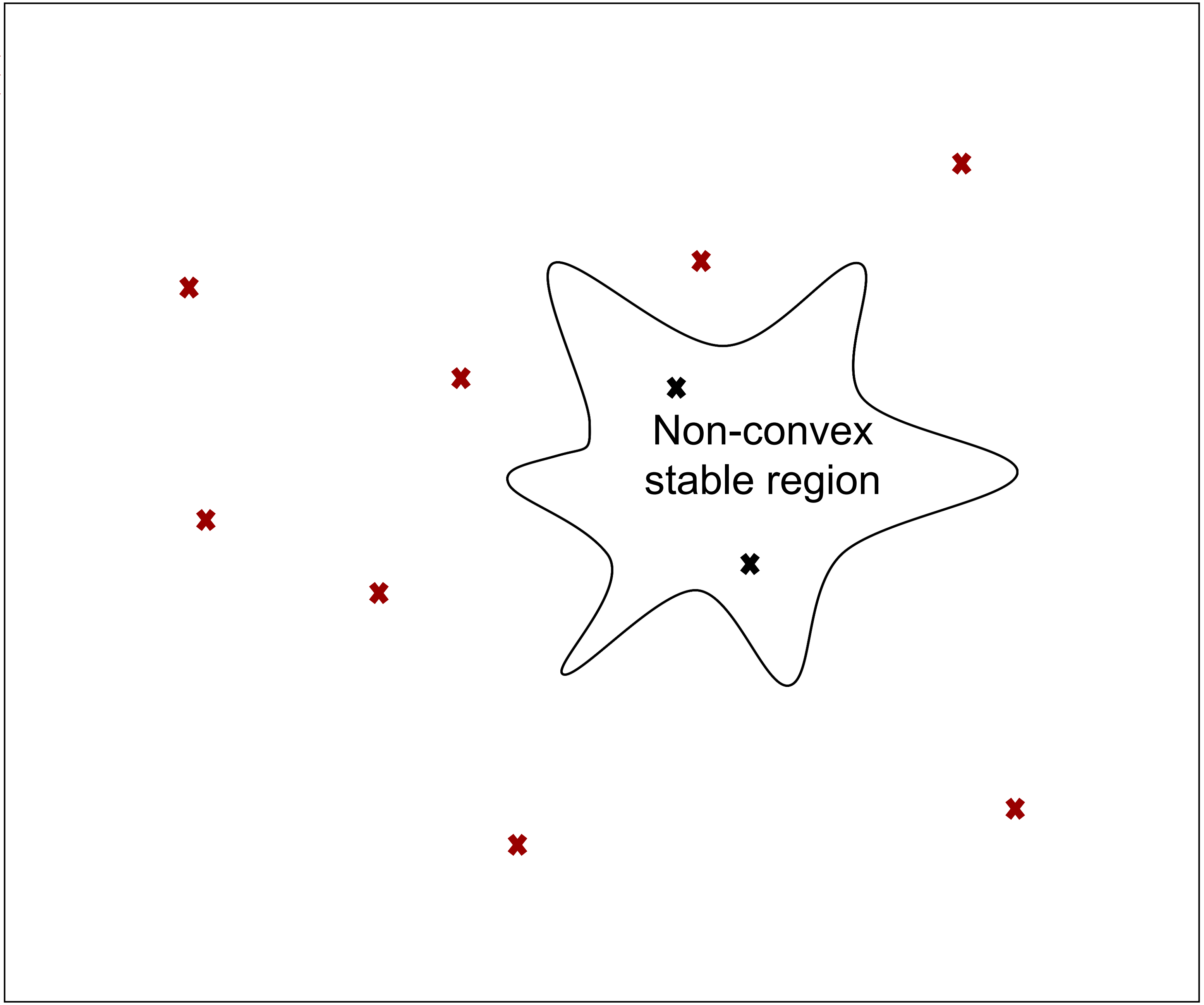
- The goal
  - **Focus** on the **boundary between stability and instability**
  - We call it: "high information content" region

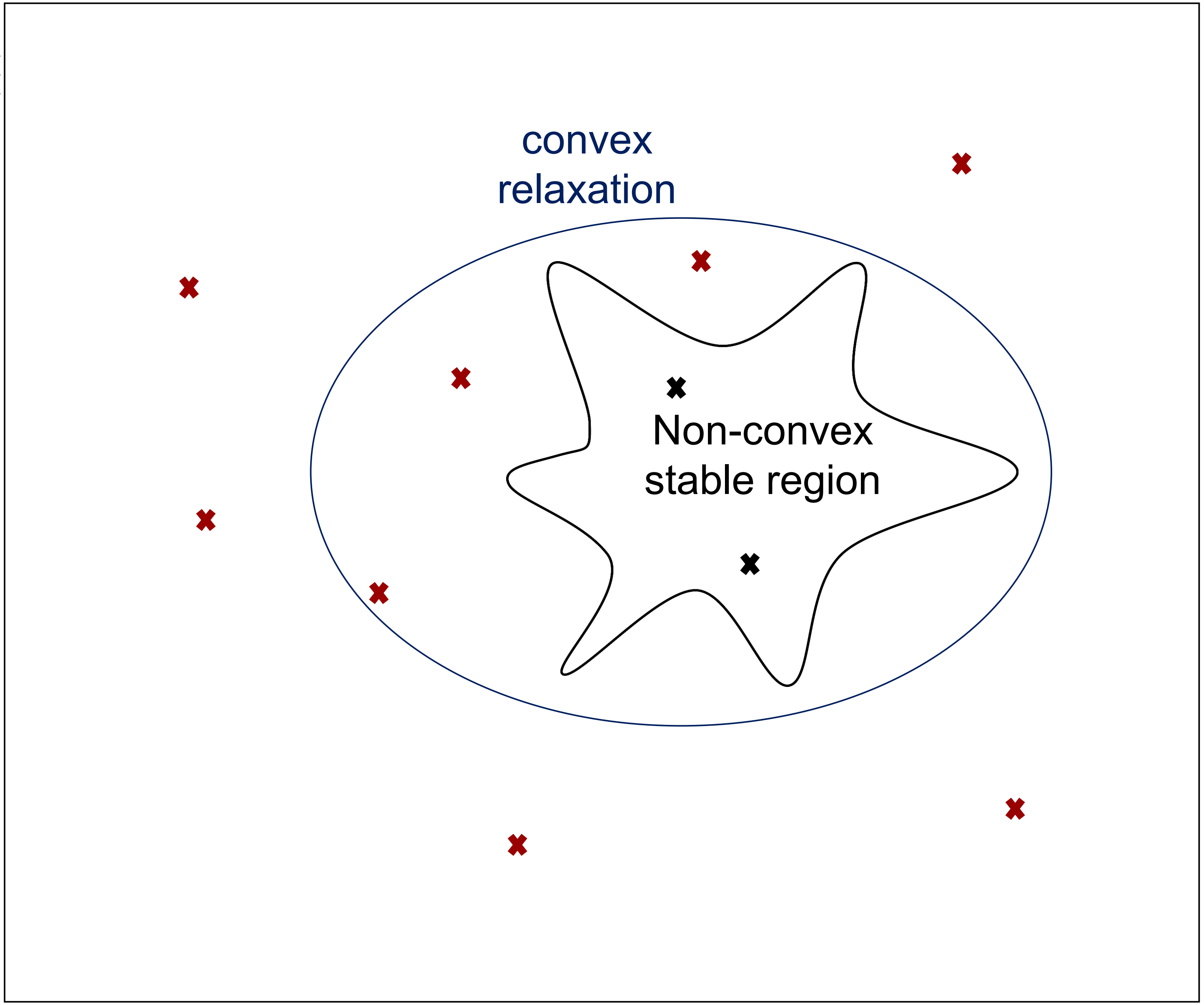
- How?
  1. Using convex relaxations
  2. And "Directed Walks"



Real data for the IEEE 14-bus system N-1 security and small-signal stability

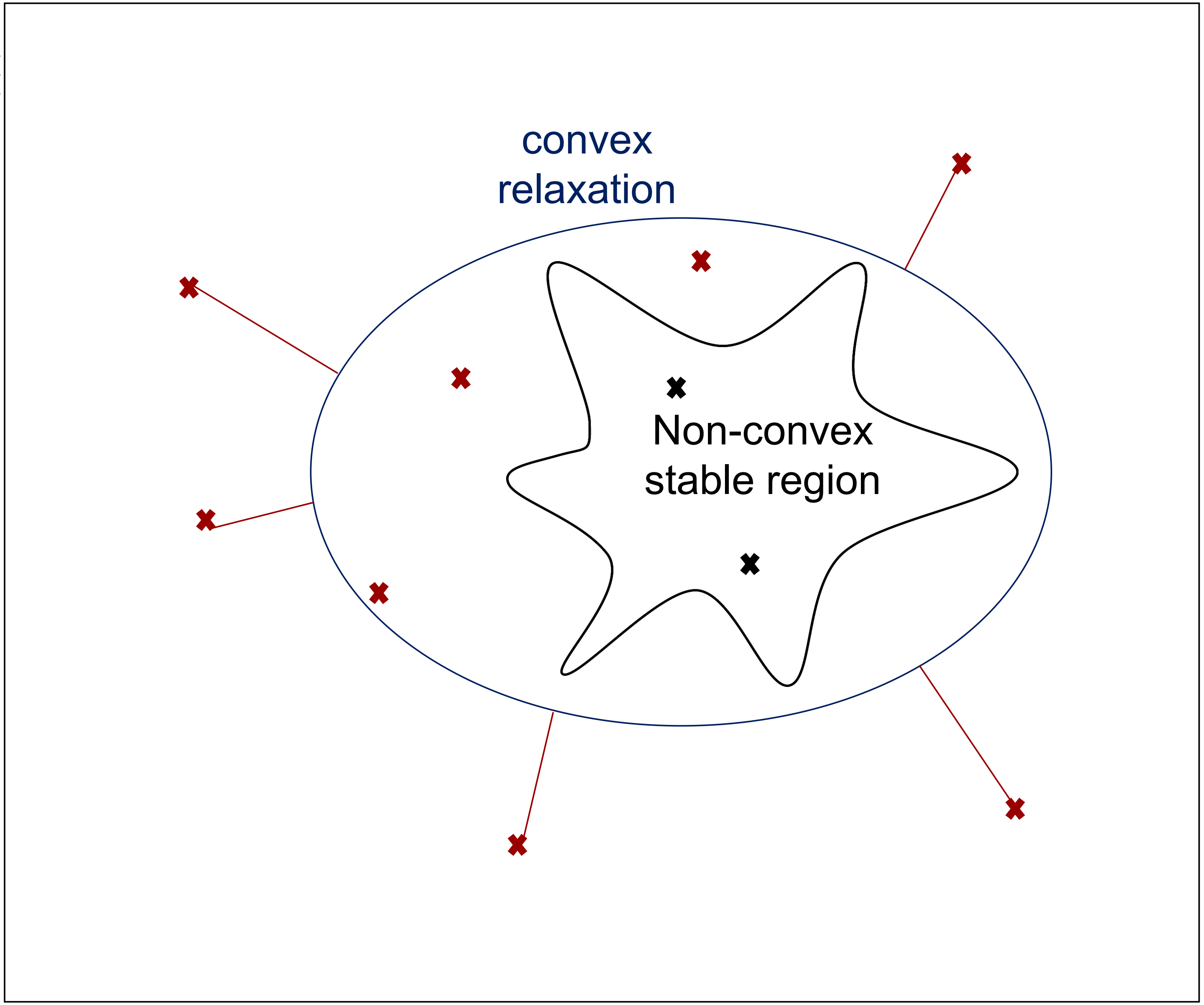
Convex relaxations to discard infeasible regions





