Machine learning for power systems: Physics-Informed Neural Networks and Verification

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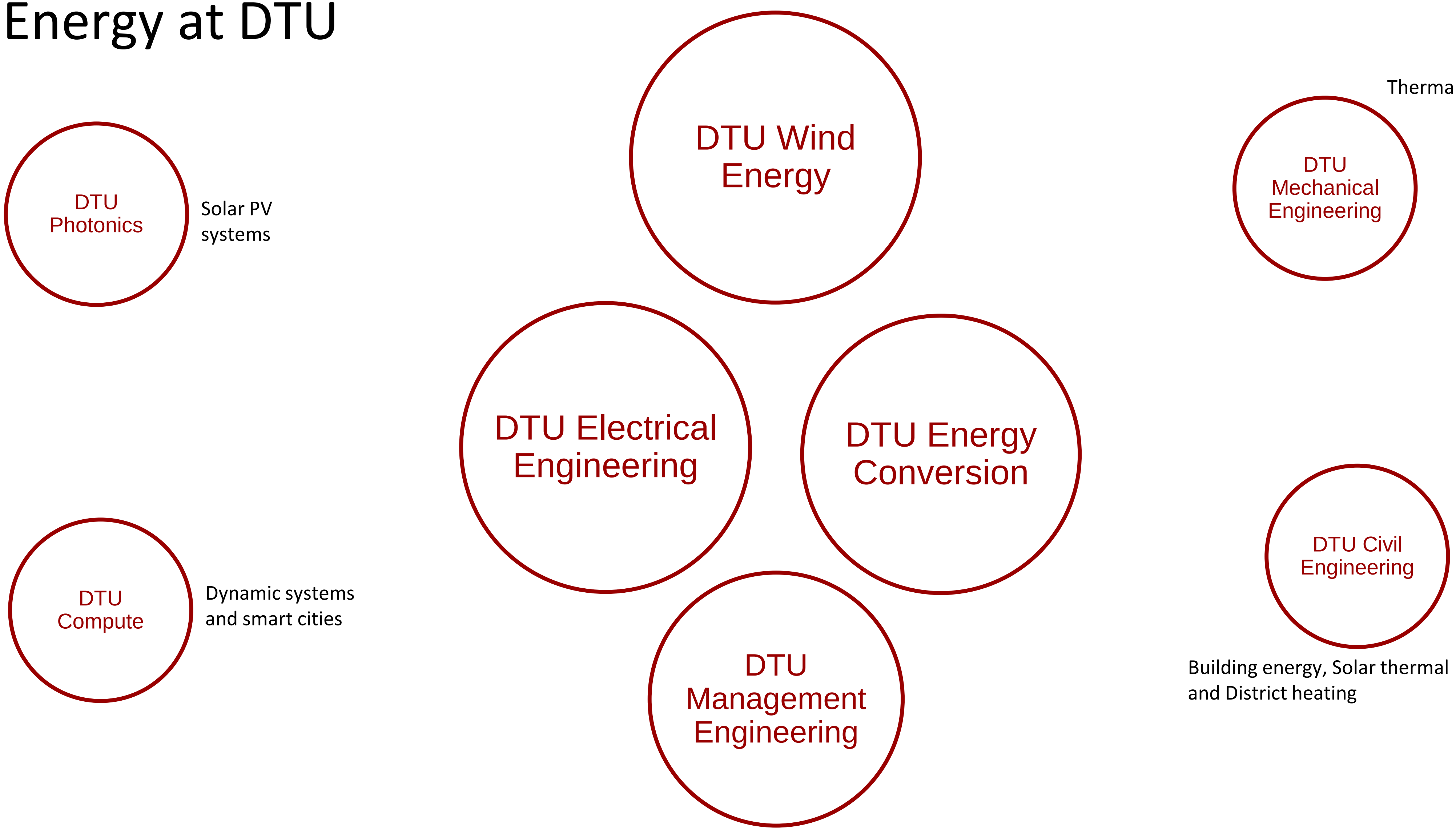


DTU Photonics

Solar PV systems

DTU Wind Energy

Thermal systems

DTU Mechanical Engineering

DTU Electrical Engineering

DTU Energy Conversion

DTU Compute

Dynamic systems and smart cities

DTU Civil Engineering

Building energy, Solar thermal and District heating

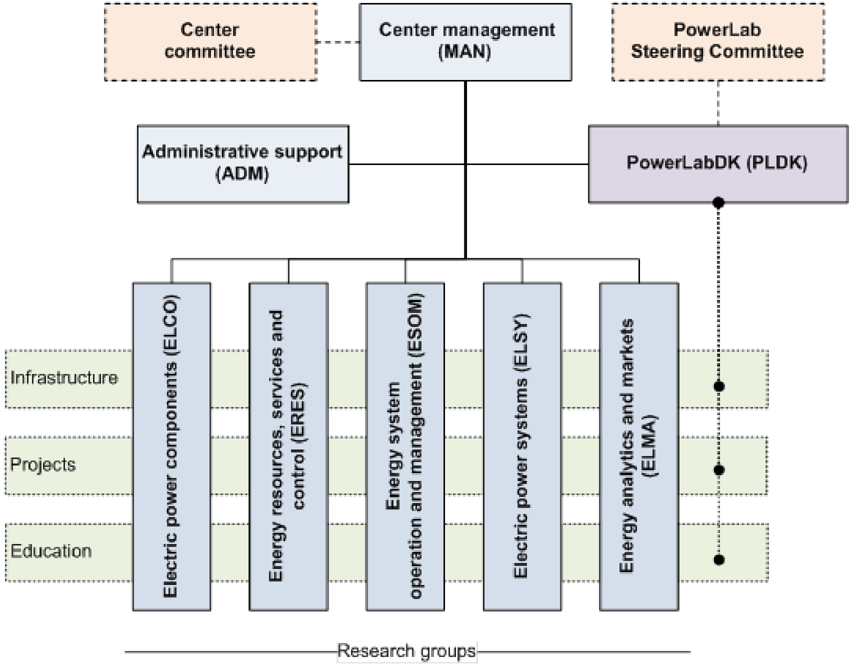
DTU Management Engineering

Energy system analysis and policy

Center for Electric Power and Energy (CEE)

- **Established 15 August 2012** by merging two existing units (Lynbgy + Risø)
  - Among the strongest university centers in Europe with approx. 110 employees and 12 faculty members
- **Bachelor and Master programs:** Sustainable Energy Design, Electrical Engineering, Wind Energy, Sustainable Energy
- **Direct support from:**

ENERGINET Ørsted SIEMENS Danfoss



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Center management (MAN)
PowerLab Steering Committee
Administrative support (ADM)
PowerLabDK (PLDK)
Infrastructure
Projects
Education
Electric power components (ELCO)
Energy resources, services and control (ERES)
Energy system operation and management (ESOM)
Electric power systems (ELSY)
Energy analytics and markets (ELMA)
Research groups

DTU has consistently ranked among the top 10 universities of the world in Energy Science and Engineering (Shanghai ranking, 2016, 2017, 2018)

Strong National and International Collaboration

Selected collaboration partners

Academic partners:

ETH Zürich (CH)

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NANYANG TECHNOLOGICAL UNIVERSITY (SG)

Tsinghua University (CN)

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NORDIC FIVE TECH

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NTNU (NO) Norwegian University of Science and Technology

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>80 formal partners

Commercial and industrial partners:

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KØBENHAVNS KOMMUNE (DK)

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>100 formal partners

s:

Smart Energy Networks Research, Development and Demonstration (DK)

MISSION INNOVATION Accelerating the Clean Energy Revolution (Global)

EERA European Energy Research Alliance (EU)

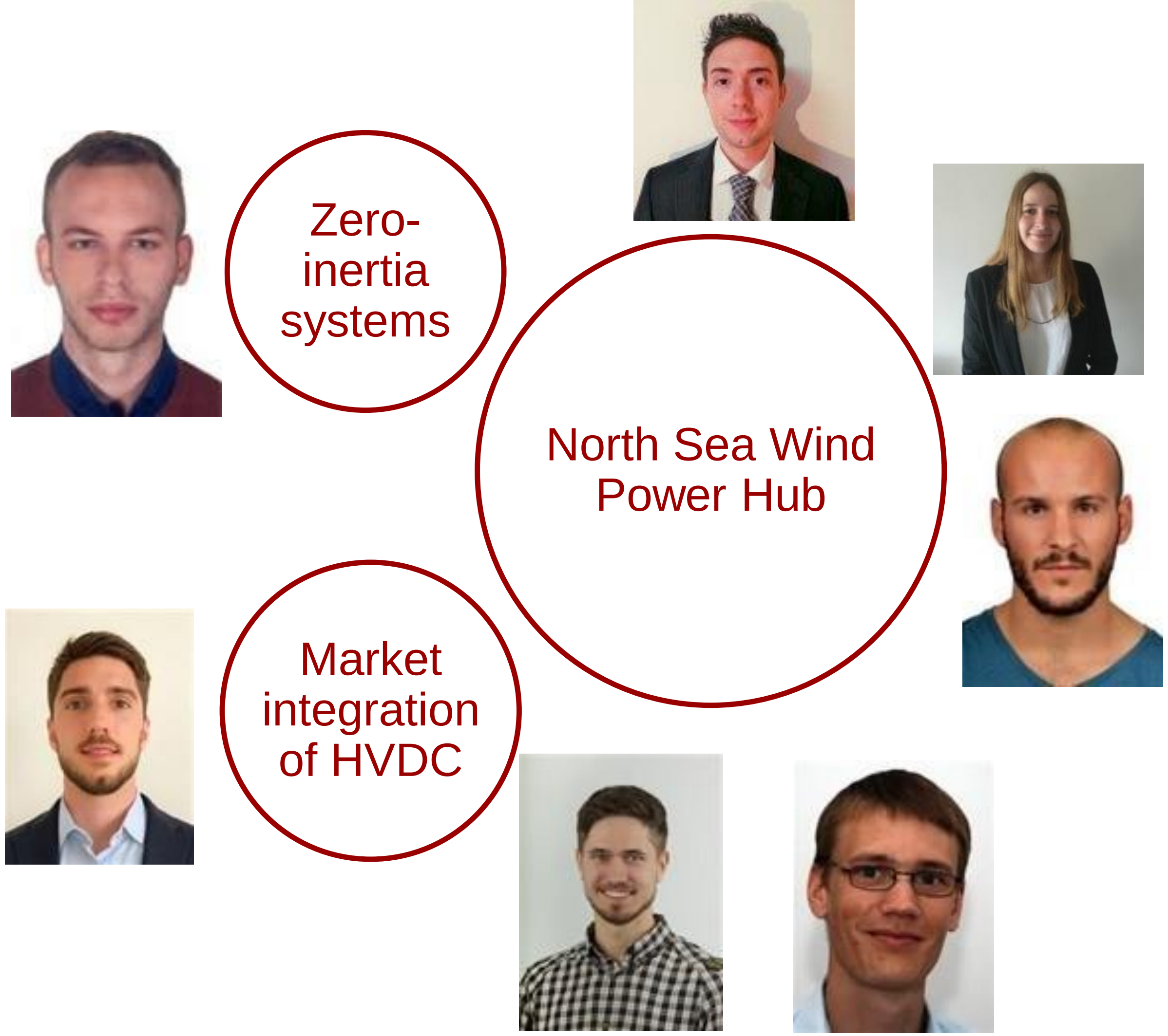
iea Energy Technology Network (Global)

ISGAN International smart grid action network

IEEE PES Power & Energy Society™ (Global)

EES-UETP Electric Energy Systems University Enterprise Training Partnership (EU)

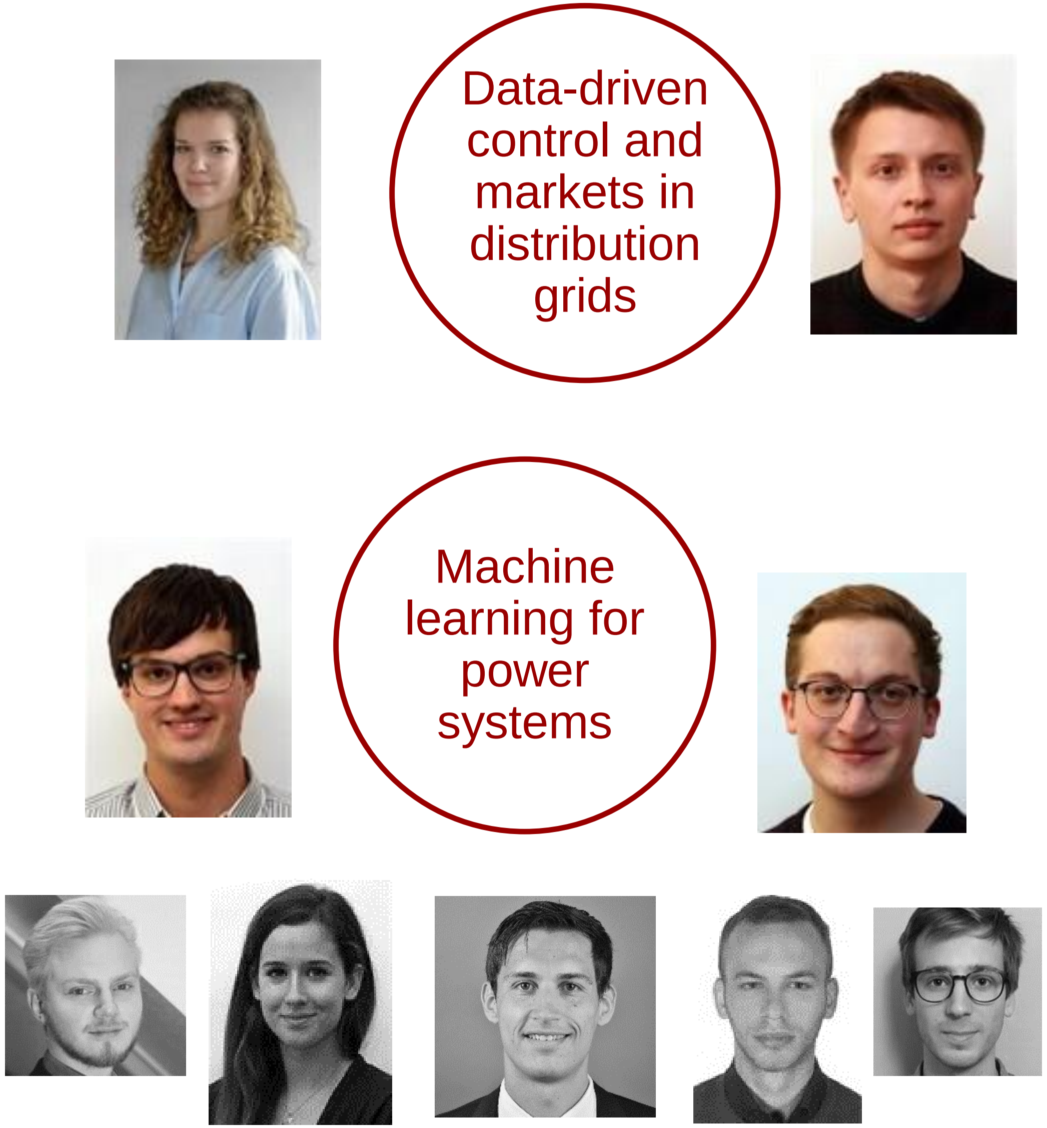
Our (my) research topics – 11 researchers – 8 nationalities



