Power System Reliability with Deep Learning

DTU PES Summer School, 20-05-2025

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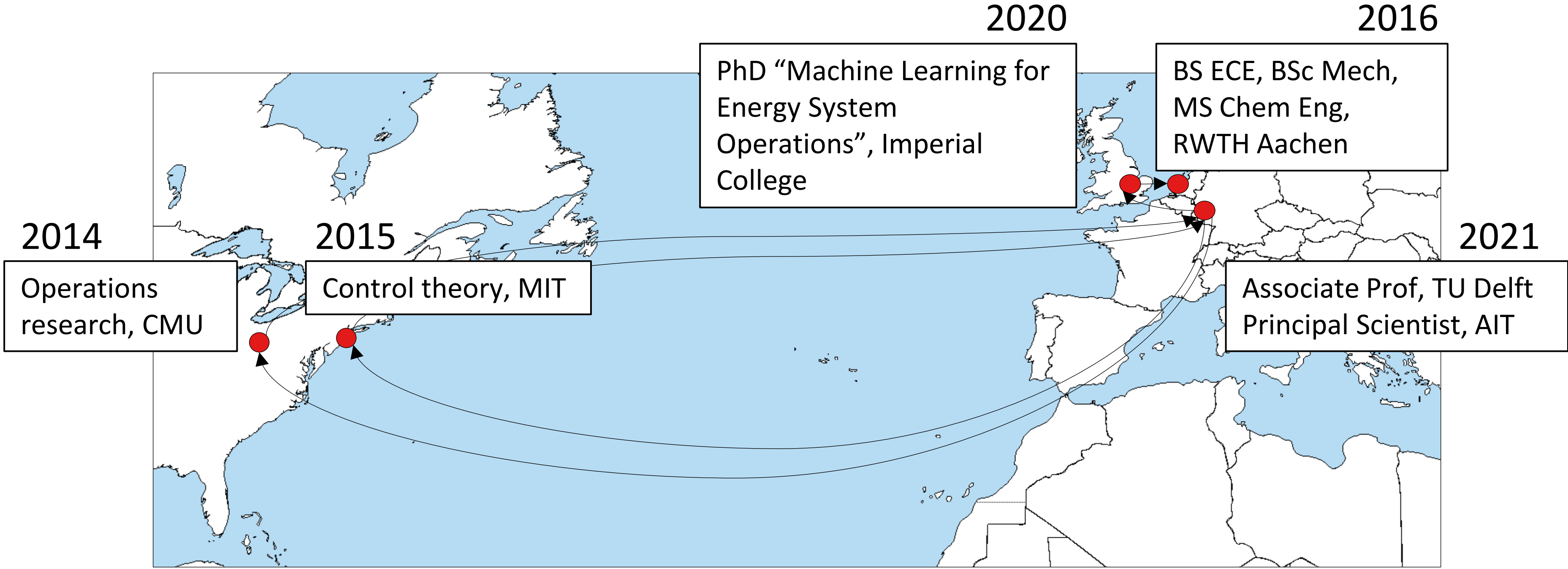
Associate Professor

TU Delft

Introduction



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Delft AI Energy Lab

Mission & objective

- combine groundbreaking ML with the reliable theory of the physical energy system
- make energy systems sustainable, reliable, effective

Education

- EE4C12 ML for Electrical Engineering
- SET 3125 Machine Learning Workflows for Digital Energy Systems
- SC42150 Statistical Signal Processing
- SC42110 Dynamic Programming and Stochastic Control
- MOOC Digitalization of Intelligent and Integrated Energy Systems
- Crash course of “Data-science”

Research

- Supervised learning for real-time grid assessment
- Distributed learning for power system congestion management
- Data-driven grid models for electricity load and weather forecasts
- Characterizing healthy/normal trajectories of complex dynamical systems using dictionary learning
- From fast Fourier transform to fast reinforcement learning

Key innovations

- AI-based algorithms for grid operation
- Real-time security assessment and anomaly detection
- Real-time learning algorithms for control and security of complex dynamical systems