Convex relaxations to discard infeasible regions

- Certificate: if point infeasible for semidefinite relaxation → infeasible for the original problem



Convex relaxations to discard infeasible regions

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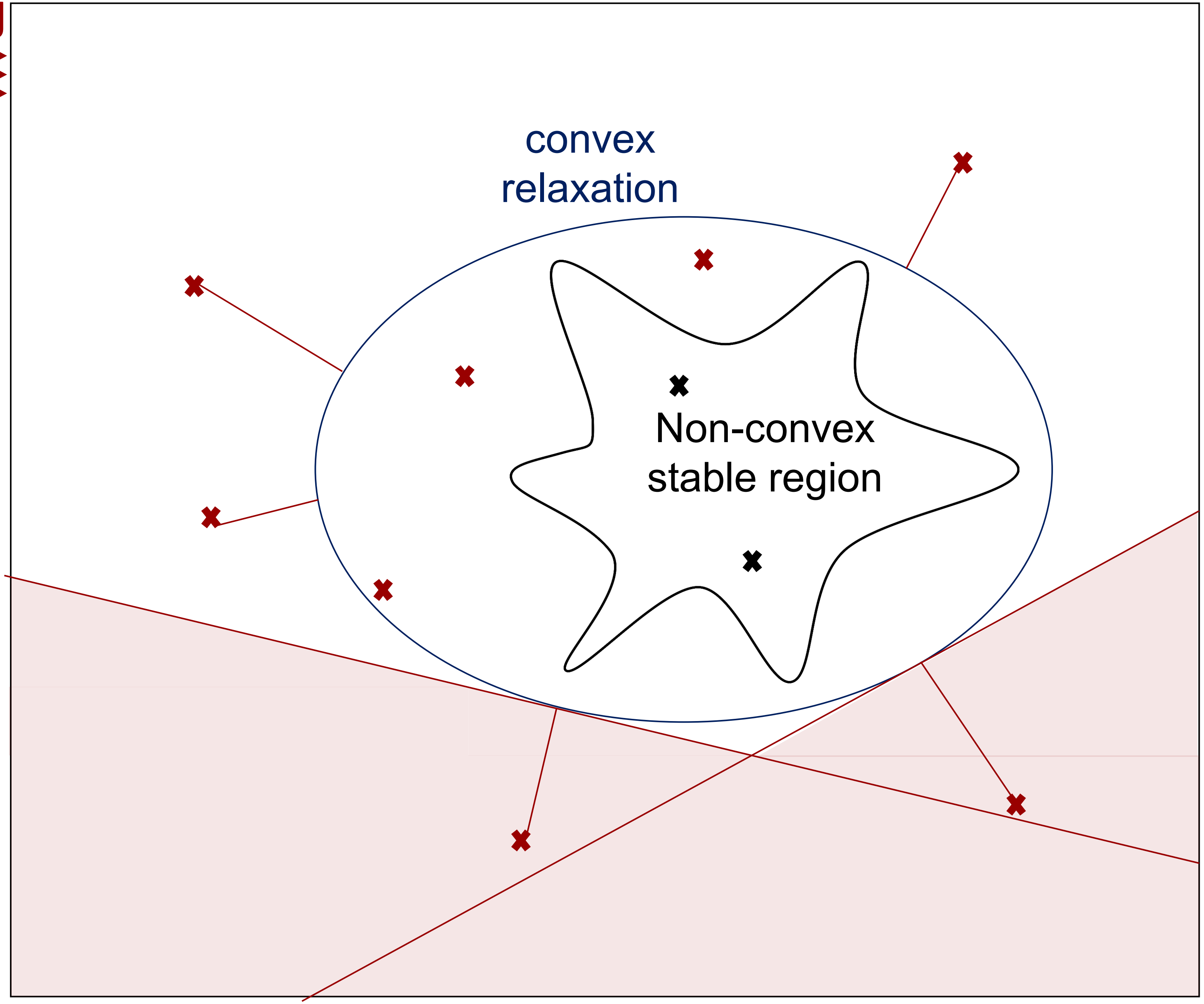


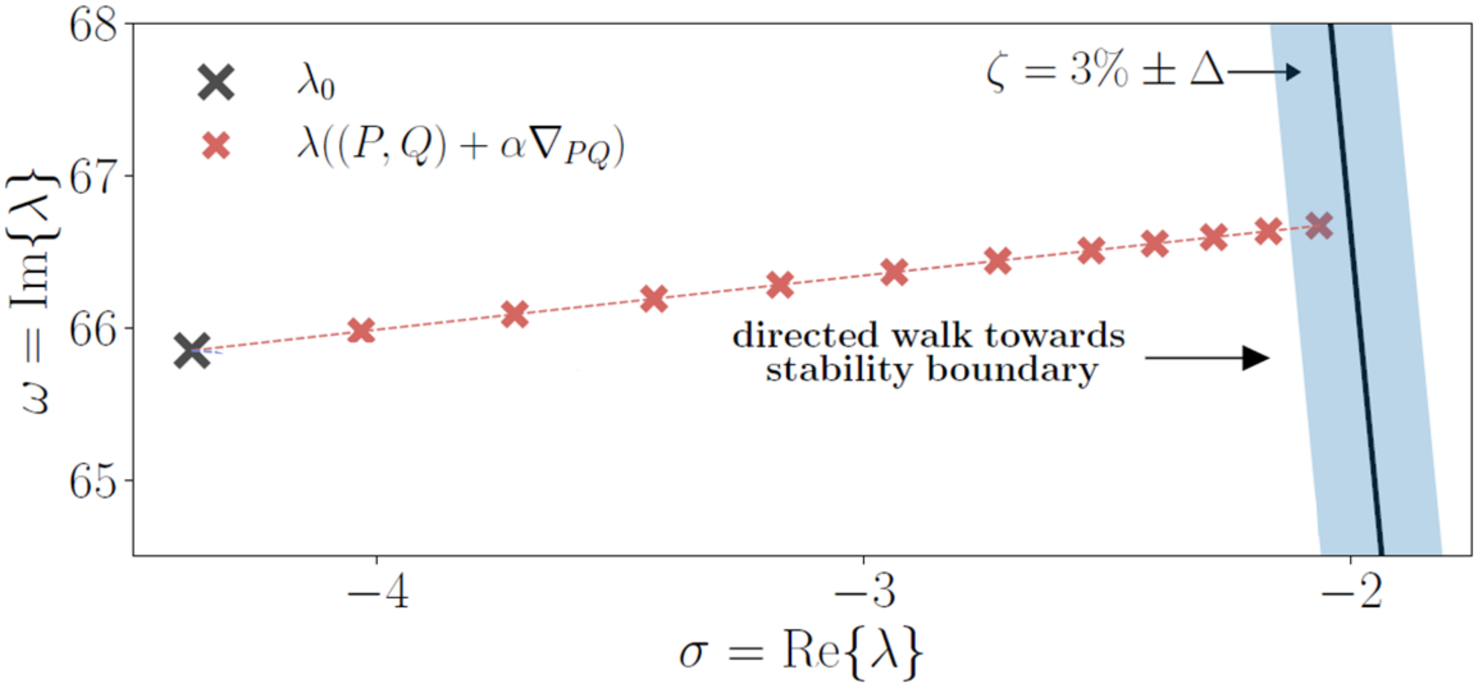
Convex relaxations to discard infeasible regions

- Certificate: if point infeasible for semidefinite relaxation → infeasible for the original problem
- If infeasible point: find minimum radius to feasibility
- Discard all points on one side of the hyperplane
- A. Venzke, D.K. Molzahn, S. Chatzivasileiadis, **Efficient Creation of Datasets for Data-Driven Power System Applications**. PSCC 2020. https://arxiv.org/pdf/1910.01794.pdf

Directed Walks

- “Directed walks”: steepest-descent based algorithm to explore the remaining search space, focusing on the area around the security boundary

1. Variable step-size
2. Parallel computation
3. Full N-1 contingency check



Results

	Points close to the security boundary (within distance γ)	
	IEEE 14-bus	NESTA 162-bus
Brute Force	100% of points in **556.0 min**	intractable
Importance Sampling	100% of points in **37.0 min**	**901 points** in 35.7 hours
Proposed Method	100% of points in **3.8 min**	**183’295 points** in 37.1 hours

NN-Informed Sampling

- Ideally: enrich the database with points near the stability boundary during NN training
  - But: impossible to know a priori which are these points

- What do we do?

NN-Informed Sampling

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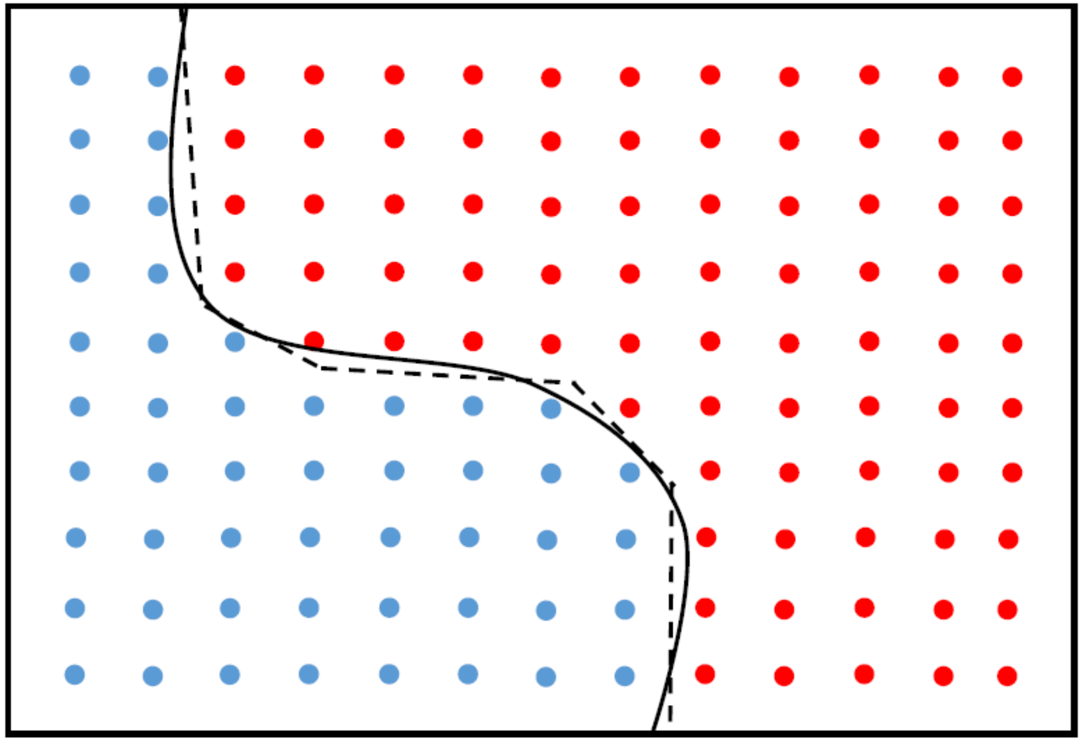
1. Sample 1’000’000 random points and have the NN assess them
   - Extremely fast → NN will take some minutes to assess all of them