Zero-inertia systems

North Sea Wind Power Hub

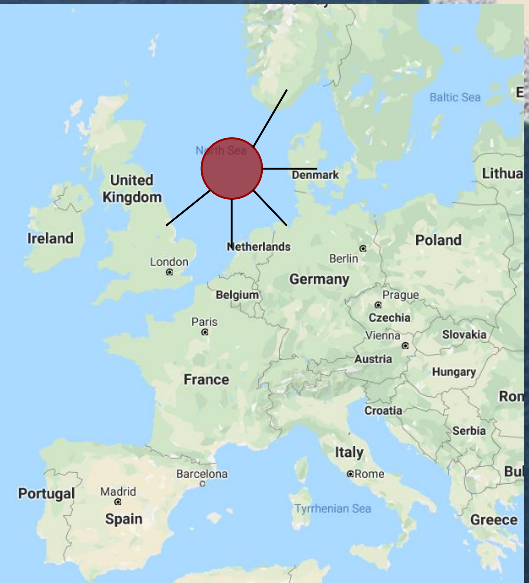
Market integration of HVDC

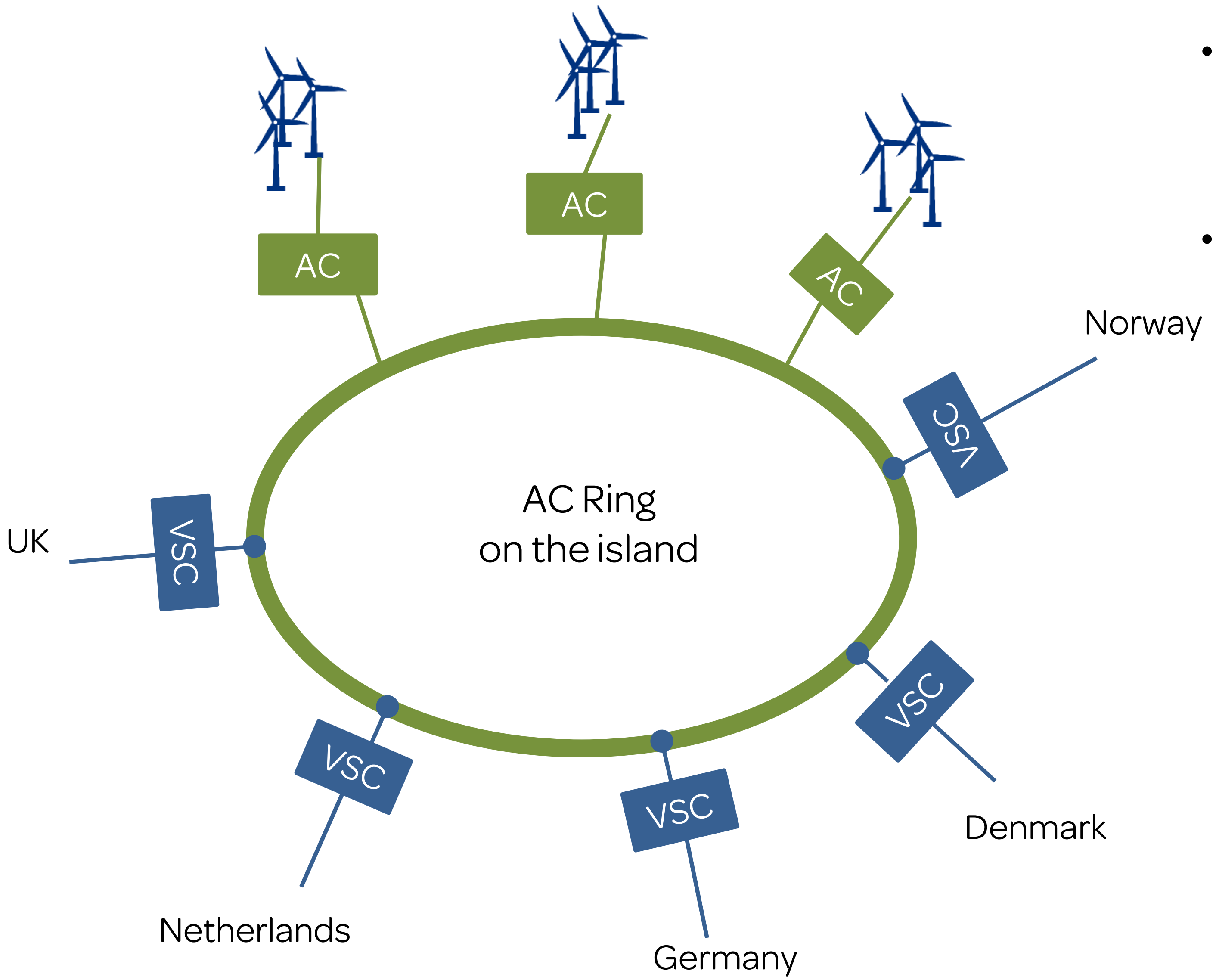


Data-driven control and markets in distribution grids

Machine learning for power systems

North Sea Wind Power Hub





- Will probably be the **first true zero-inertia AC system in the world**

- A range of challenges:
  - How do you **ensure N-1** between grid-forming converters?
  - What kind of **controls** are necessary to maintain stability against much faster transients?
  - Need for **new simulation tools** (RMS-based tools, e.g. standard Powerfactory or PSS/E, insufficient to capture stability)

More on www.multi-dc.eu !

Our (my) research topics – 11 researchers – 8 nationalities

Zero-inertia systems

North Sea Wind Power Hub

Market integration of HVDC

Data-driven control and markets in distribution grids

Machine learning for power systems

Motivation

- Electric power grid: the **largest machine** humans ever built

- Over the past few years: **explosion of the number of machine learning applications** in power systems
  - (Deep) neural networks, (deep) reinforcement learning, etc.
  - Can handle high complexity extremely fast

But:

- Power systems are **safety-critical** systems:
  - “Black-box” methods for critical operations will never be adopted (e.g. neural networks for security assessment)
- There is an **abundant number of good models** for power system components
  - Why use machine learning that neglects all this information?

This talk:

Neural network verification: neural networks are no longer a black-box

Physics-informed neural networks: exploit the underlying physical models

Outline

1. Guiding Application: Power System Security Assessment

2. Training Database: Sampling beyond Statistics

3. Neural Network Verification

4. Physics-Informed Neural Networks for Power Systems

Blackouts are rare but costly!

- Frequency of power interruptions
  - 1 hour per year
- Economic damage from power interruptions
  - about 80 billion USD/year (US only, 2005)
- Total electric energy cost in the US:
  - 370 billion USD/year

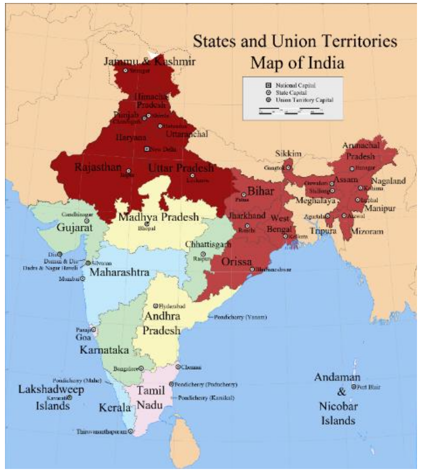
North East Blackout 2003: affected 55 million people

2 days (!) for full restoration!

India Blackout 2012:

affected 700 million people (!)

(region in red)



Operators run every day a security assessment

Energinet Control Room, Denmark

- Security Assessment:
  - Screen contingency list every 15 mins
  - Prepare contingency plans for critical scenarios

- Run both:
  - Steady-state, i.e. power flows to check N-1 and violation of limits
  - Dynamic simulations

Challenges

- Dynamic simulations are hard
  - System of differential-algebraic equations with 10k degrees of freedom

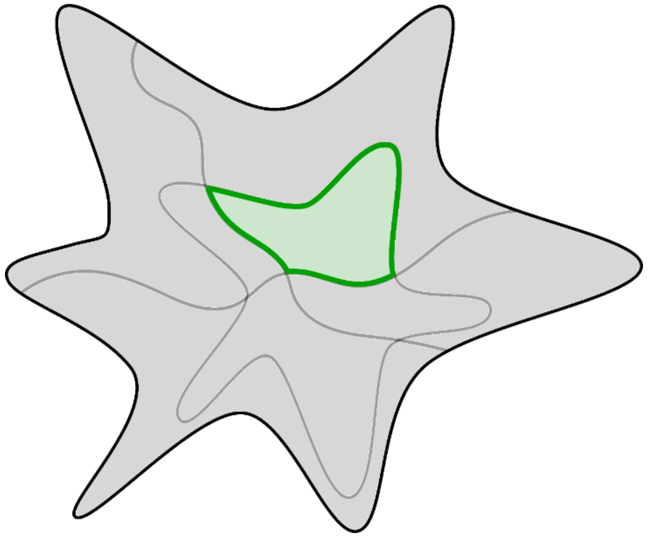
- Checking for N-k contingencies is a hard combinatorial problem
  - Usually computationally impossible to check even for all N-2 in a realistic system with thousands of buses

- The safe operating region is a non-linear non-convex region
  - Impossible to use analytical tricks to determine it

So.... what do we do?

So... what do we do?

Identifying the power system security region



- Run a lot of simulations assessing each operating point
  - Several approaches for efficient approximations to boost computation speed
- Stability certificates
  - Extract **sufficient conditions** for sub-areas of the security region
- Machine learning approaches
  - Train for a given dataset and **infer** for all new points
  - Potential: extremely fast computing times, with potential to generalize **if trained well** → assess thousands of possible scenarios at a fraction of the time

Focus of this talk:
Machine Learning for Power System Security Assessment

Possible Machine Learning Tools

- Decision Trees
  - First proposed by Louis Wehenkel (Univ of Liege) in the ‘90s
  - Very successful; Applications in the industry
  - Research is still ongoing; latest focus is on interpretability

- Neural networks (several papers)

- Deep Neural Networks (same as neural networks but deep ☺)
  - One paper on feature extraction (Sun, Konstantelos, Strbac, 2018)
  - One paper inspired by image processing (Hidalgo, Hancharou, Thams, Chatzivasileiadis, 2019)
  - Few additional papers over the past 12 months

- **For a recent overview see**: L. Duchesne, E. Karangelos, L. Wehenkel, *Recent Developments in Machine Learning for Energy Systems Reliability Management*, https://orbi.uliege.be/bitstream/2268/246570/1/ML4RM.pdf

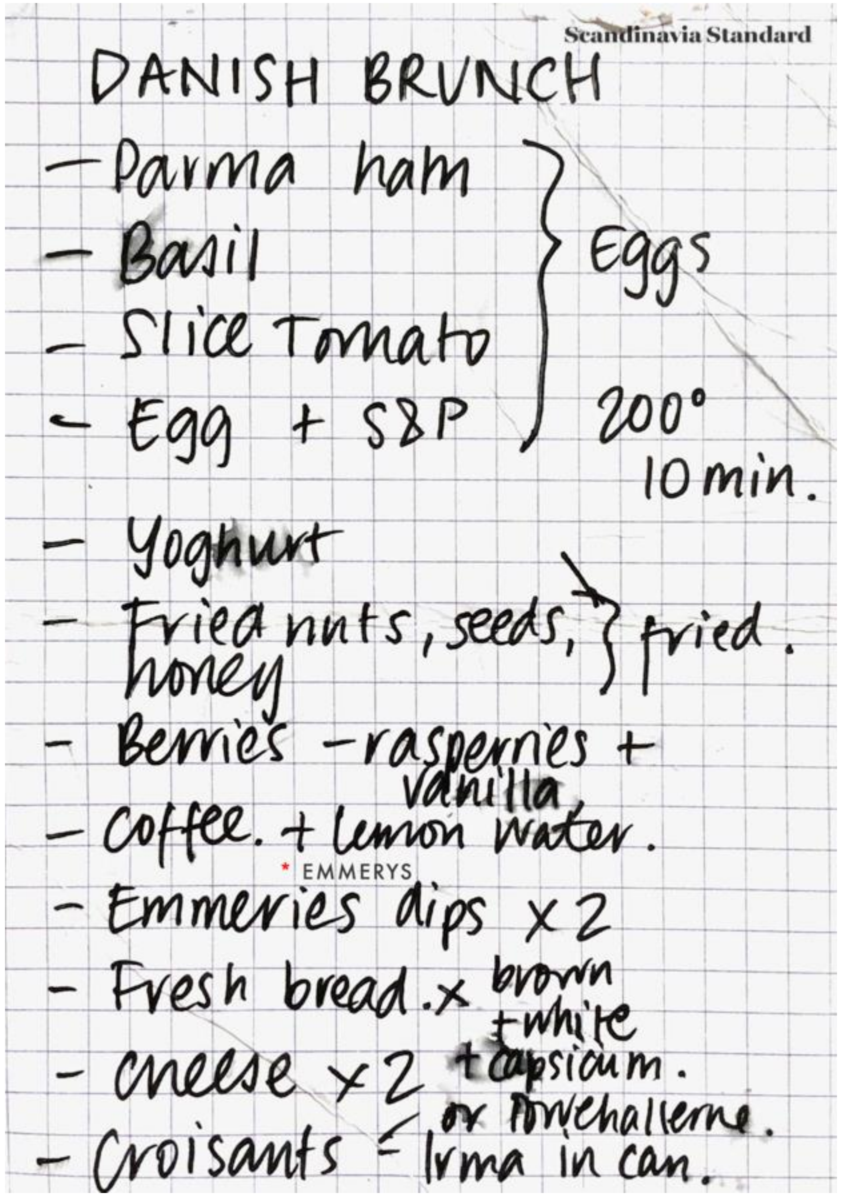
Machine learning applications

(for power system security assessment)

A very short overview

The ingredients

- A training database
- A training algorithm (e.g. for neural networks)
- A test database
  - To test accuracy of the approach



Scandinavia Standard

DANISH BRUNCH

- Parma ham
- Basil
- Slice Tomato
- Egg + S&P

} Eggs 200° 10 min.