Team


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TU Delft | AI Initiative

https://www.tudelft.nl/ai/delft-ai-energy-lab

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Outline

Reliability management and data in control rooms

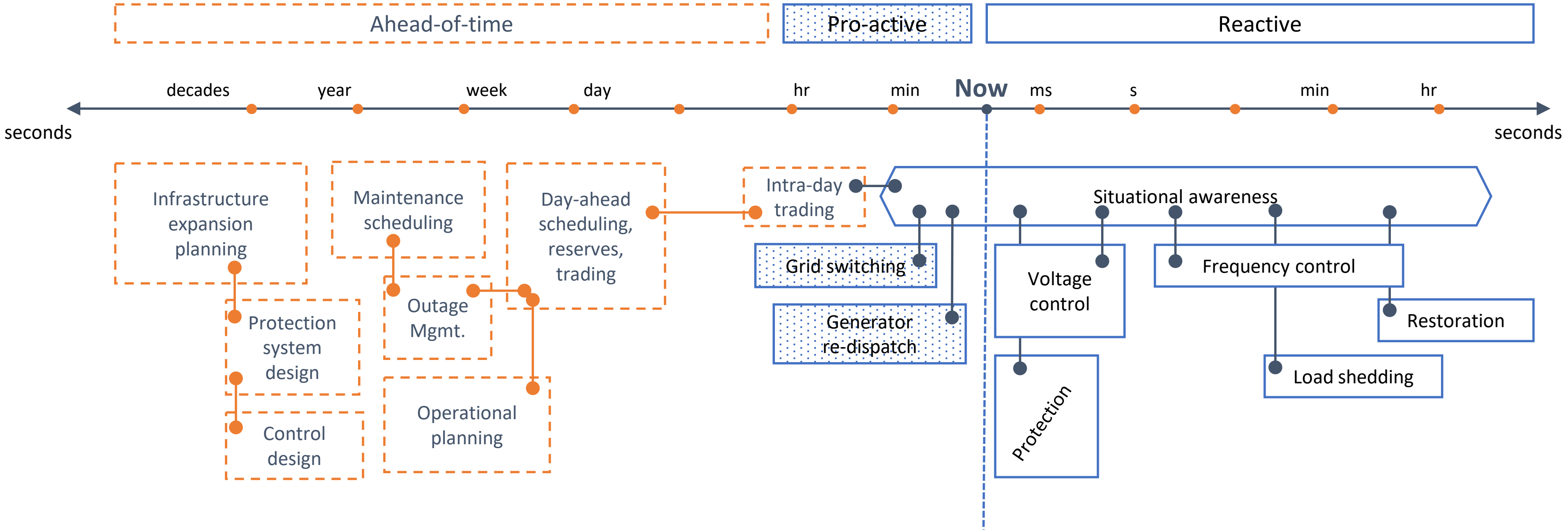
1. Introduction to reliability management
2. Machine learning approaches
3. Security assessment with cost-sensitive supervised learning

Learning models for secure system operation

4. Learning with domain knowledge
5. State estimation with graph neural networks
6. Weakly-supervised learning for secure operation
7. Challenges applying ML to reliability

Experts are in charge to manually operate the power system based on **experience** and with **the support of tools**