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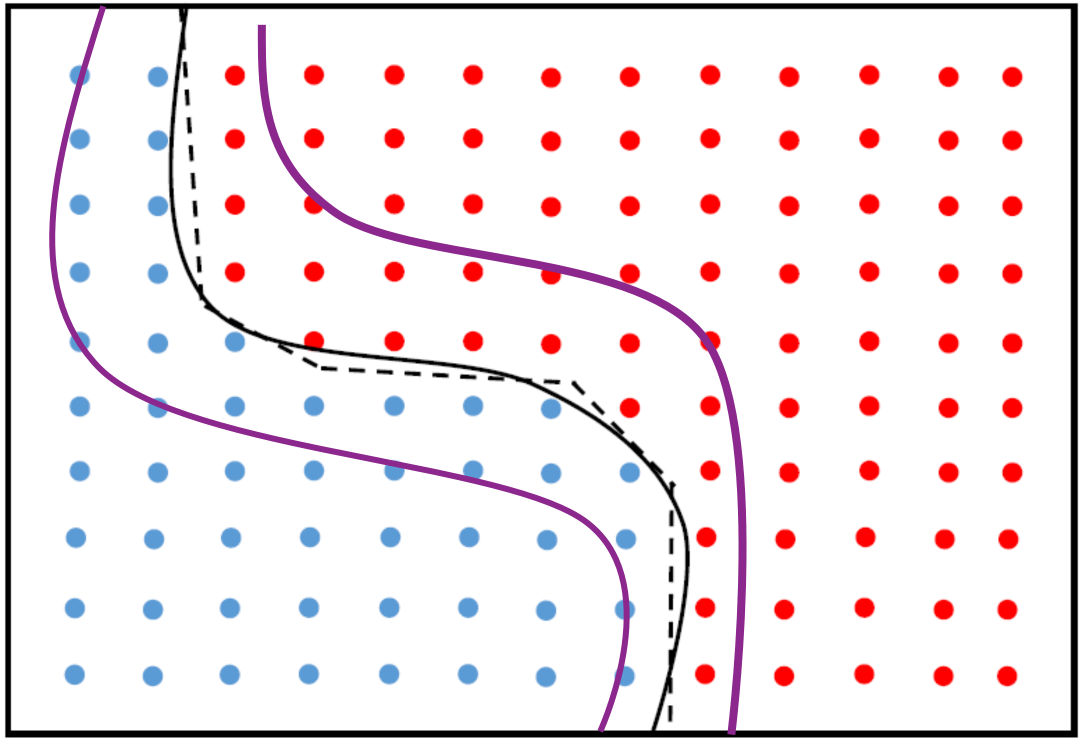

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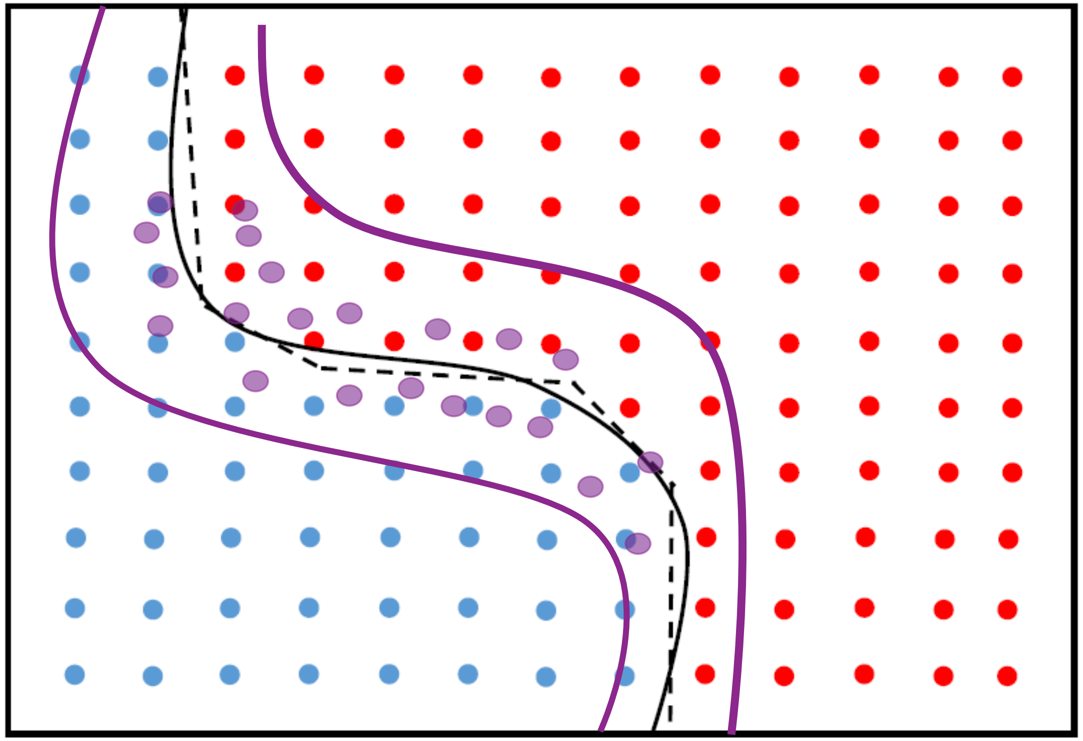
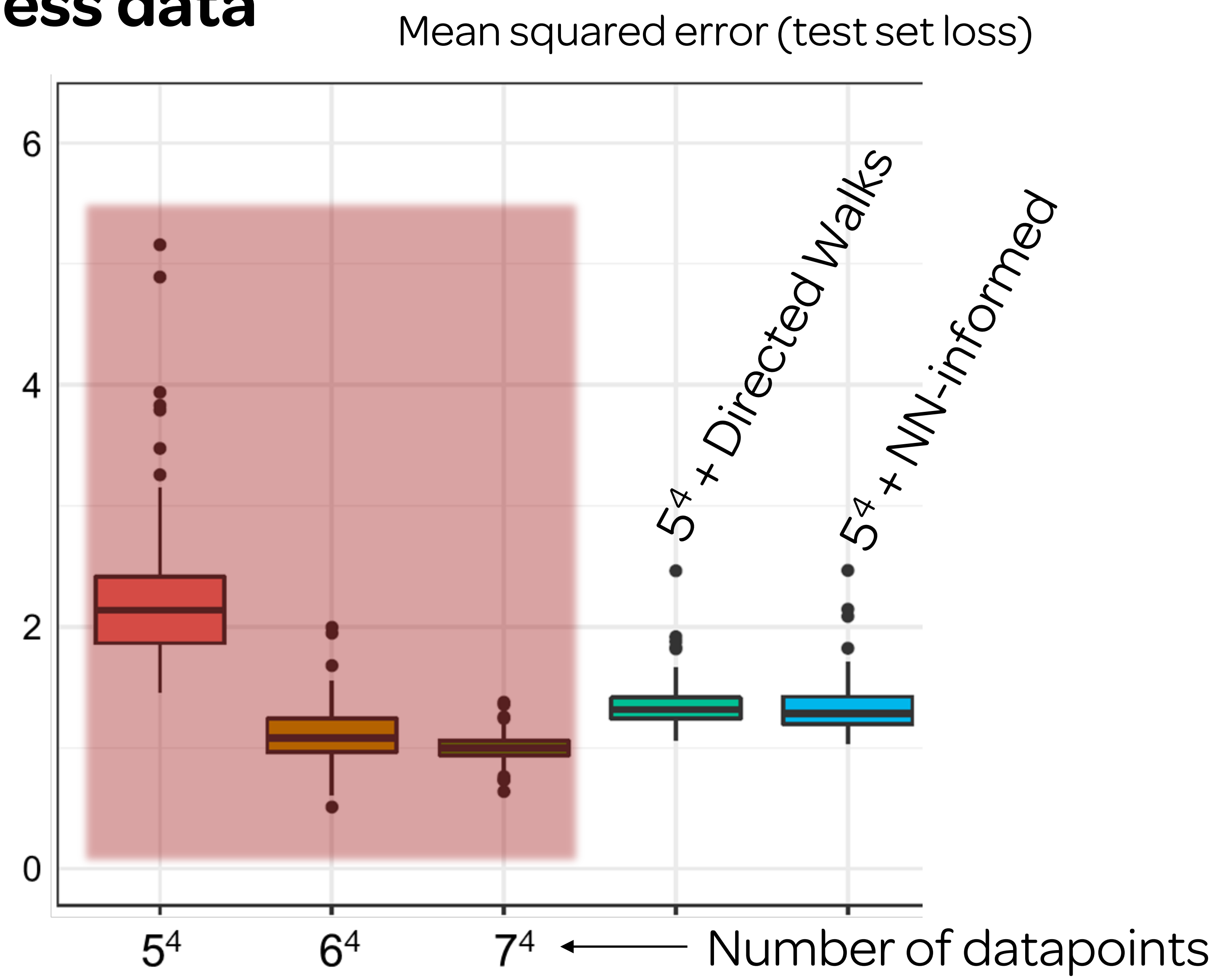
3. Sample 200 points in this region, compute the ground truth (=run N-1 and small signal stability), and enrich the database



Sampling beyond statistics: Better results with less data

- Larger datasets achieve lower error
  - 6^4 : ~2x more data than 5^4
  - 7^4 : ~4x more data than 5^4

- The directed walks and the NN-informed resampling achieve the **same performance with half the datapoints**



Note: Actual performance of DW and NI depends on the case study. But the trend remains the same across all our experiments