- Yoghurt
- Fried nuts, seeds, honey } fried.
- Berries - rasperries + vanilla
- Coffee. + lemon water.
- Emmeries dips x 2

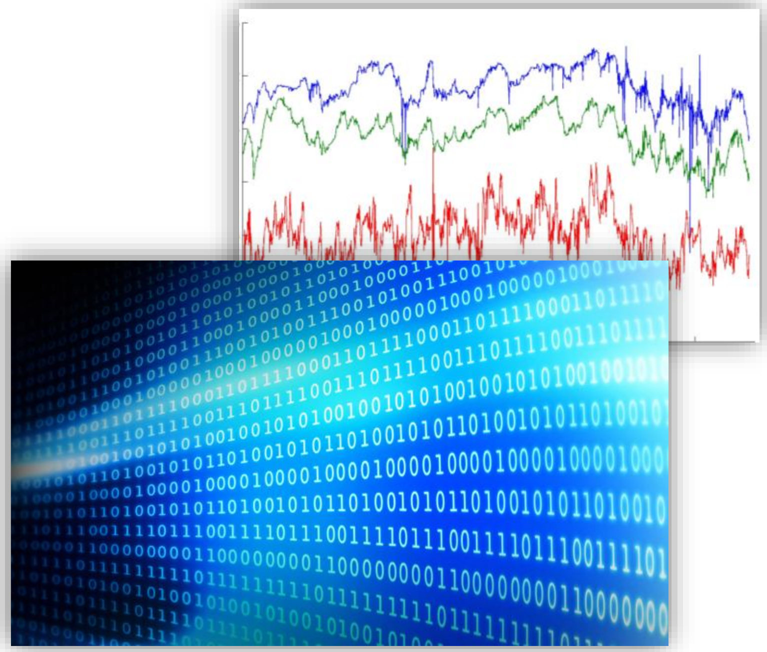
* EMMERYS

- Fresh bread. x brown + white
- Cheese x 2 + capsicum.
- Croisants ≤ or Torvehallerne. Irma in can.

Training database:
Sampling beyond Statistics

Machine Learning needs data!

- **Historical data is not enough**
  - Contain very limited number of abnormal situations
  - (and are difficult to obtain)
- Highly unbalanced and non-linear regions → **Uniform sampling is not good enough**
  - Unbalanced datasets → cannot assess accuracy appropriately
  - Not enough data with high information content (e.g. random in the space; not close to the boundary)
- **Extremely computationally intensive**
  - Assessing the stability of 100’000s of operating points is an extremely demanding task → immense search space



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- **Extremely computationally intensive**
  - Combination of N-1, small-signal stability, transient stability → immense search space

- **Example:** Assume 1000 datapoints
  - Actually safe: 20
Classified Correctly: 1
  - Actually unsafe: 980
Classified correctly: 950

$$\text{Accuracy} = \frac{1+950}{20+980} = 95\%$$

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Classified correctly: 950

$$\text{Accuracy} = \frac{1+950}{20+980} = 95\%$$

- 95% accurate but we have misclassified almost all truly safe points!
- Uniform sampling is not sufficient for heavily unbalanced classes!

Sampling beyond Statistics: Efficient Database Generation

- Modular and highly efficient algorithm

- 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

- Our use case: N-1 security + small-signal stability

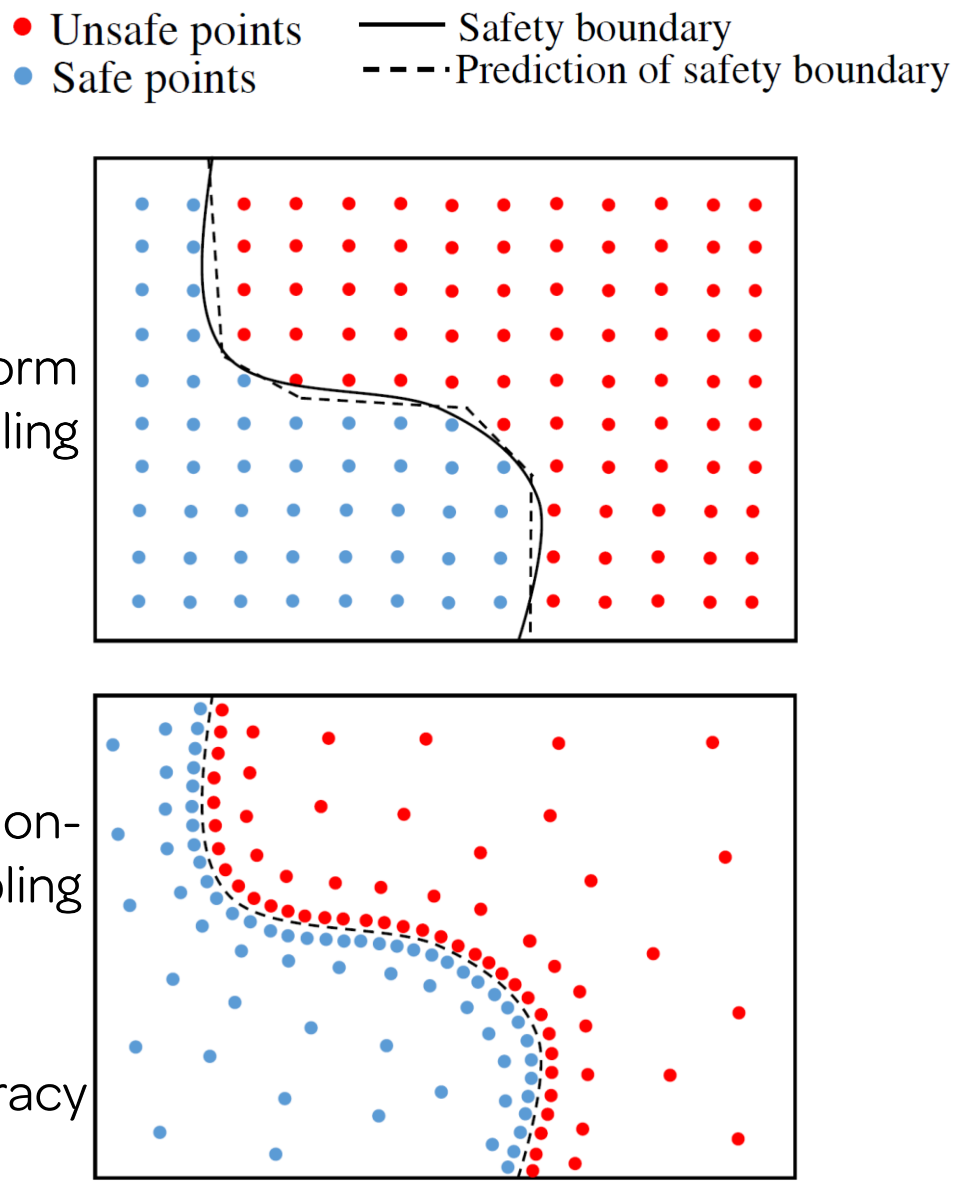
- Generated Database for NESTA 162-bus system online available!
  https://github.com/johnnyDEDK/OPs_Nesta162Bus (>500,000 points)

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

Sampling beyond Statistics: Efficient Database Generation

- **The goal**
  - Go beyond uniform sampling
  - Improve NN Performance: Focus on the boundary between stability and instability (i.e. high-information content)

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

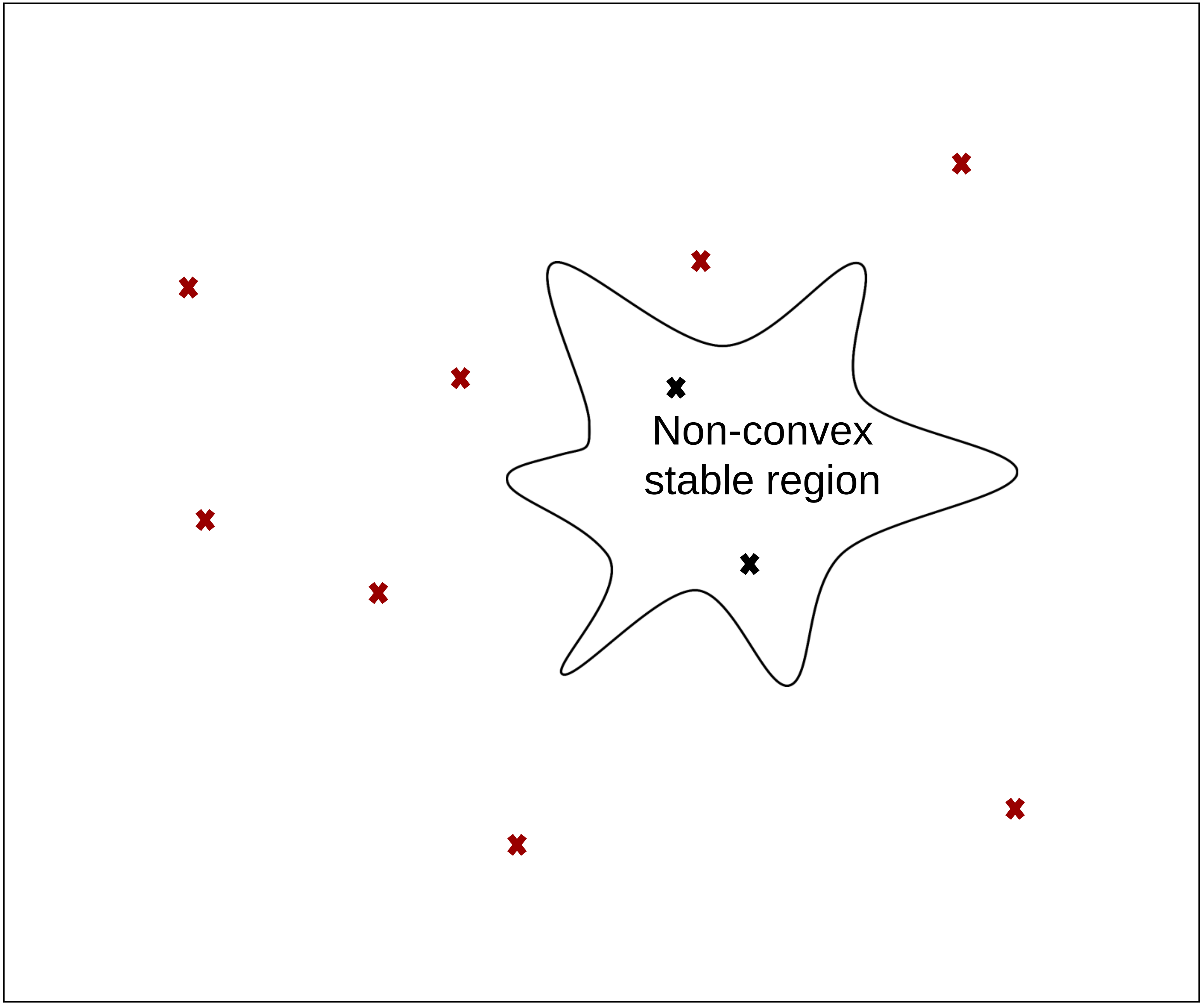


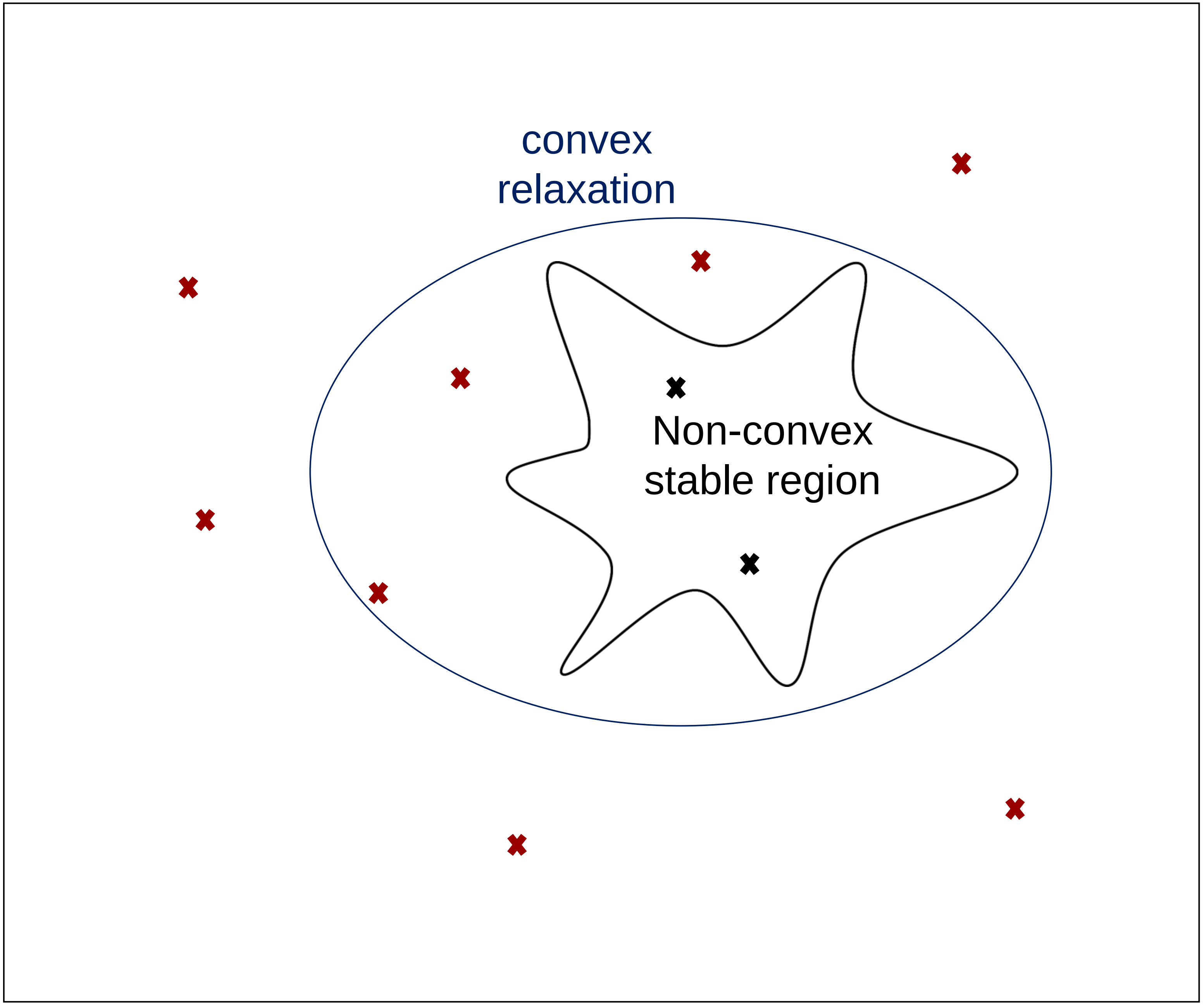
Uniform Sampling

High-Information-Content Sampling

Higher Prediction Accuracy

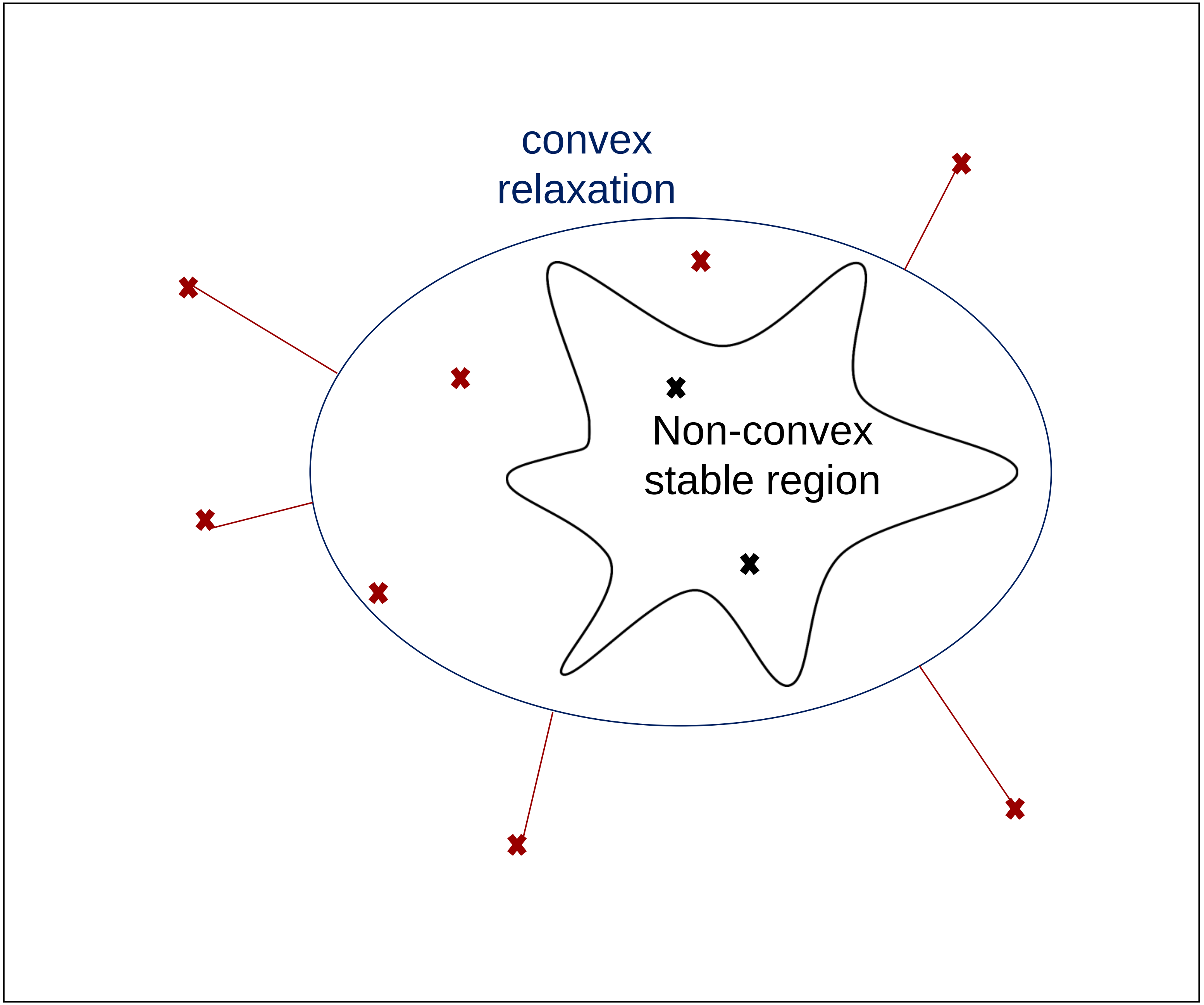
Convex relaxations to discard infeasible regions





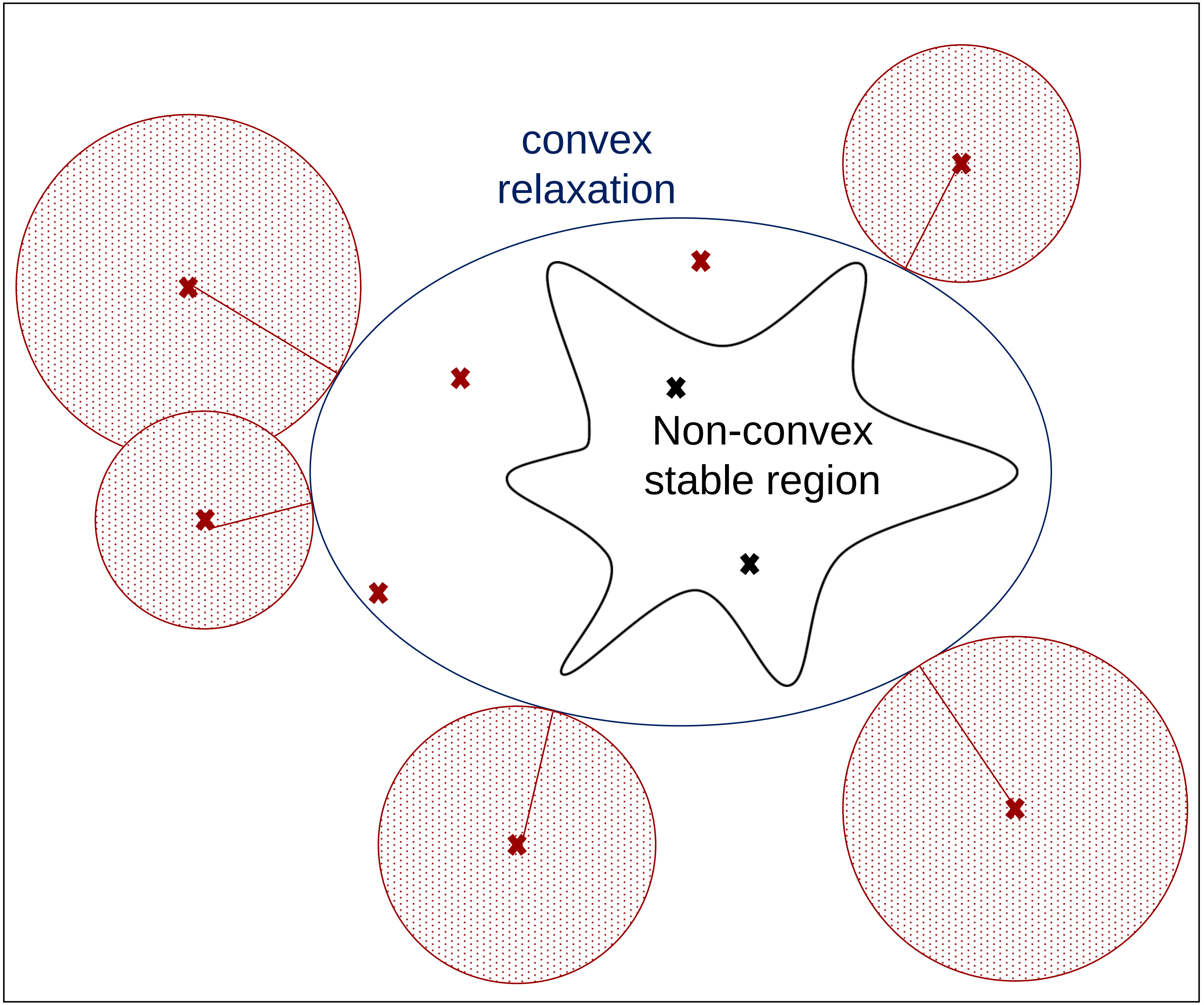
Convex relaxations to discard infeasible regions

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



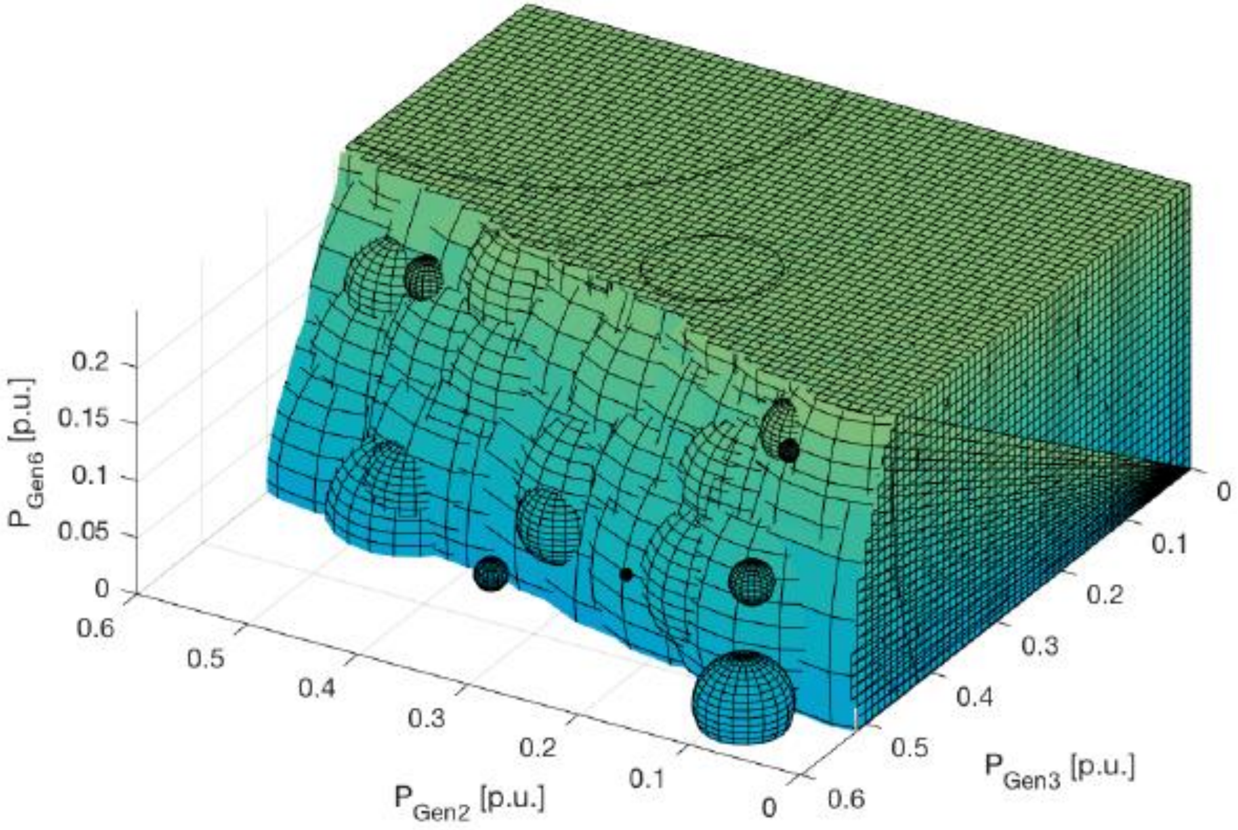
Convex relaxations to discard infeasible regions

- Certificate: if point infeasible for semidefinite relaxation → infeasible for the original problem
- If infeasible point: find minimum radius to feasibility



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 inside the (hyper)sphere

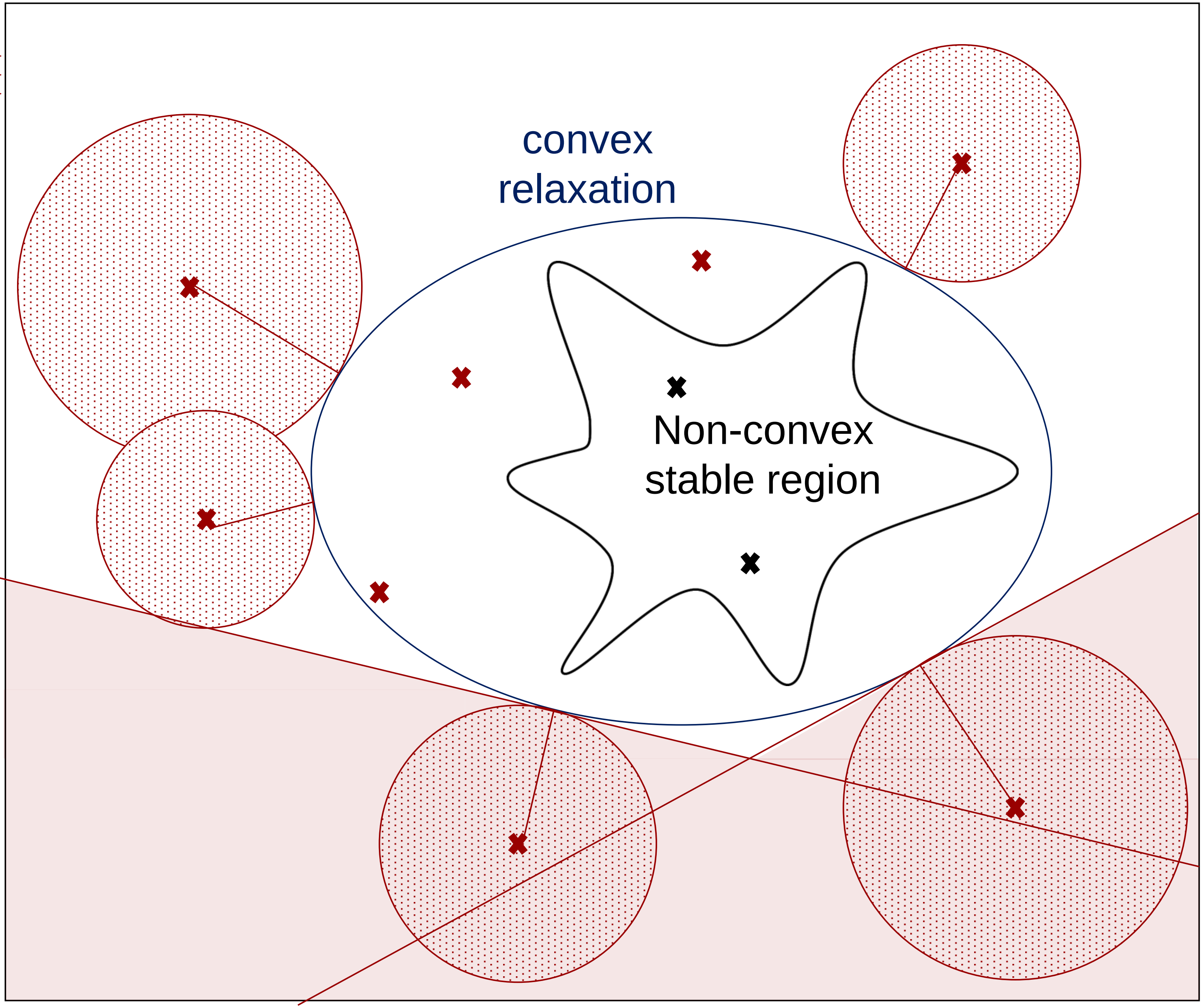


- 3D projection of hyperspheres

- IEEE 14-bus system

- Rapidly discarding (=classifying) large chunks of the search space as infeasible to focus on the boundary