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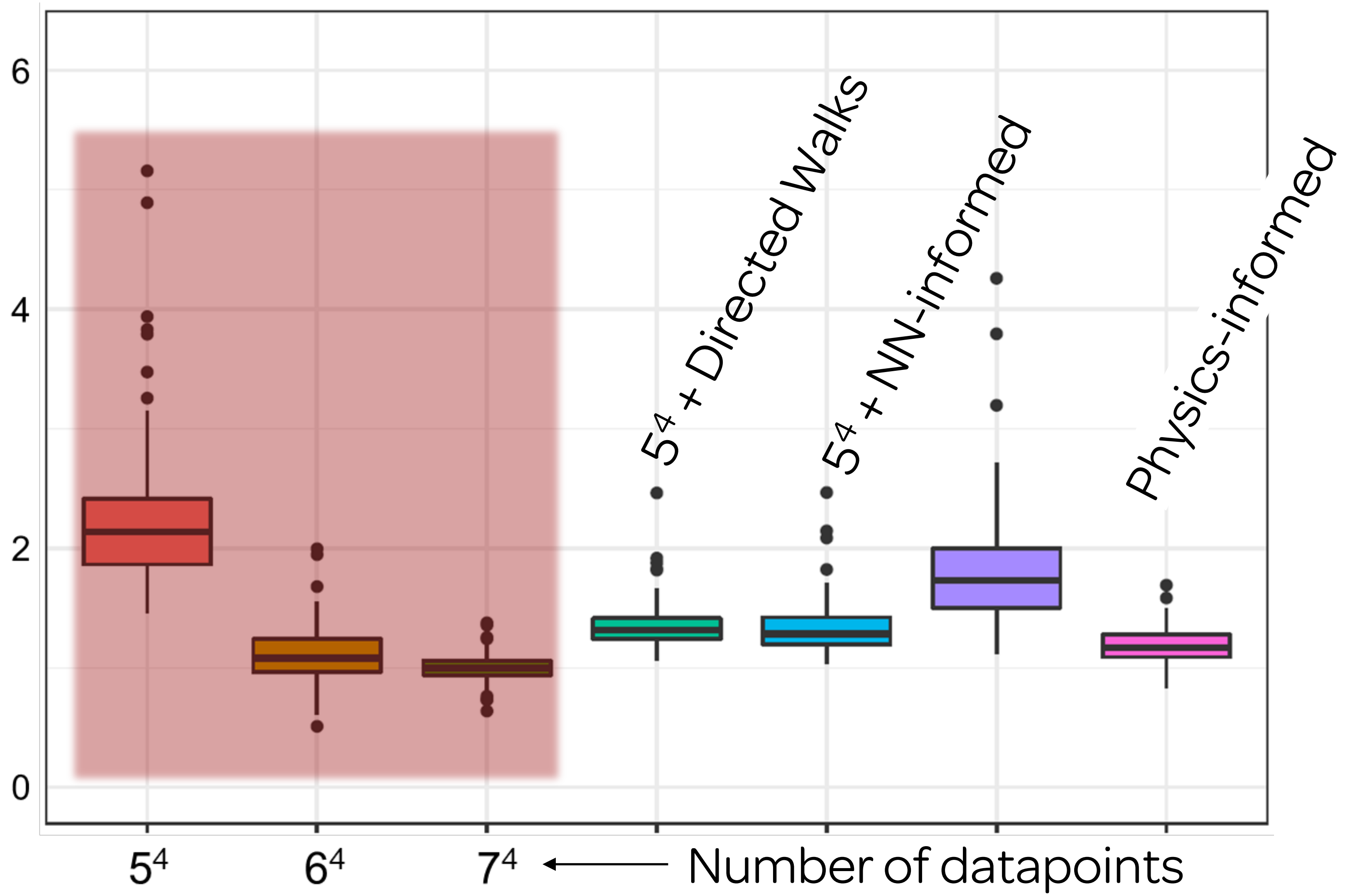
- The directed walks and the NN-informed resampling achieve the **same performance with half the datapoints**
- **Physics-Informed Neural Networks can achieve similar results**

Note: Actual performance of DW, NI, and PINNs depends on the case study. But the trend remains the same across all our experiments

Mean squared error (test set loss)

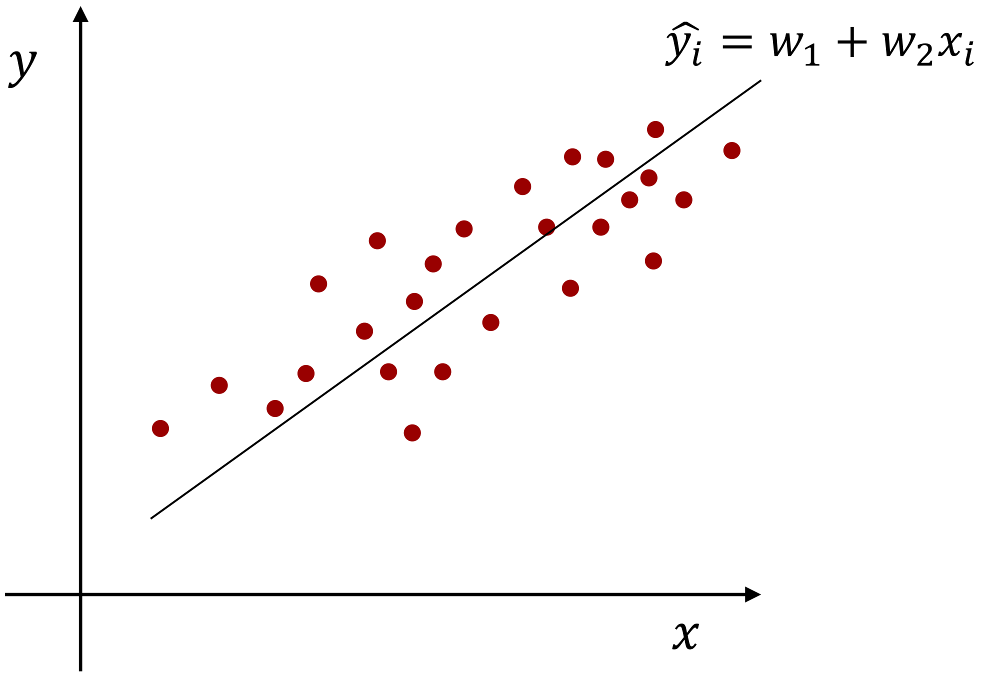


Physics-Informed Neural Networks for Power Systems

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

- Automatic differentiation: derivatives of the neural network output with respect to the input can be computed during the training procedure
- A differential-algebraic model of a physical system can be included in the neural network training*
- Neural networks can now exploit knowledge of the actual physical system
- Machine learning platforms (e.g. Tensorflow) enable these capabilities

*M. Raissi, P. Perdikaris, and G. Karniadakis, Physics-Informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations", Journal of Computational Physics, vol.378, pp. 686-707, 2019

Physics-Informed Neural Networks for Power Systems

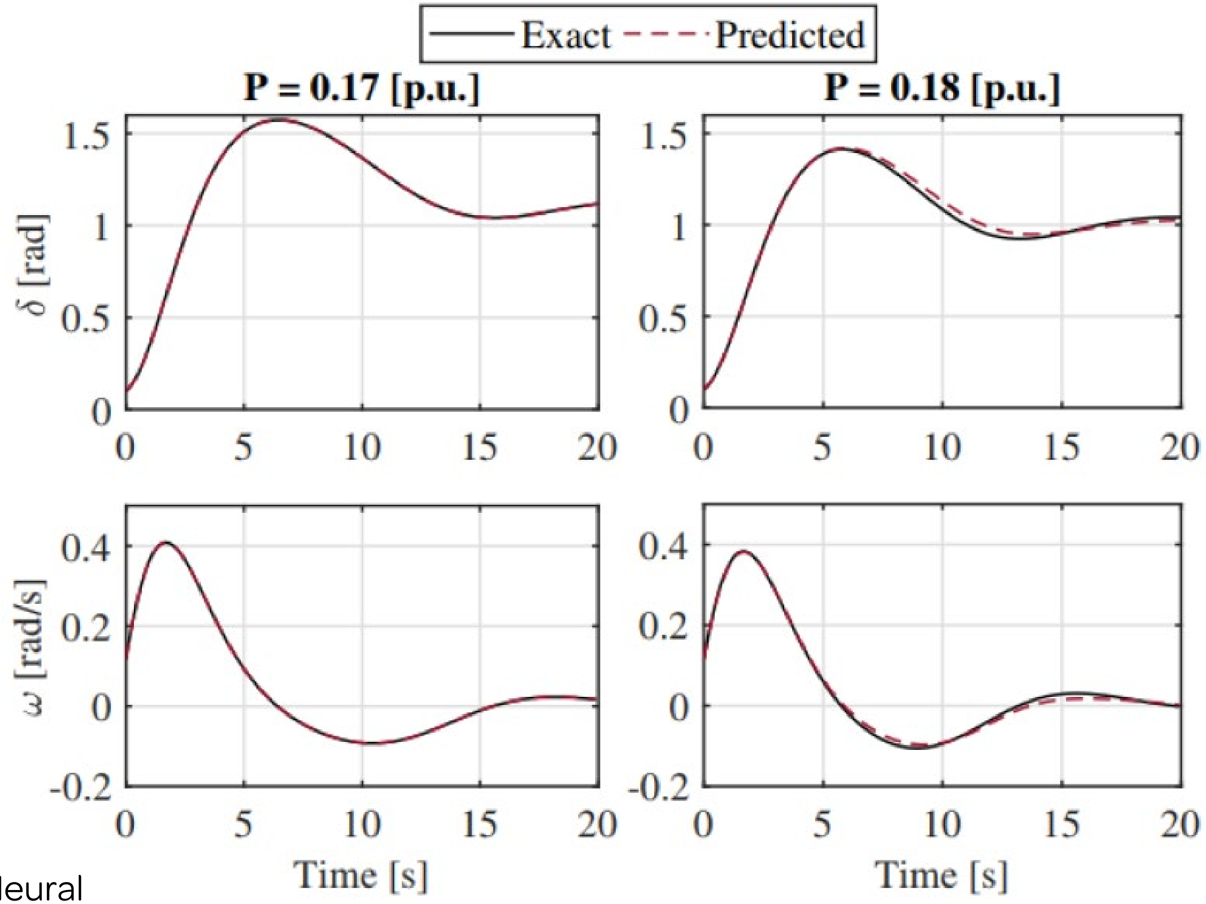
"Original"
Loss function

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

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

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

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



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

“Original” Loss function

“Physics-Informed” term

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

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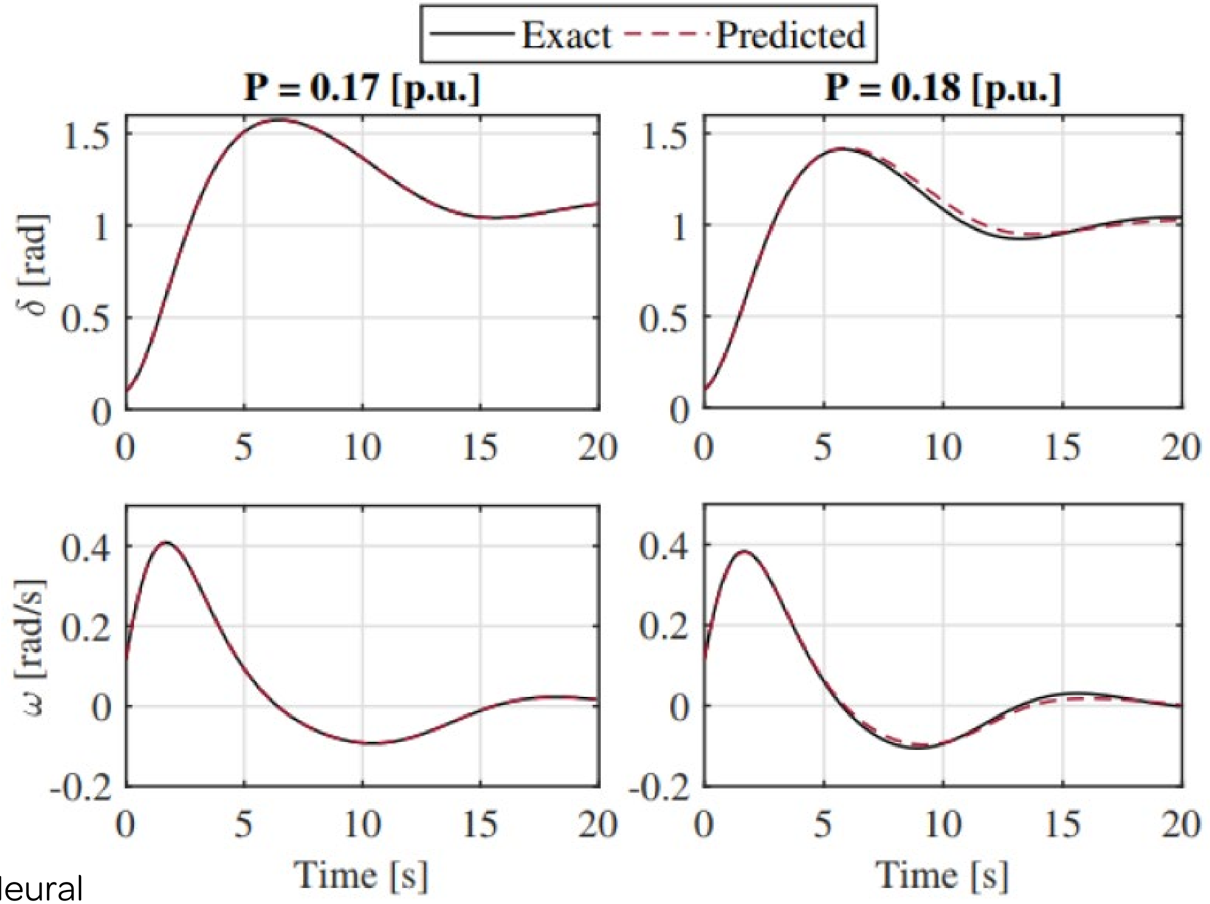
$$\boxed{f(\hat{\delta}) = M\ddot{\hat{\delta}} + D\dot{\hat{\delta}} + A\sin\hat{\delta} - P_m} \tag{6d}$$

Swing equation



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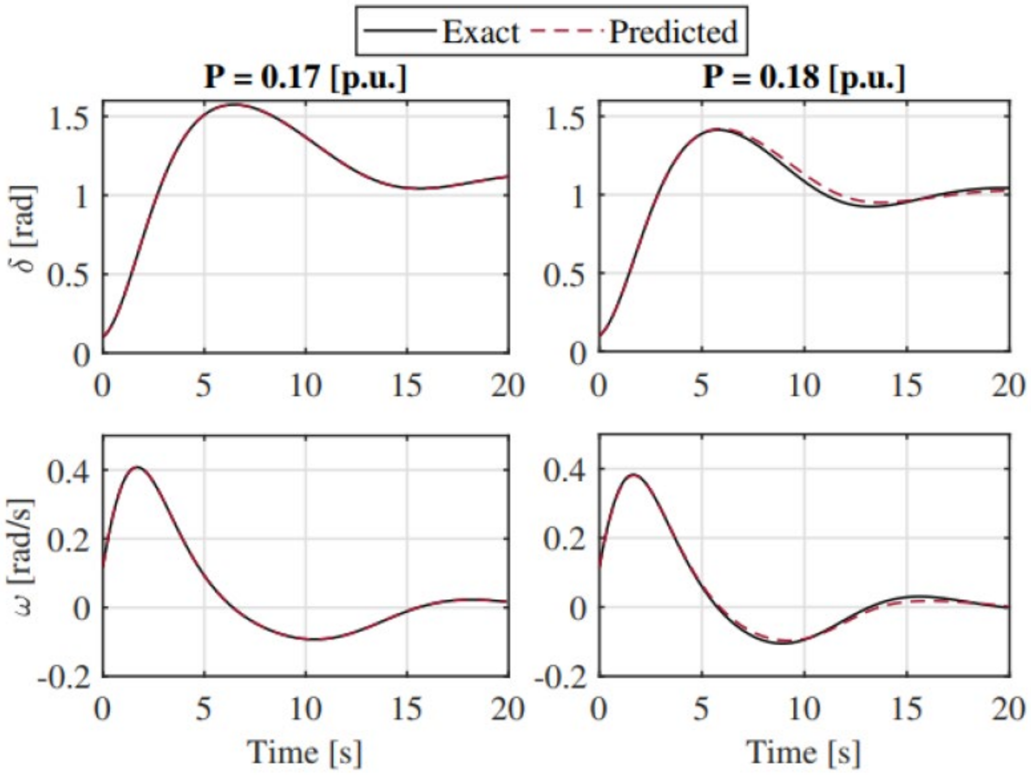
Physics-Informed Neural Networks for Power Systems

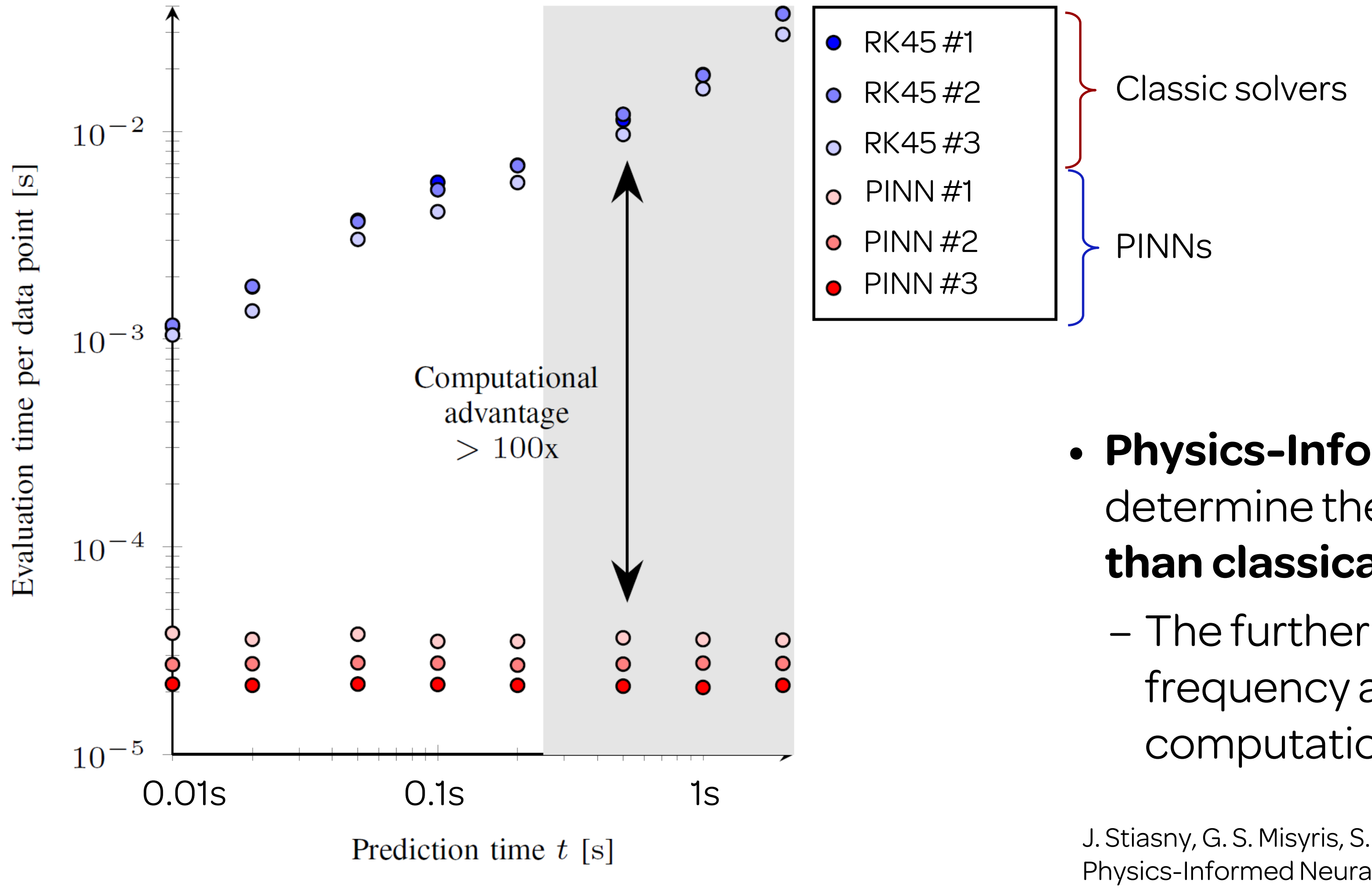
- Physics-Informed Neural Networks (PINN) could potentially replace solvers for systems of differential-algebraic equations in the long-term
  - **Probable power system application: Extremely fast screening of critical contingencies**
- In our example: PINN 87 times faster than ODE solver
- Can **directly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

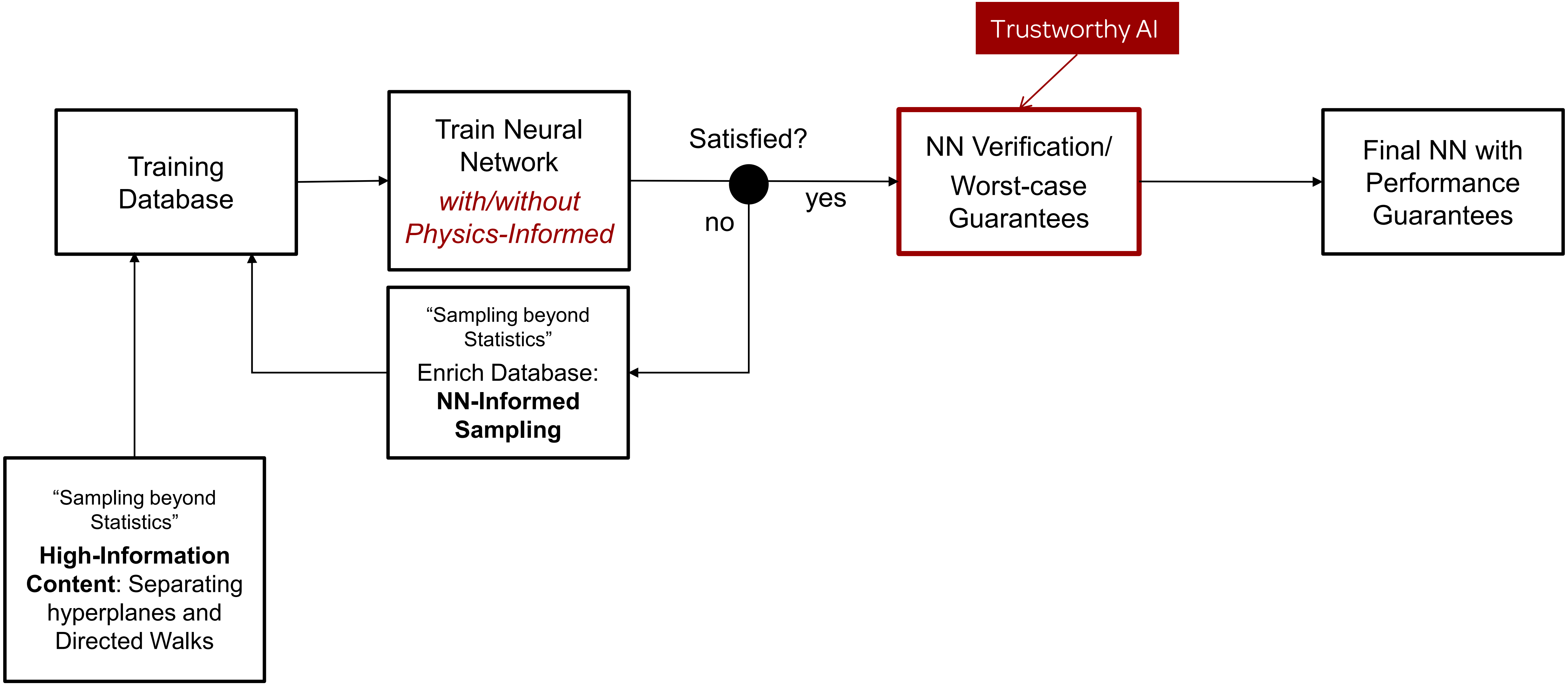
Computation time: Classical numerical solvers vs. Physics-Informed NNs