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

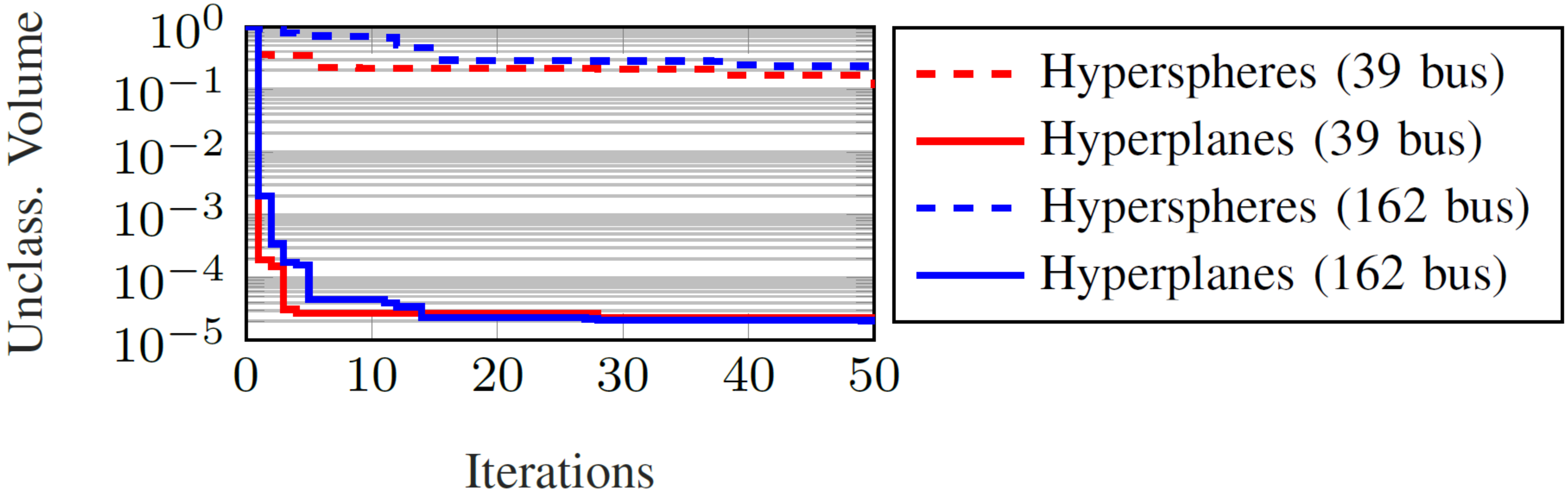


Convex relaxations to discard infeasible regions

- Extension of this work to hyperplanes

A. Venzke, D.K. Molzahn, S. Chatzivasileiadis, **Efficient Creation of Datasets for Data-Driven Power System Applications.** Accepted at PSCC 2020. https://arxiv.org/pdf/1910.01794.pdf

Hyperplanes discard large unsafe regions much faster

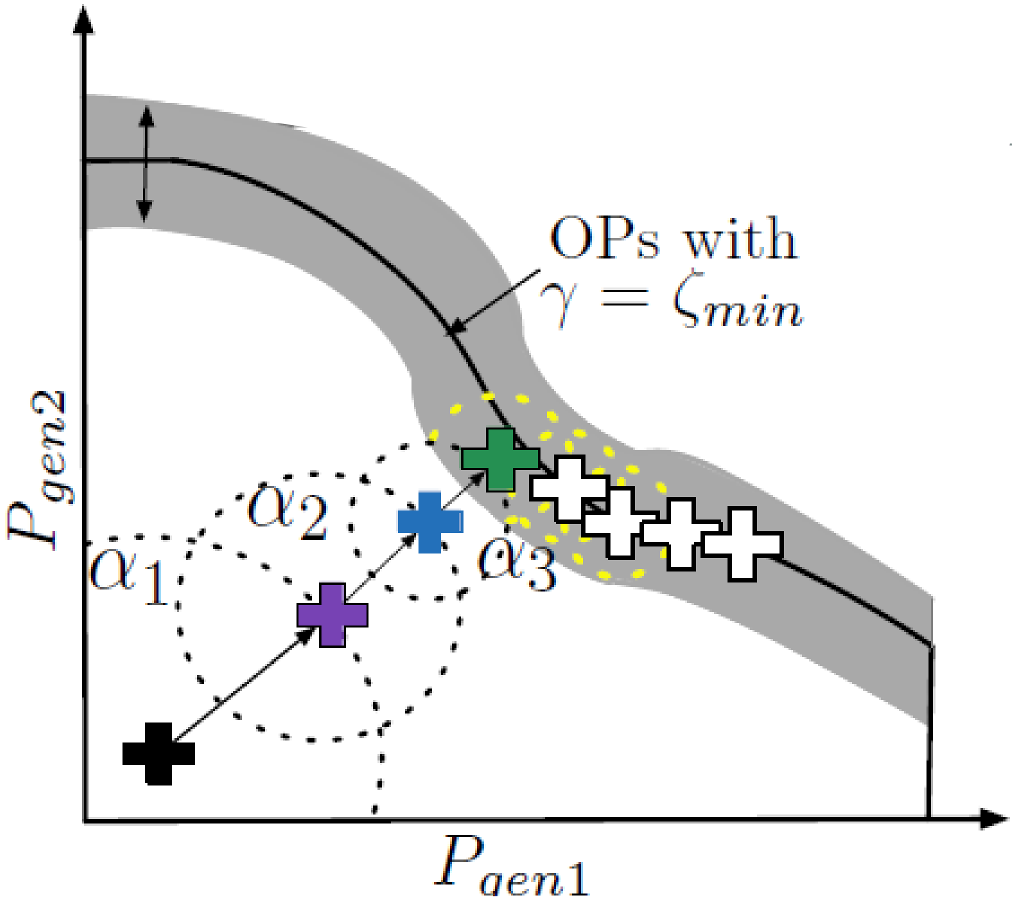


A. Venzke, D.K. Molzahn, S. Chatzivasileiadis, **Efficient Creation of Datasets for Data-Driven Power System Applications**. Accepted at PSCC 2020. https://arxiv.org/pdf/1910.01794.pdf

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

- We tested these databases with decision trees. Further benefits for the decision trees:
  - Higher accuracy
  - Better classification quality (Matthews correlation coefficient)

Generated Database for NESTA 162-bus system online available!
https://github.com/johnnyDEDK/OPs_Nesta162Bus

Neural Network Verification

A. Venzke, S. Chatzivasileiadis. Verification of Neural Network Behaviour: Formal Guarantees for Power System Applications. Under Review. 2019. [*https://arxiv.org/pdf/1910.01624.pdf*](https://arxiv.org/pdf/1910.01624.pdf)

Why is neural network verification important?

- Neural networks have been shown to be extremely fast
  - Assess if an operating point is safe or unsafe 100x-300x faster (combination of different security criteria)
  - Application in optimization: find the optimal point >100x faster

- However, neural networks will never be applied in critical (power system) operations, if there are no guarantees about how they behave

- Until recently, the only way to assess the output of the neural networks was to **individually test** each input of interest and pass it through the neural network
  - Accuracy was purely statistical
  - **Challenge #1:** No way to guarantee what the output is for a **continuous** range of inputs

Evaluating Accuracy: Test Database

Traditionally:

- Split training database to e.g. 80% training samples and 20% test samples
- Train with the 80%
- Test with the 20%

Modern toolboxes have this integrated and automatized →only need to provide a training database

Challenge #2:

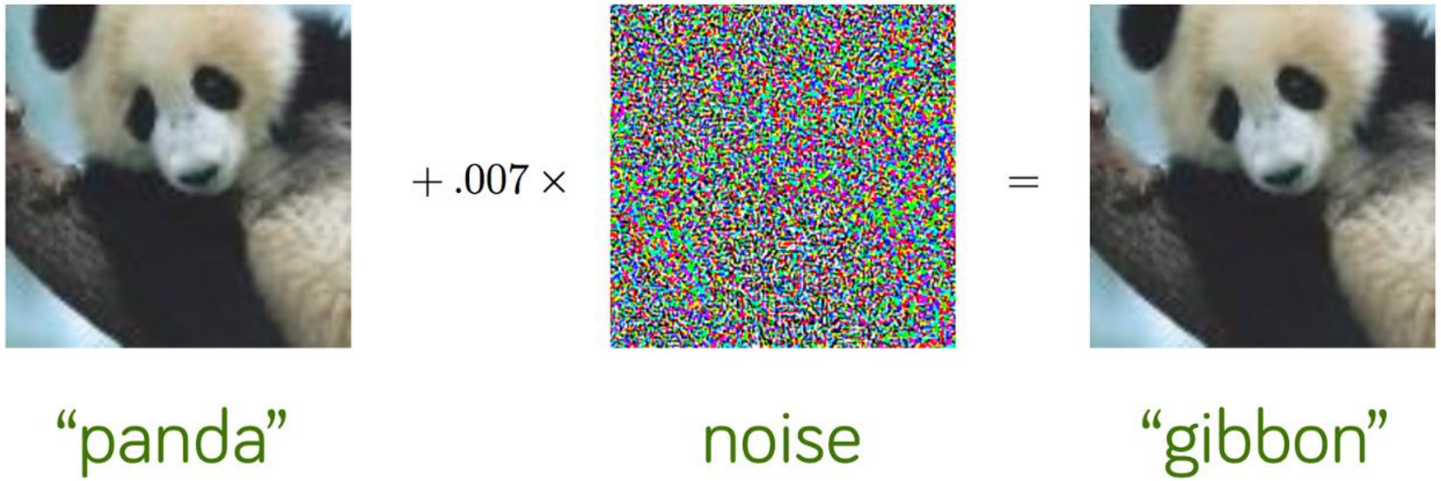
The test database determines the performance of the neural network. If the test data come from the same simulations as your training data, the accuracy can be deceivingly high. Would it be equally high in reality?

Ideally → use a different real-life dataset

Neural network verification overcomes this challenge too

Adversarial examples

- Adversarial example: small perturbations lead to a false prediction



Adversarial examples

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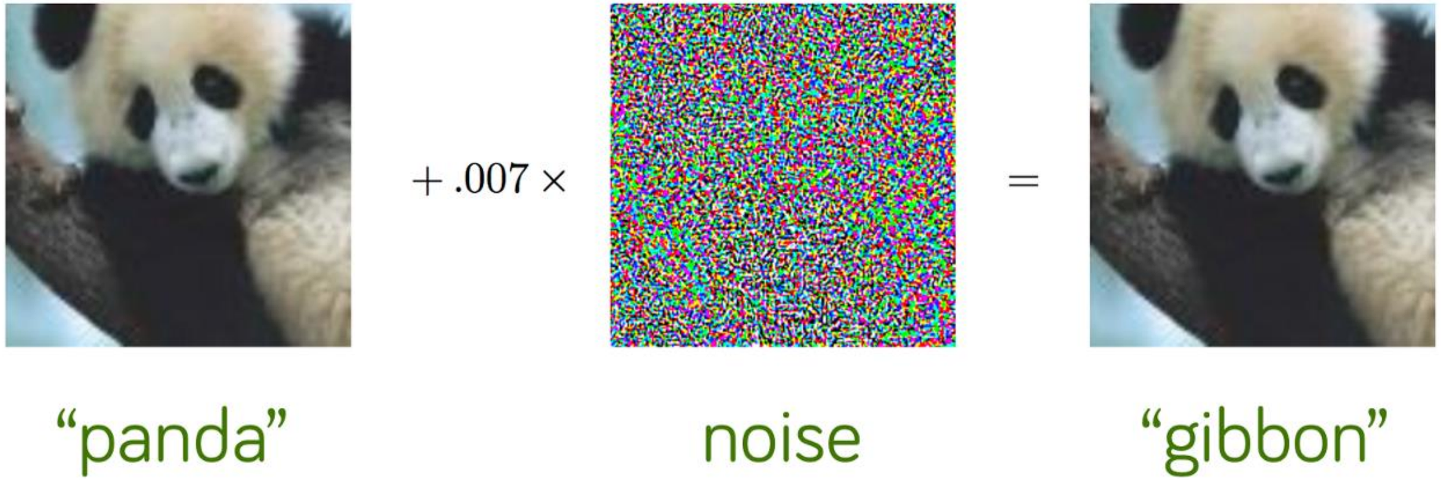


- **Challenge #3: No way to systematically identify adversarial examples**

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

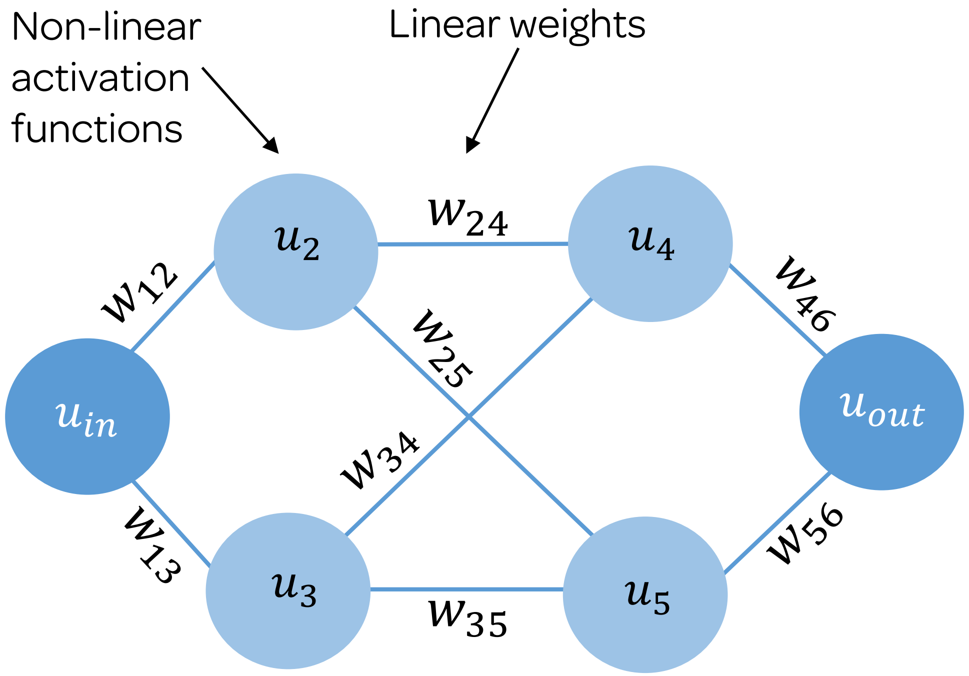
2. Formulate an optimization problem (MILP)

3. Solve the MILP to zero duality gap (find the global optimal) → certificate for the behavior for neural network

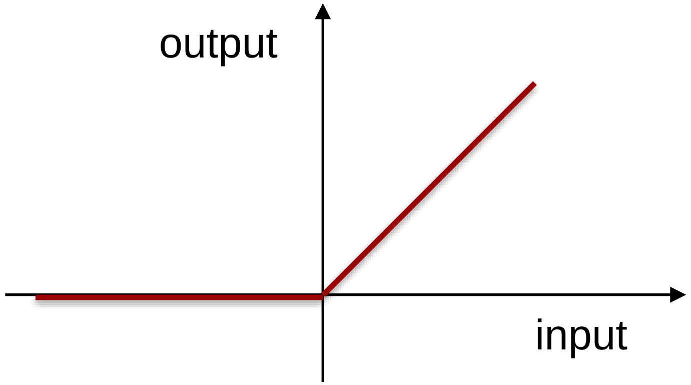
4. Assess if the neural network output complies with the ground truth

- Two types of optimization problems:
  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)

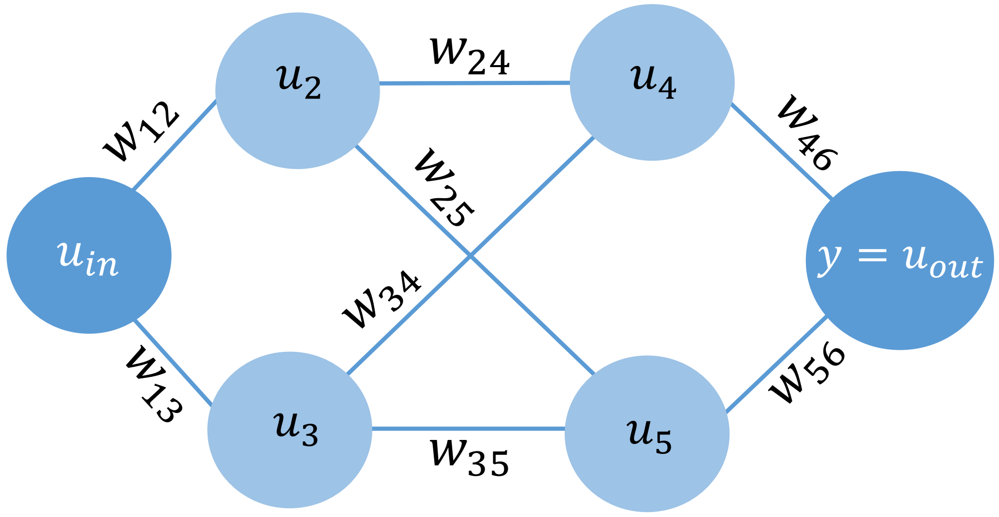
From Neural Networks to Mixed-Integer Linear Programming



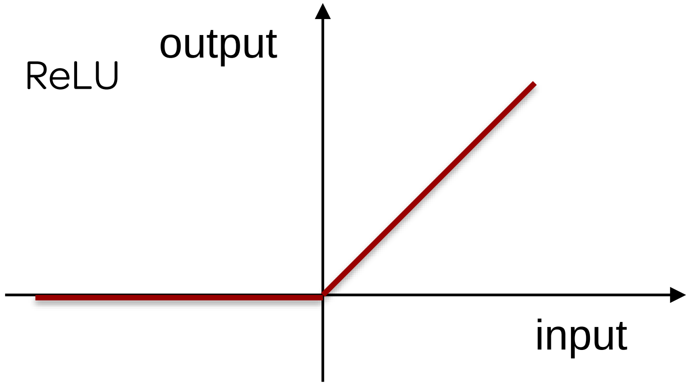
- Most usual activation function: ReLU
- ReLU: Rectifier Linear Unit



From Neural Networks to Mixed-Integer Linear Programming



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



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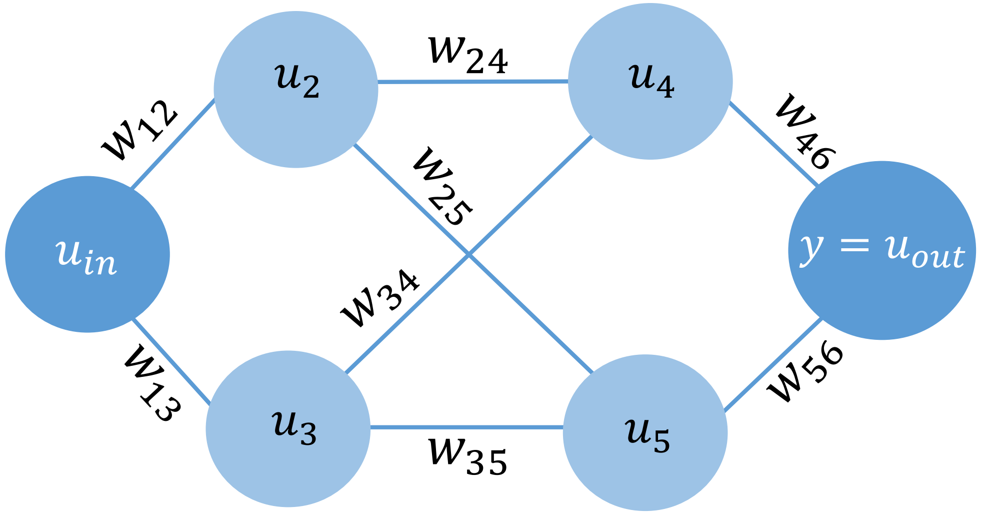
MILP

From Neural Networks to Mixed-Integer Linear Programming



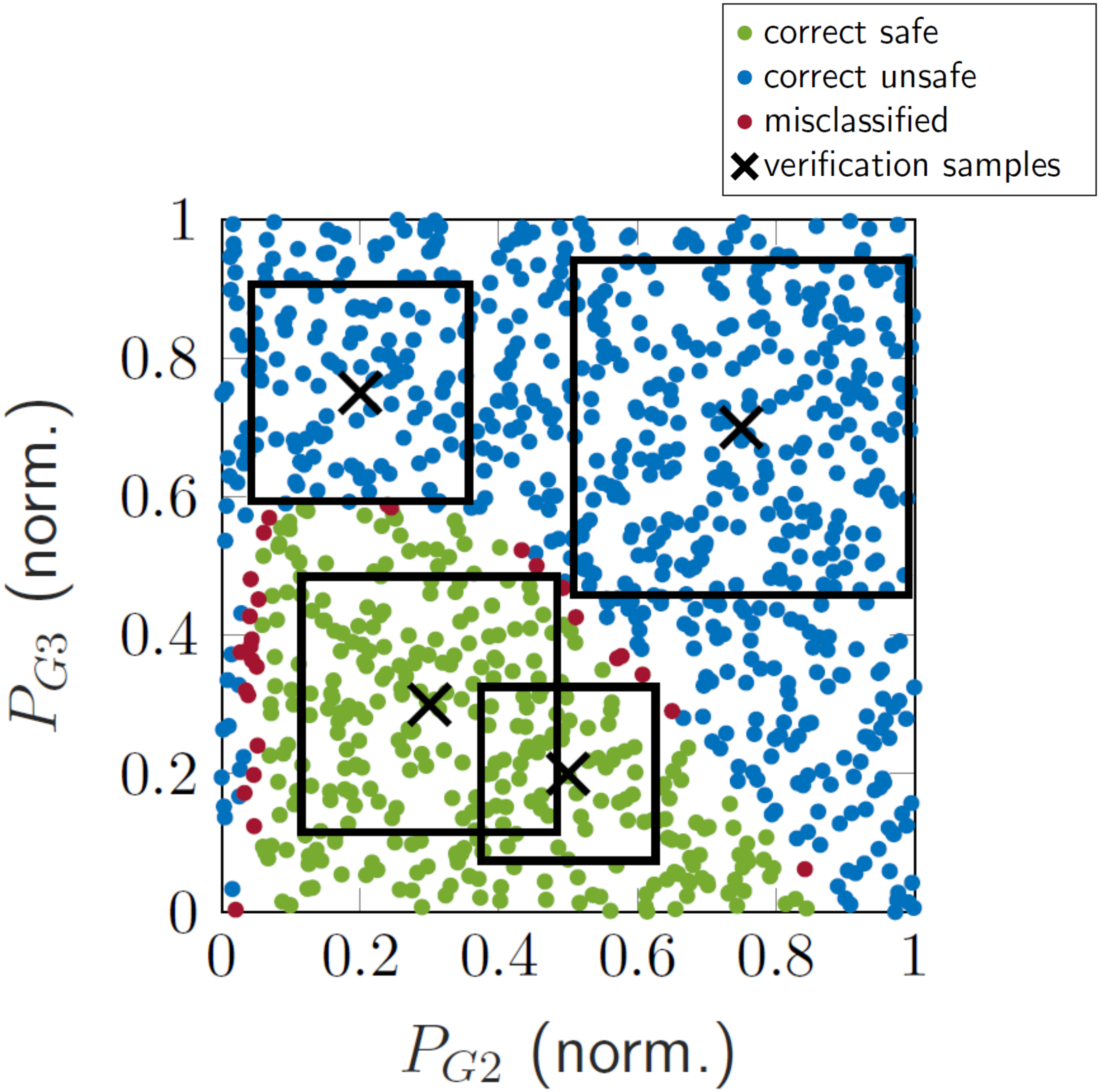
- Output
  - For now: binary classification
  - Security assessment for power systems
  - Output vector y with two elements:
    - $y_1 \geq y_2$: safe
    - $y_2 \geq y_1$: unsafe

Certify the output for a continuous range of inputs

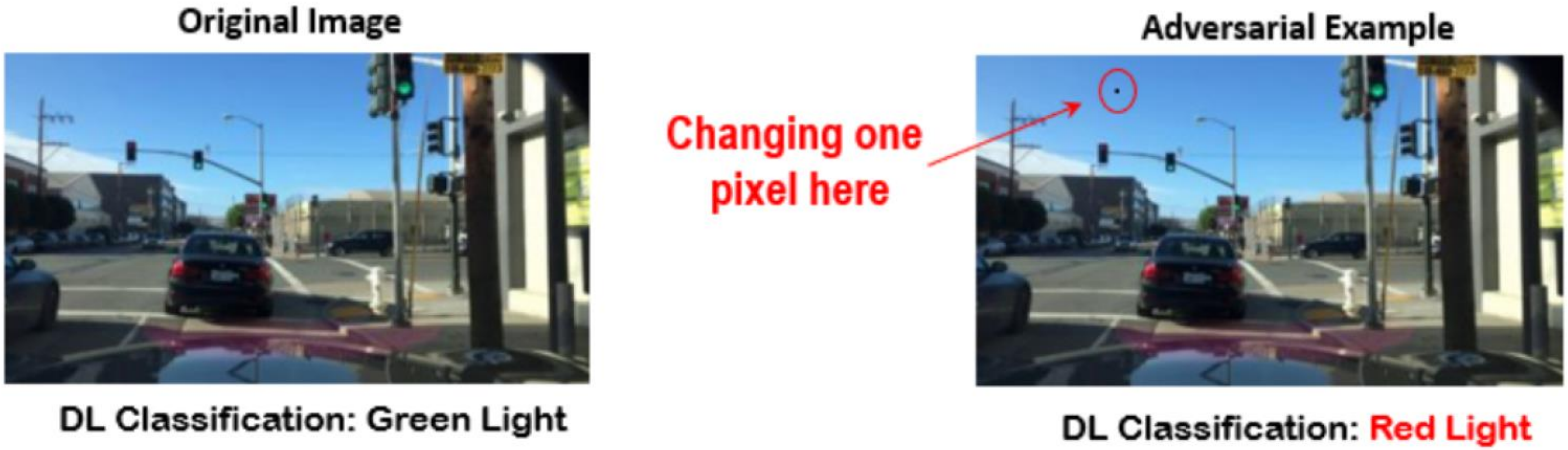
- We assume a given input x_{ref} with classification y: $y_1 > y_2$

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

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



Adversarial examples in safety-critical systems



source: Wu et al. A game-based approximate verification of deep neural networks with provable guarantees. arXiv:1807.03571.

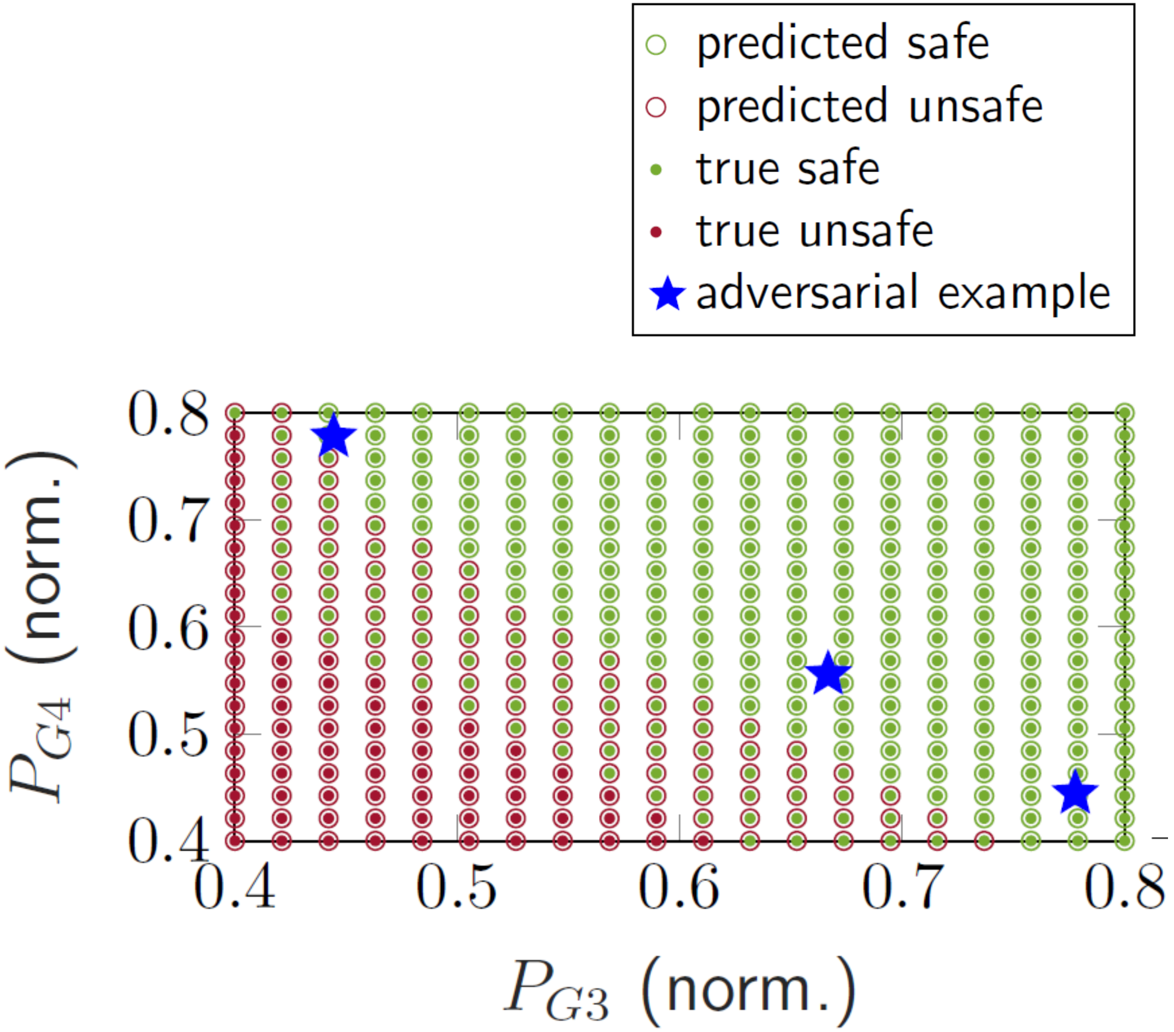
- Adversarial examples exist in many (deep) applications
- Major barrier for adoption of machine learning techniques in safety-critical systems!