- **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]

Closing the Loop: Trustworthy ML for Power Systems



Neural Network Verification

for classification NNs in 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

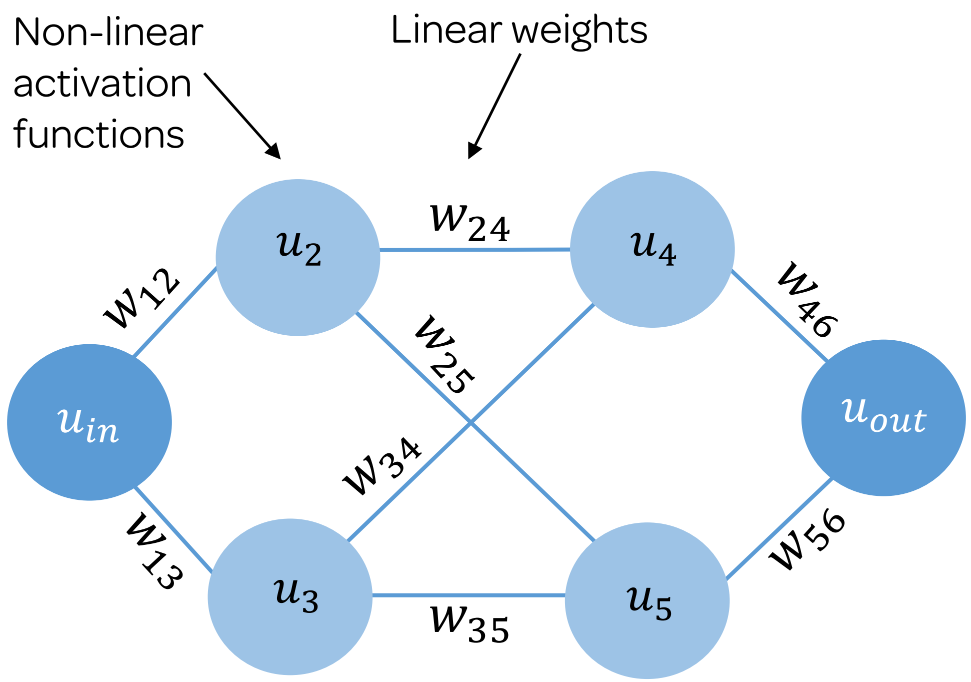
Neural Network Verification: HOW?

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

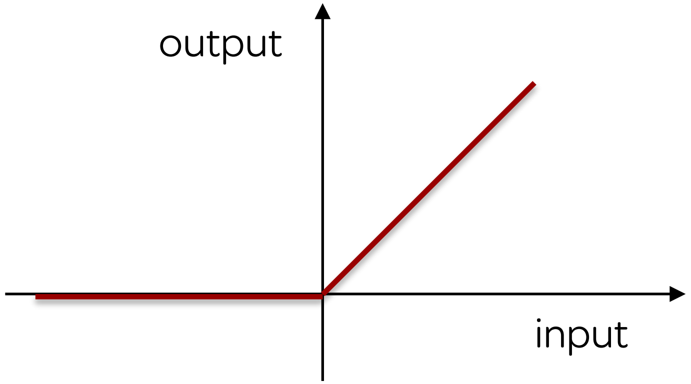
2. Formulate an **optimization** problem (MILP) and solve it → certificate for NN behavior

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

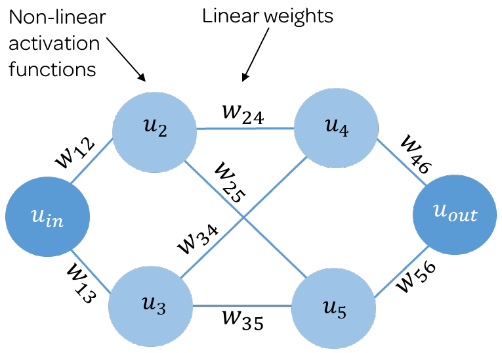
From Neural Networks to Mixed-Integer Linear Programming



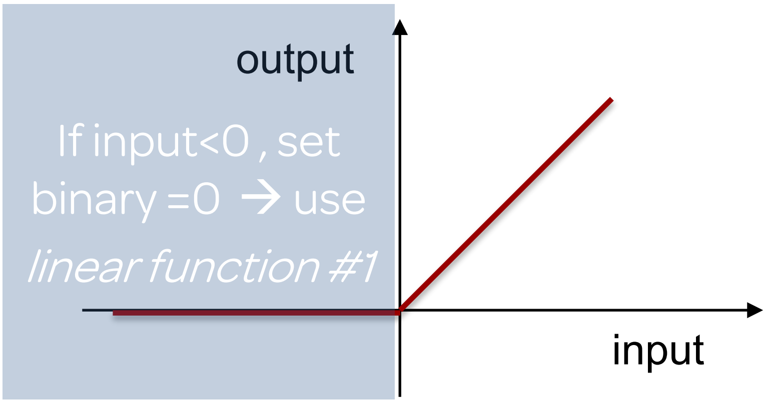
- Most usual activation function: ReLU
- **ReLU:** Rectifier Linear Unit



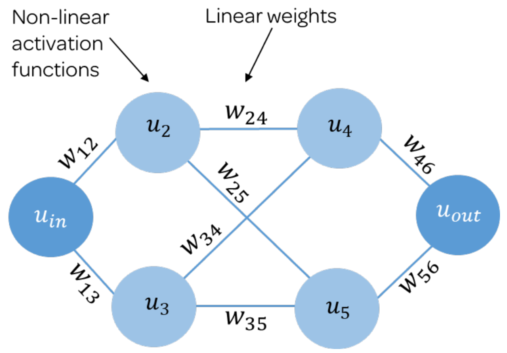
From Neural Networks to Mixed-Integer Linear Programming



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



From Neural Networks to Mixed-Integer Linear Programming



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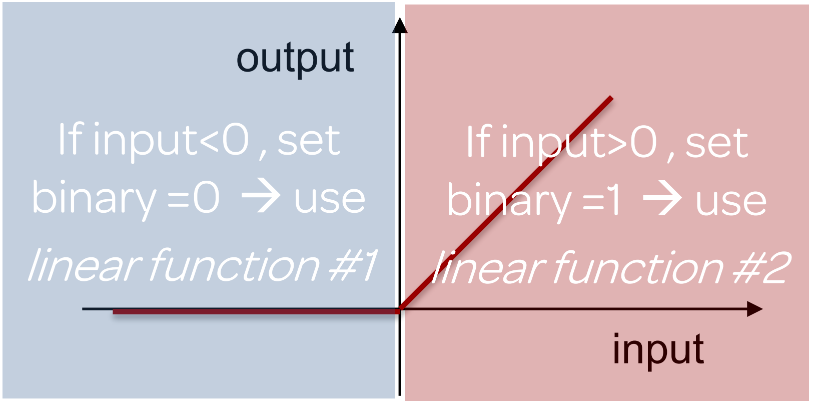

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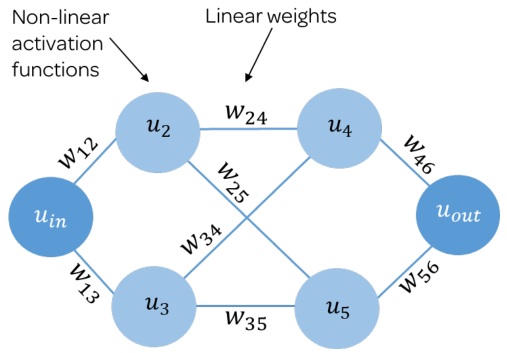
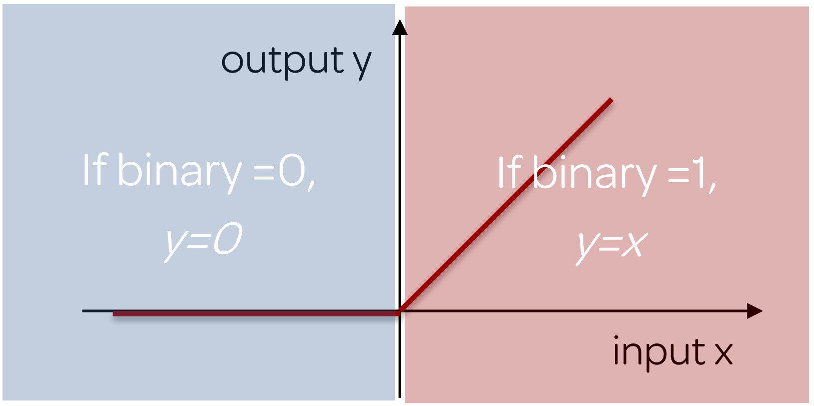


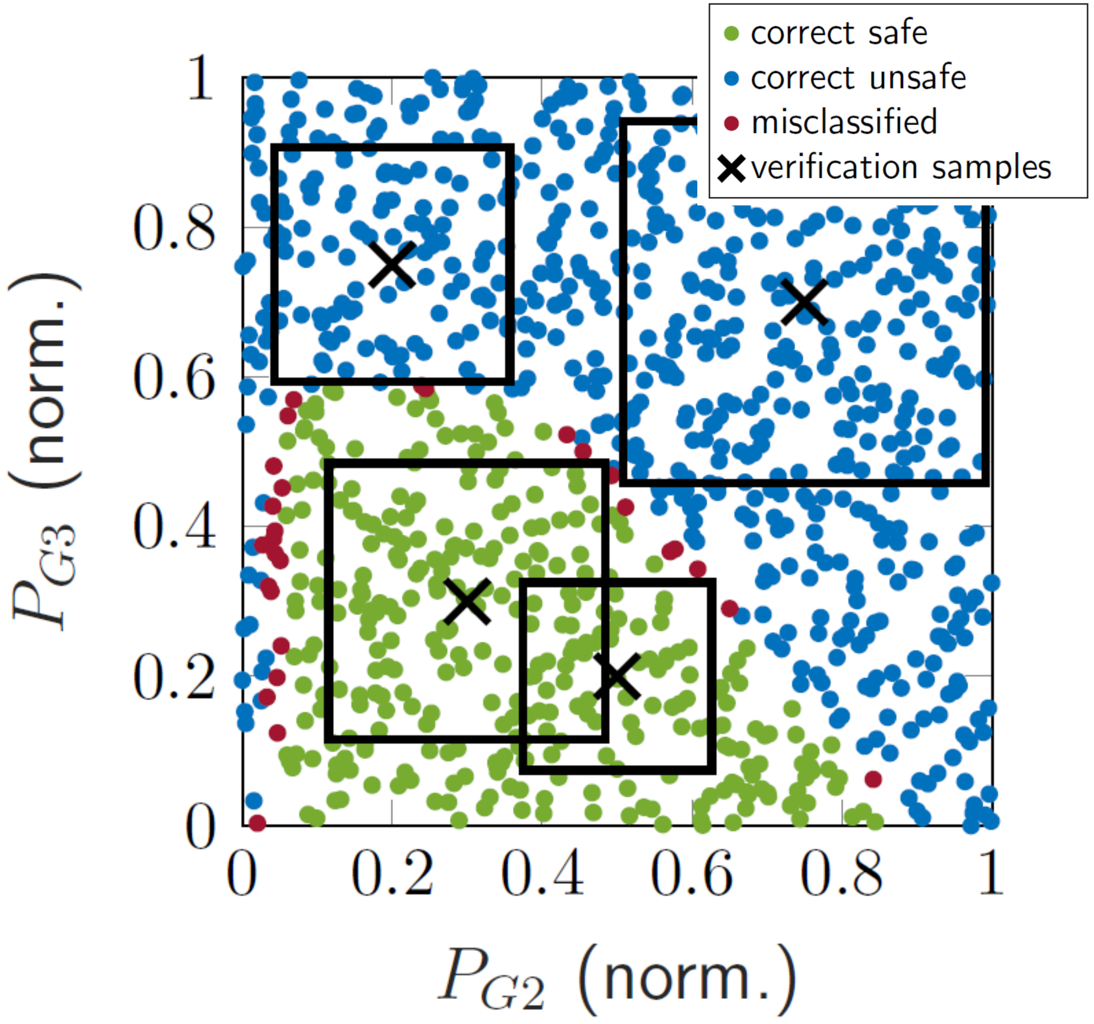
1. But **ReLU** can be transformed to a **piecewise linear function with binaries**