Systematically identify adversarial examples

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

2. Minimize distance ϵ from $\mathbf{x}_{\text{ref}}$ to input $\mathbf{x}$ with classification y_2

$$\begin{aligned} \min_{\mathbf{x},\mathbf{y},\epsilon} \quad & \epsilon \\ \text{s.t.} \quad & \mathbf{y} = NN(\mathbf{x}) \\ & |\mathbf{x} - \mathbf{x}_{\text{ref}}|_\infty \leq \epsilon \\ & y_2 \geq y_1 \end{aligned}$$



Challenges

- **Tractability** for large neural networks
  - Up to now, we have verified NNs with 4 layers and 100 nodes at each layer (NN used for the 162-bus system)
  - We require weight sparsification, bound tightening, and ReLU pruning (remove binary variables) to maintain tractability

- **Connect verification with ground truth assessment**
  - Currently, we can first certify the neural network output, and we should then assess if this output is correct (i.e. that the NN can be trusted in real operation)
  - Now working on a verification procedure that will be integrated in the training of the neural network → NN training will offer a certificate of performance (no more statistics!)

- **Retraining** is necessary to avoid adversarial examples
  - The **quality of the training database is crucial** for good performance!

(very short break)

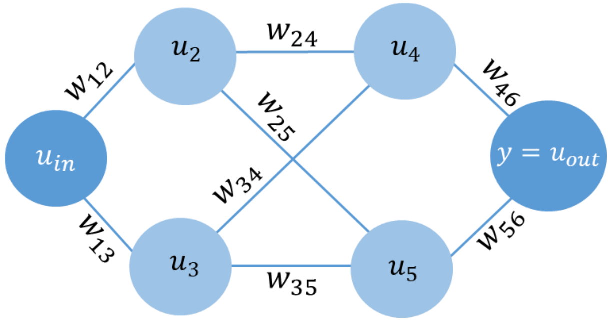
From Neural Networks to MILP:
Capturing constraints impossible to capture before

Data-driven Security Constrained OPF
How does it work?

Database of secure/insecure operating points

Any combination of **static/dynamic security** criteria

e.g. N-1 & Small-signal stability (Small-Signal Stab. up to now impossible to *directly* include in an OPF)



Train a neural network → "encode" all information about secure and insecure regions

Tractable small-signal stability-constrained OPF

$$
\begin{aligned}
\min_{\substack{p,q,v,\theta\\ \hat{y},y,z}} \quad & f(p_g) \\
\text{s.t.} \quad & p_g^{\min} \le p_g \le p_g^{\max} \\
& v_g^{\min} \le v_g \le v_g^{\max} \\
& s_{\text{balance}}(p^0, q^0, v^0, \theta^0) = 0 \\
& \hat{u}_k = W_k u_{k-1} + b_k \\
& u_k = \max(\hat{u}_k, 0) \quad \Rightarrow \quad \left\{ \begin{aligned} & y_k \le \hat{u}_k - \hat{u}_k^{\min}(1 - b_k) \\ & u_k \ge \hat{u}_k \\ & u_k \le \hat{u}_k^{\max} b_k \\ & u_k \ge 0 \\ & b_k \in \{0,1\}^{N_k} \end{aligned} \right. \\
& y = u_{out} \\
& y_1 \ge y_2
\end{aligned}
$$

Exact reformulation to MILP

A. Venzke, D. T. Viola, J. Mermet-Guyennet, G. S. Misyris, S. Chatzivasileiadis. Neural Networks for Encoding Dynamic Security-Constrained Optimal Power Flow to Mixed-Integer Linear Programs. 2020. https://arxiv.org/pdf/2003.07939.pdf

Code available: https://gitlab.com/violatimon/power_system_database_generation

L. Halilbašić, F. Thams, A. Venzke, S. Chatzivasileiadis, and P. Pinson, "Data-driven security-constrained AC-OPF for operations and markets," *PSCC* 2018. [.pdf]

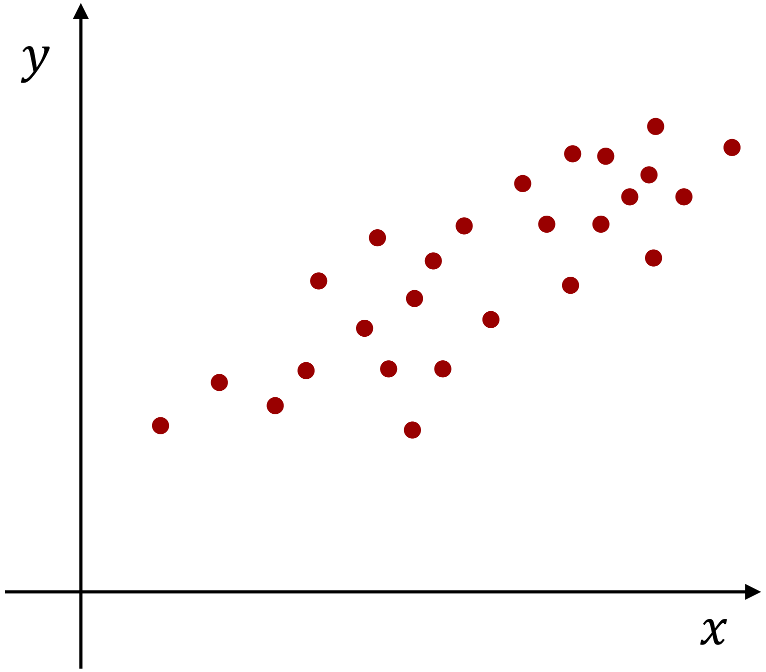
F. Thams, L. Halilbašić, P. Pinson, S. Chatzivasileiadis, and R. Eriksson, "Data-driven security-constrained OPF," *IREP* 2017. [.pdf]

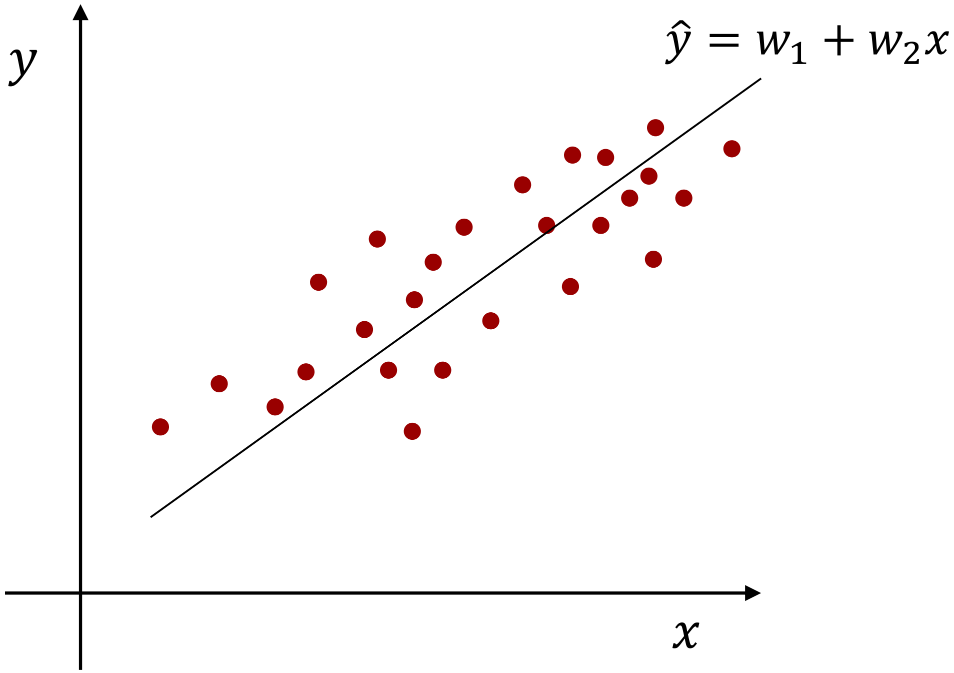
Physics-Informed Neural Networks for Power Systems

Neural Networks: An advanced form of non-linear regression

Example from linear regression; neural networks work similarly

Goal: *estimate* w_1, w_2 *to fit* $\hat{y} = w_1 + w_2 x$

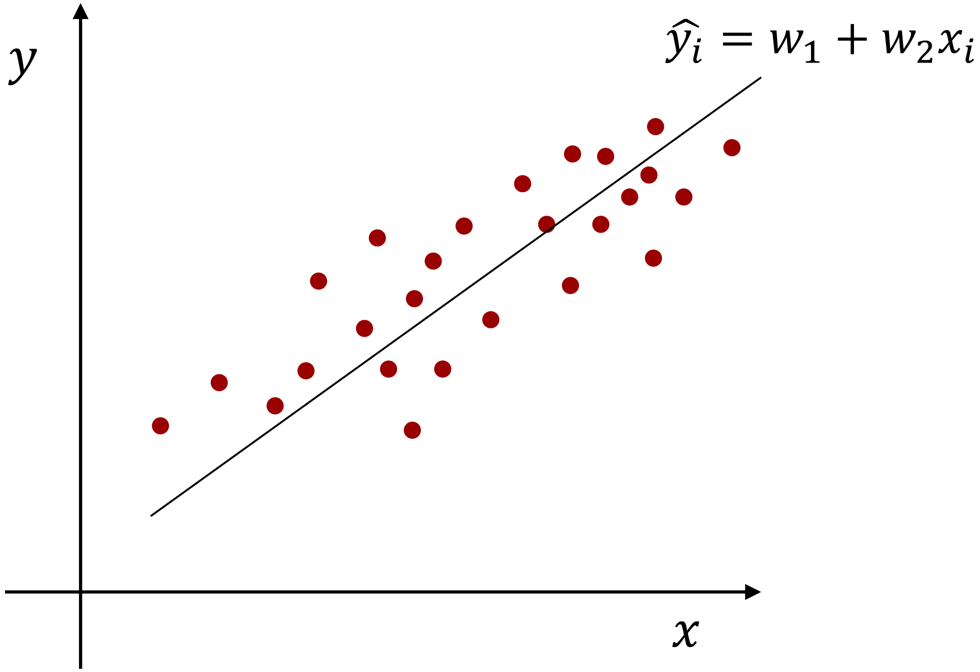




Loss function: Estimate best w_1, w_2 to fit the training data

y_i: actual/correct value

$\hat{y}_i$: estimated value



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

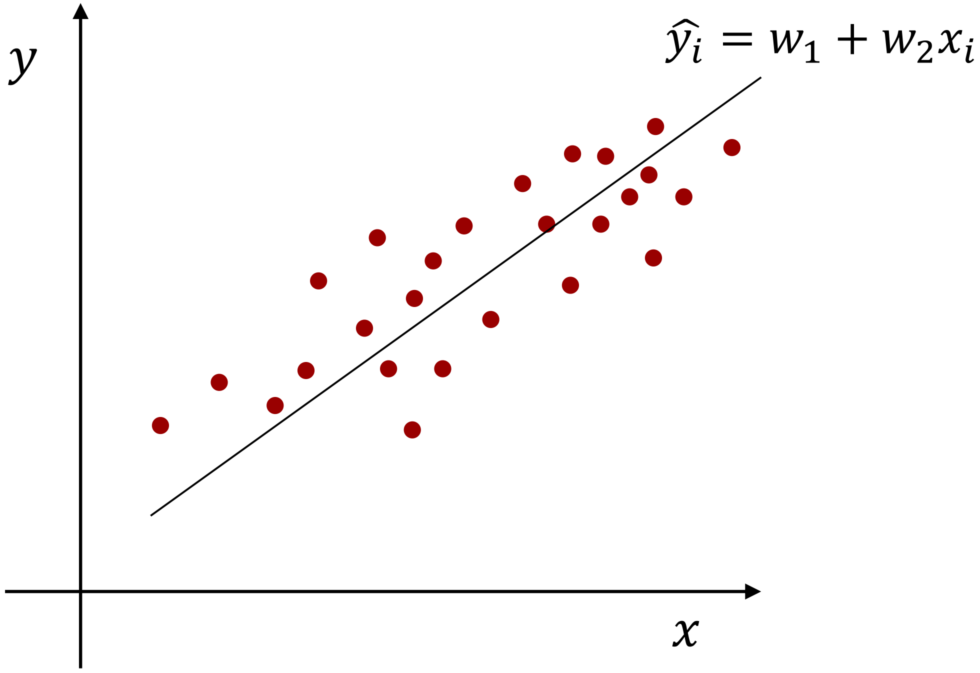
s.t.

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

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

y_i: actual/correct value

$\hat{y}_i$: estimated value



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

s.t.