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**

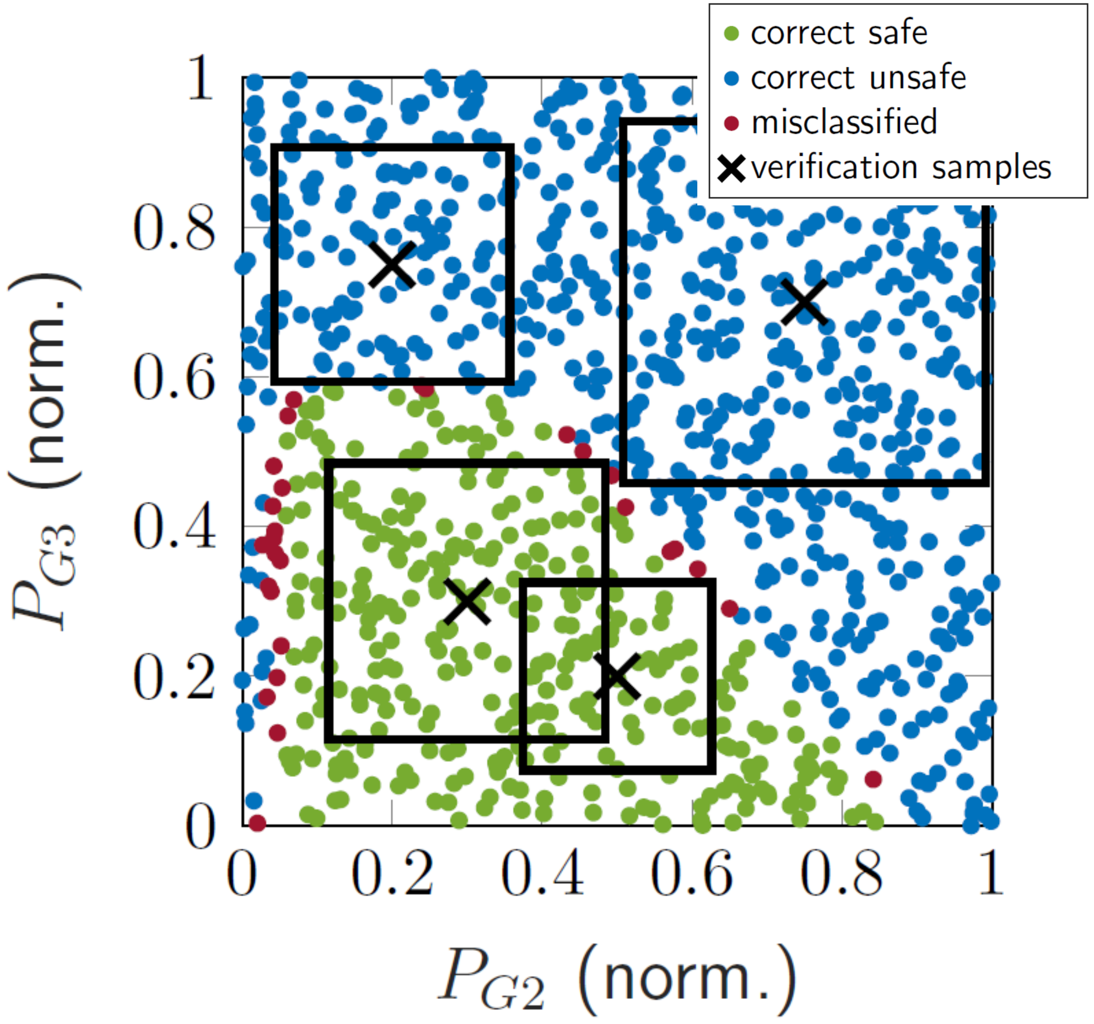
Certify the output for a continuous range of inputs



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

Certify the output for a continuous range of inputs



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 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

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

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 Optimal Power Flow

Optimal Power Flow

Minimize Total Generation Cost

Subject to:

Total supply = Total load demand

Transmission line limits

Generator limits

Several recent approaches in literature **apply Neural Networks** to estimate the optimal point

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

We have developed methods that can for the first time **determine these worst-case violations** (of any Neural Network to an OPF)

- Key point: Convert NN to a MILP

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

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	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**

	Empirical lower bound		Exact worst-case guarantee	
Test cases	ν_{g} (MW)	ν_{line} (MW)	ν_{g} (MW)	ν_{line} (MW)
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ν_{g} Maximum violation of generator limits

ν_{line} Maximum violation of line limits

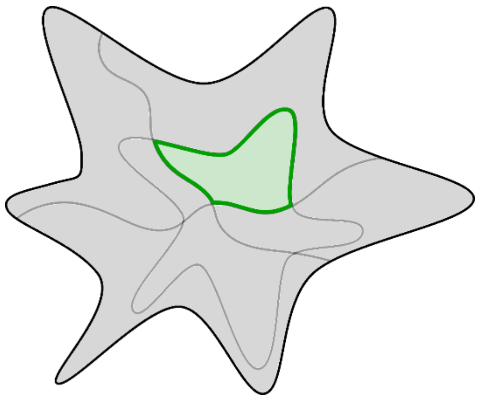
We can now provide **guarantees that no NN output will violate the line limits** over the whole input domain

The opportunity

“AI for Optimization”

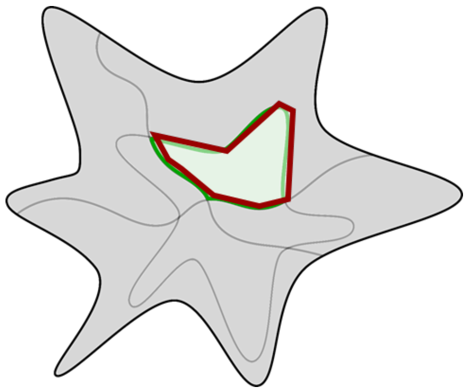
The opportunity: 1-slide summary

1. Take any non-convex region



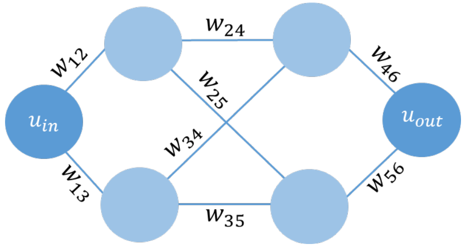
Intersection of all security/stability criteria: Non-linear and non-convex security region

2. Train a NN to approximate it

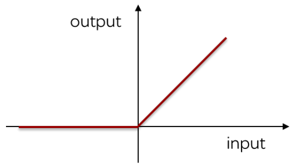


3. Convert NN to a MILP

(remember NN verification?)

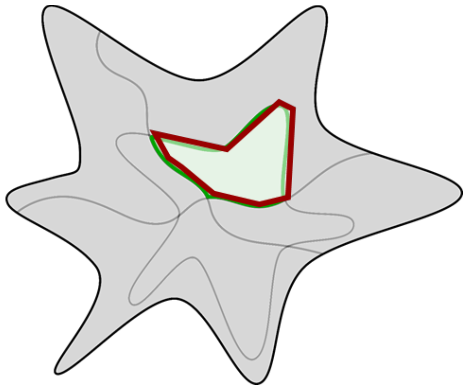


RELUs as activ. functions



MILP

4. Solve any problem



Example[1]: Instead of running e.g. 10'000 simulations to determine the critical clearing time for a set of disturbances, run a single optimization:

max *fault clearing time*

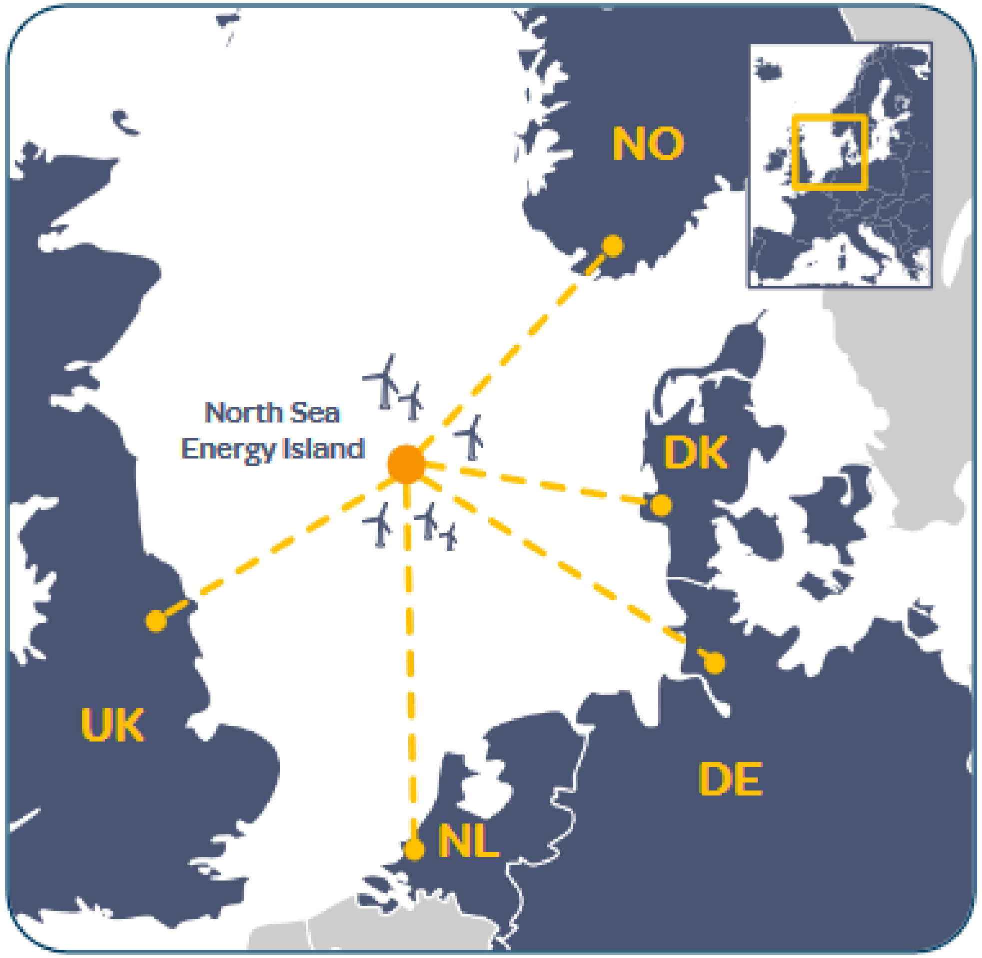
s.t. system=safe

[1]Misyris, Stiasny, Chatzivasileiadis, CDC, 2021

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

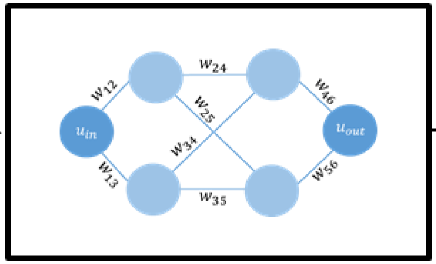


J. Stiasny, S. Chevalier, R. Nellikkath, B. Sævarsson, S. Chatzivasileiadis. **Closing the Loop: A Framework for Trustworthy Machine Learning in Power Systems**. Accepted to *2022 iREP Symposium - Bulk Power System Dynamics and Control - XI (iREP)*. Banff, Canada. 2022. [paper | code]

Opportunity: Convert Verified Neural Network to an Optimization Problem

Final Verified NN with Performance Guarantees

P
Q
$K_{p,f}$
K_v

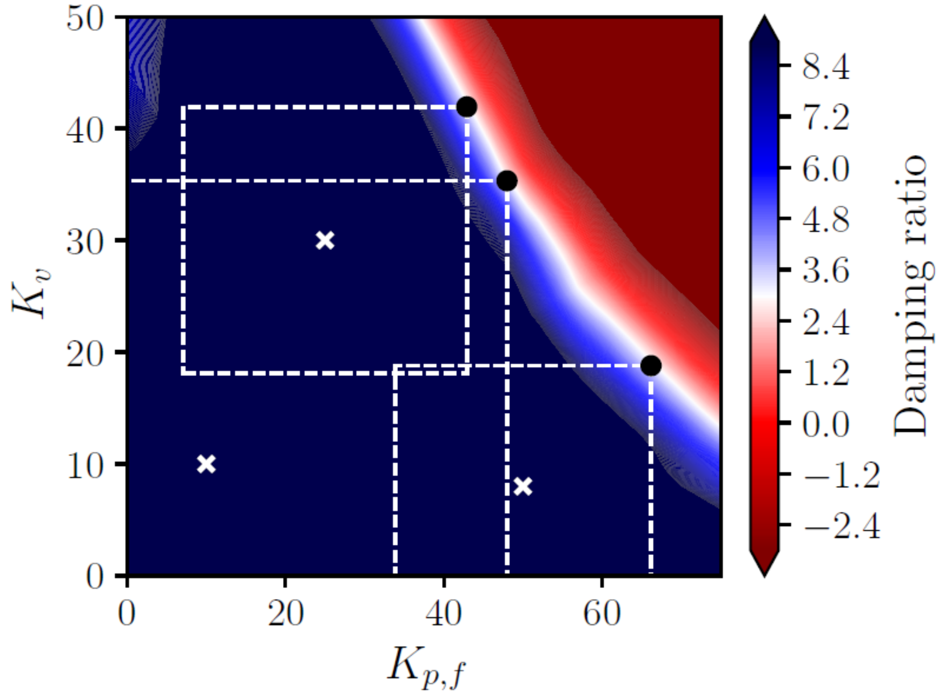


Small-signal stable for all N-1?

MILP

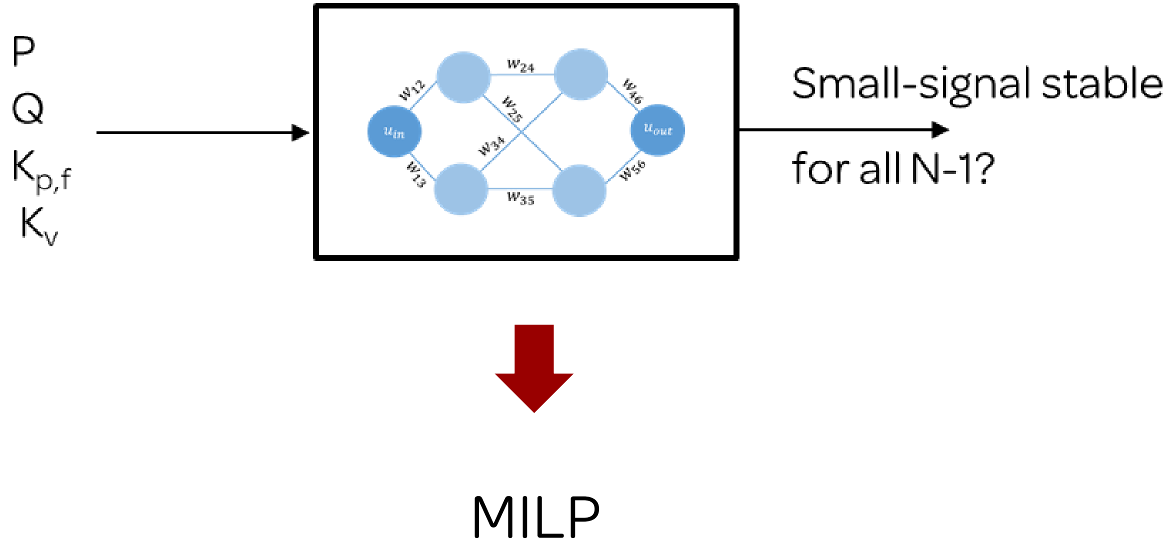
Optimization Problem #1

For given operating point (P^*_{ref}, Q^*_{ref}), what is the maximum range of frequency and voltage control parameters $(K_{p,f}$ and $K_v)$ that ensures small-signal stability for all N-1 contingencies?



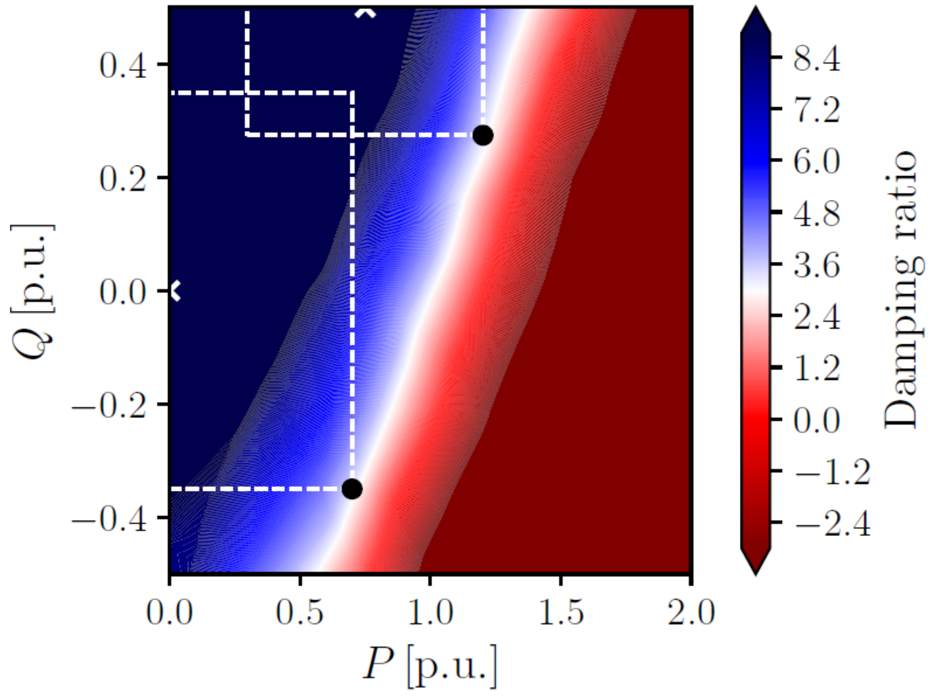
Opportunity: Convert Verified Neural Network to an Optimization Problem

Final Verified NN with Performance Guarantees



Optimization Problem #2

For given frequency and voltage control, what is the maximum permissible range of active and reactive power (P and Q) that ensures small-signal stability for all N-1 contingencies?



Wrap-up

1. **Sampling beyond statistics** can yield high quality training databases with smaller amounts of data

2. **Physics-informed neural networks** exploit the underlying physics in the training procedure.

3. **Neural network verification** builds the missing trust; necessary in safety-critical systems.

4. **From 1000s of simulations to a single optimization:** Neural Networks can capture previously intractable constraints and embed them in any optimization problem

"Data-centric AI movement"
(Andrew Ng, Stanford, and others)

"Small [data] is the new big"
(IEEE Spectrum, Apr. 2022)

Exploit the prior knowledge

What did I not talk about

Exploring a wide range of research directions

1. Accelerating MILPs: using Decision Trees to estimate the active set and drastically reduce the number of binary variables [https://arxiv.org/pdf/2010.06344.pdf , IEEE Trans. Power Systems]

2. Contracting Neural-Newton Solver: Derive convergence guarantees for Neural Networks that can replace conventional Newton solvers [https://arxiv.org/pdf/2106.02543.pdf , L4DC 2022]

3. Interpretable Machine Learning: Direct association of the SHAP Values with the Power Transfer Distribution Factors (PTDFs) [https://arxiv.org/pdf/2209.05793.pdf , submitted]

4. Input Convex NNs for convex approximations of non-convex optimization problems [https://arxiv.org/pdf/2209.08645.pdf , submitted]

5. Physics-Informed Neural Networks for Fast Dynamic Security Assessment [https://arxiv.org/pdf/2106.13638.pdf, code: https://github.com/jbesty/PINNs_transient_stability_analysis]

6. Neural Network Training with by-design worst-case guarantees [soon on ArXiV]

and others…

Interested in a postdoc or PhD?

- Come work with us!
- Wide range of topics around ML and beyond:
  - Trustworthy Machine Learning, Physics-Informed Neural Networks, capturing intractable constraints with NNs, and more!
  - Working with real datasets, and industry collaboration
  - Opportunities for open academic research and/or toolbox development for practical applications
- Open positions online!
- Contact: spchatz@dtu.dk

Thank you!

Spyros Chatzivasileiadis

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spchatz@dtu.dk

- A. Venzke, S. Chatzivasileiadis. Verification of Neural Network Behaviour: Formal Guarantees for Power System Applications. Accepted at IEEE Trans. on Smartgrid. 2020. 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.[.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
- R. Nellikkath, S. Chatzivasileiadis, Physics-Informed Neural Networks for AC Optimal Power Flow https://arxiv.org/abs/2110.02672 [code]
- J. Stiasny, G. S. Misyris, S. Chatzivasileiadis, Transient Stability Analysis with Physics-Informed Neural Networks. https://arxiv.org/abs/2106.13638 [code]
- 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]

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]

All publications available at:

www.chatziva.com/publications.html

Some code available at:

www.chatziva.com/downloads.html