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

Rewrite:

$$\min_{w_1,w_2} \quad \|y_i - (w_1 + w_2 x_i)\| \quad \forall i$$

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 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 such as 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

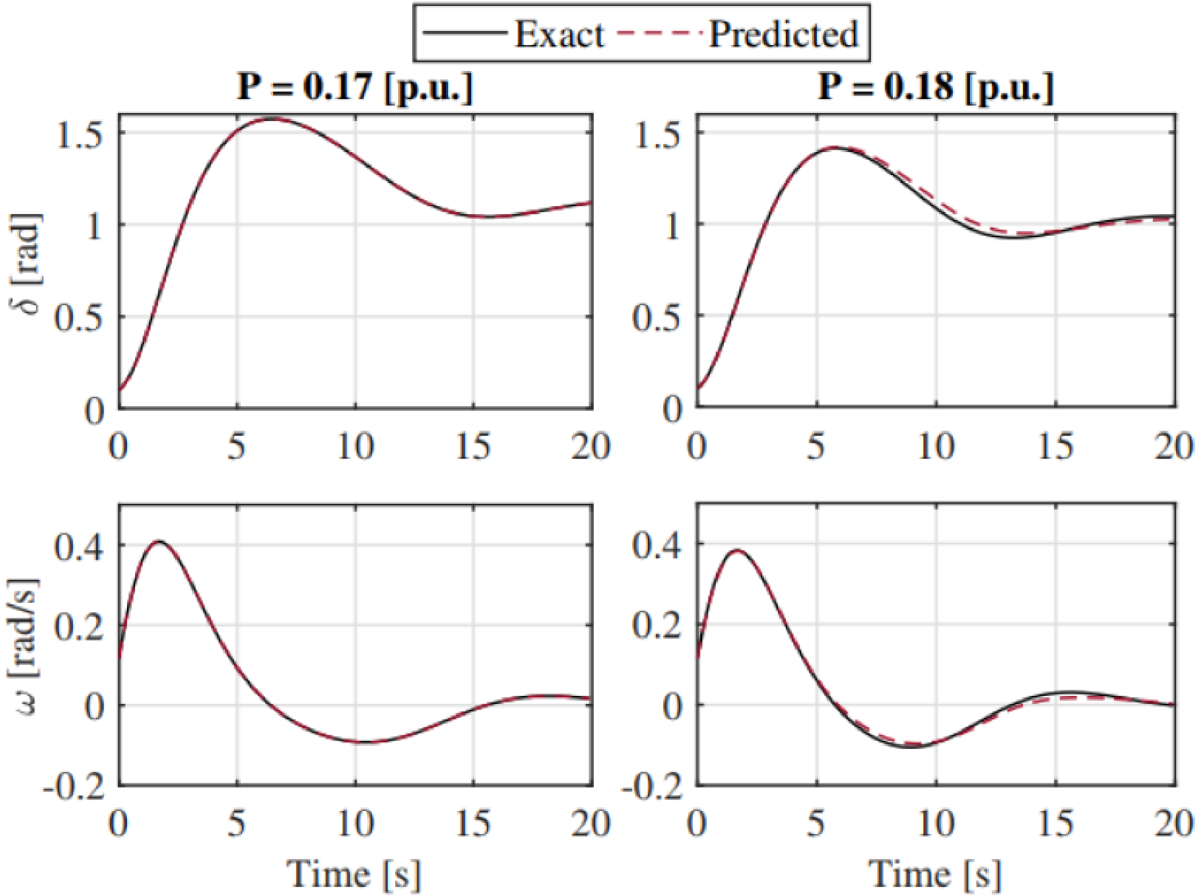
$$\boxed{\min_{\mathbf{W},\mathbf{b}} \quad \frac{1}{|N_\delta|}\sum_{i\in N_\delta}|\hat{\delta}-\delta^i|^2} + \frac{1}{|N_f|}\sum_{i\in N_f}|f(\hat{\delta})|^2 \tag{6a}$$

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

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

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

Swing equation



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

Physics-Informed Neural Networks for Power Systems

"Original" Loss function

"Physics-Informed" term

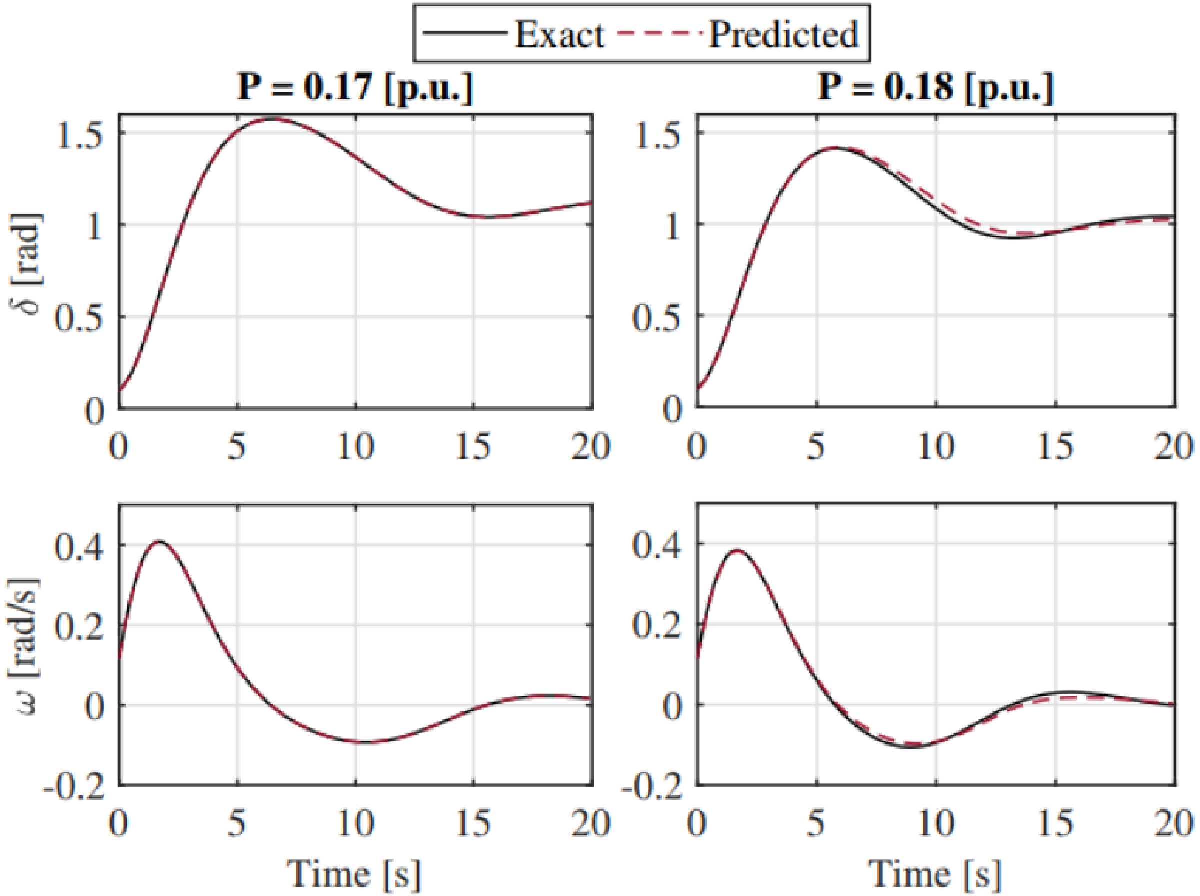
$$\min_{\mathbf{W},\mathbf{b}} \quad \frac{1}{|N_\delta|}\sum_{i\in N_\delta}|\hat{\delta}-\delta^i|^2 + \boxed{\frac{1}{|N_f|}\sum_{i\in N_f}|f(\hat{\delta})|^2} \tag{6a}$$

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

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

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

Swing equation



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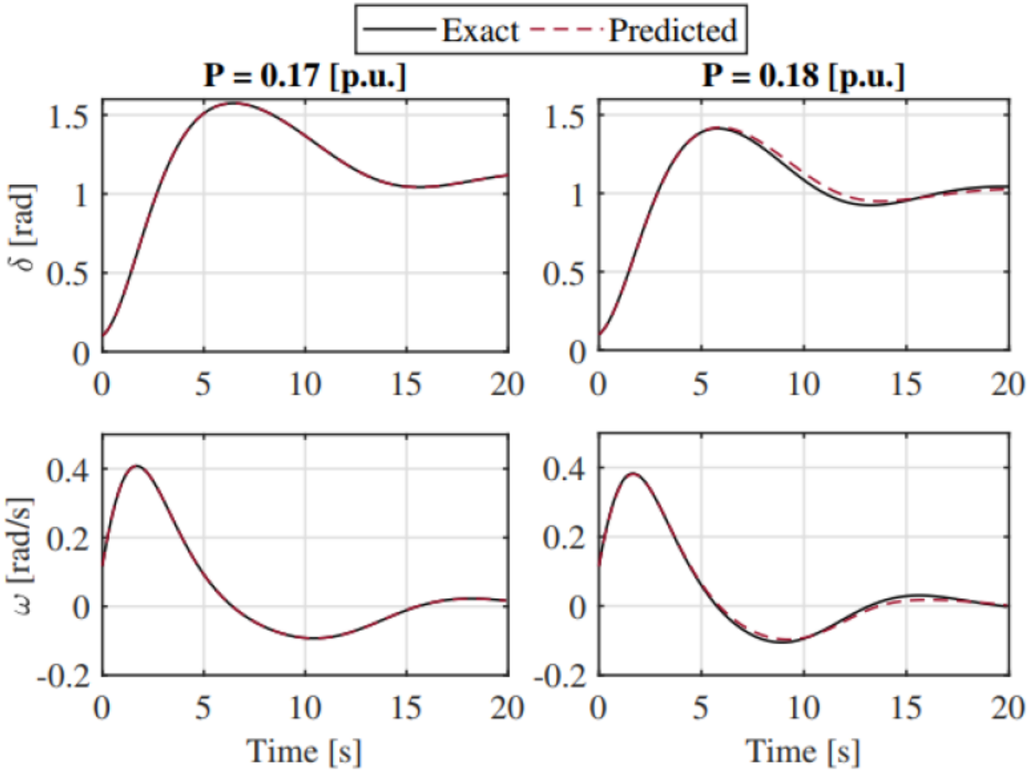
Physics-Informed Neural Networks for Power Systems

- Physics-Informed Neural Networks (PINN) **can potentially replace** solvers for systems of differential-algebraic equations

- 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/gmisy/Physics-Informed-Neural-Networks-for-Power-Systems/

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

Physics-Informed Neural Networks for Power Systems

Potential applications

1. Replacing ODE Solvers
   - Solving extremely fast systems of differential-algebraic equations
   - Estimating evolution of δ, ω, V, etc.
   - Limited need for input data

2. System Identification
   - With limited data, estimate inertia, damping, etc.

3. Others?

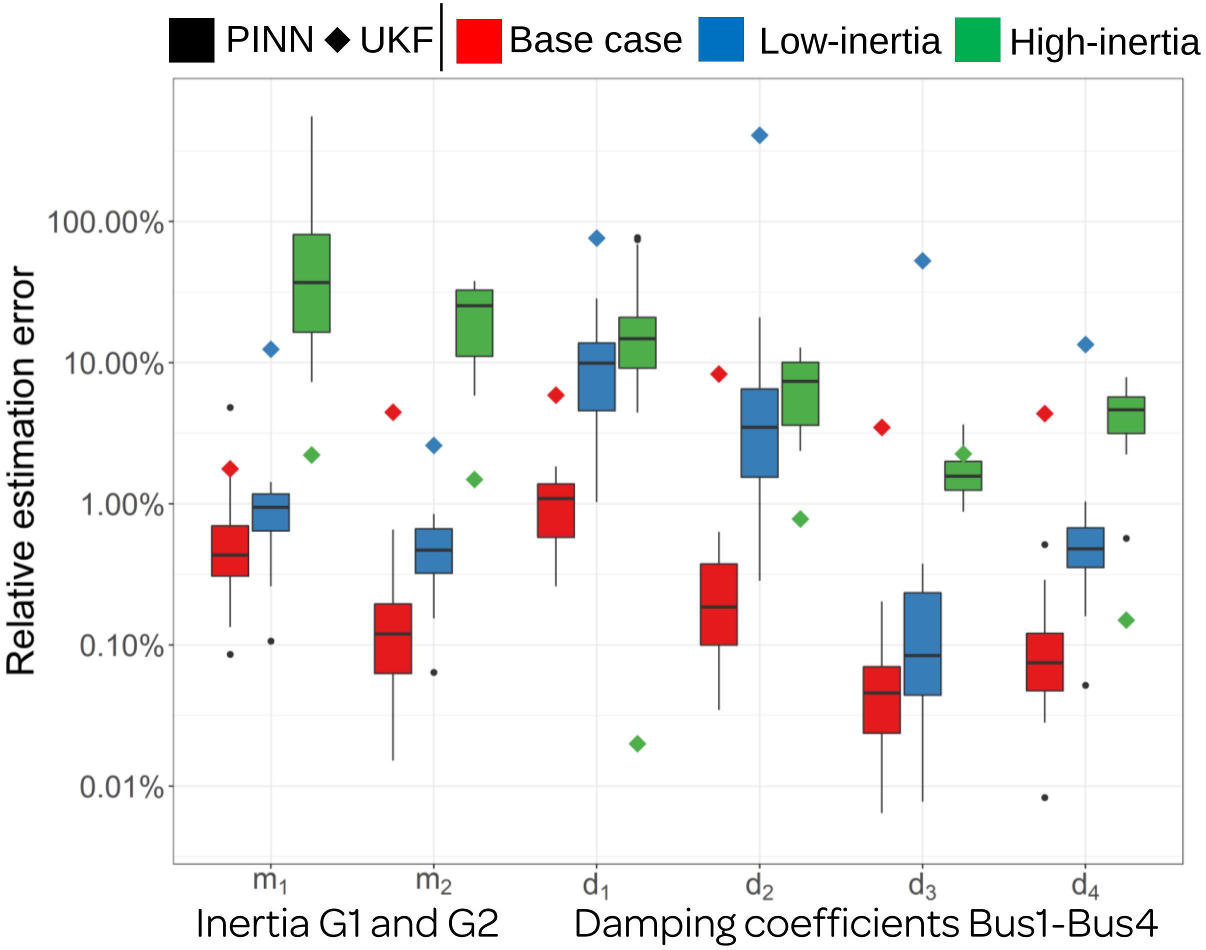
Physics-Informed Neural Networks for System Identification

- **Physics-Informed NN (PINN)** perform better for systems with **faster dynamics** (i.e. low-inertia systems)

- **Unscented Kalman Filter (UKF)** performs better with **slower dynamics**
  - NN training procedure gets trapped to local minima, as the optimization landscape is flat

- **PINN perform better** where there **is limited training data,** or **high noise.** But they are also **more computationally intensive.**

- **Way forward**: Combine the strengths of PINN and UKF in one method



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

J. Stiasny, G. S. Misyris, S. Chatzivasileiadis, Physics-Informed Neural Networks for Non-linear System Identification applied to Power System Dynamics. 2020. https://arxiv.org/pdf/2004.04026.pdf

Wrap-up

- **Sampling beyond statistics: ML needs high-quality data**
  - Need to exploit physics to create the training databases -- an open research topic
  - Highly unbalanced and non-convex regions → go beyond uniform sampling
- **Neural network verification**
  - A world of new opportunities for practical applications in power systems
  - Certify the behavior of neural networks
  - Systematically identify adversarial examples
- **Physics-Informed Neural Networks**
  - Exploit the underlying physical model in the neural network training
  - Extremely fast computing times: no need to integrate $t_0 \rightarrow t_1$, can directly estimate $x(t_1)$
  - Potential to replace differential-algebraic solvers for real-time applications?

Thank you!

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A. Venzke, S. Chatzivasileiadis. Verification of Neural Network Behaviour: Formal Guarantees for Power System Applications. Under Review. 2019. https://arxiv.org/pdf/1910.01624.pdf

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L. Halilbašić, F. Thams, A. Venzke, S. Chatzivasileiadis, and P. Pinson, ”Data-driven security-constrained AC-OPF for operations and markets,” *PSCC* 2018. [.pdf]

Some code available at:

www.chatziva.com/downloads.html