A complex process



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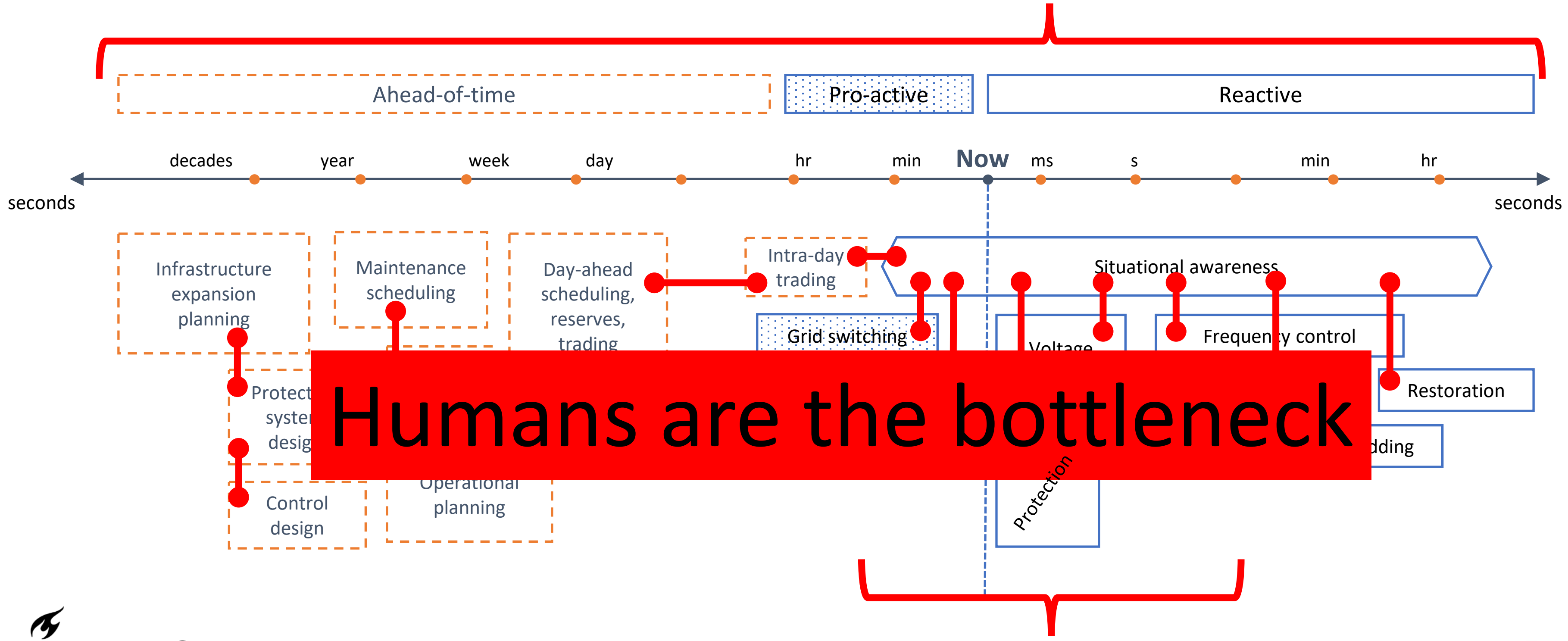
Hitachi Energy

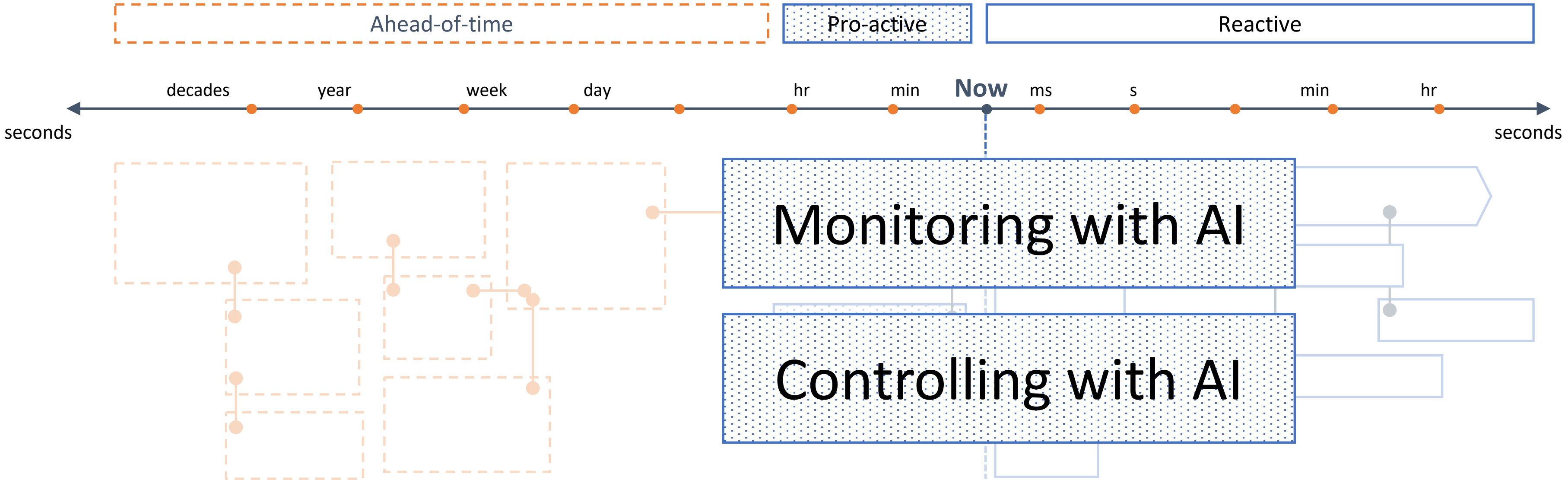
What’s the issue?

Interdependencies
challenge manual rules

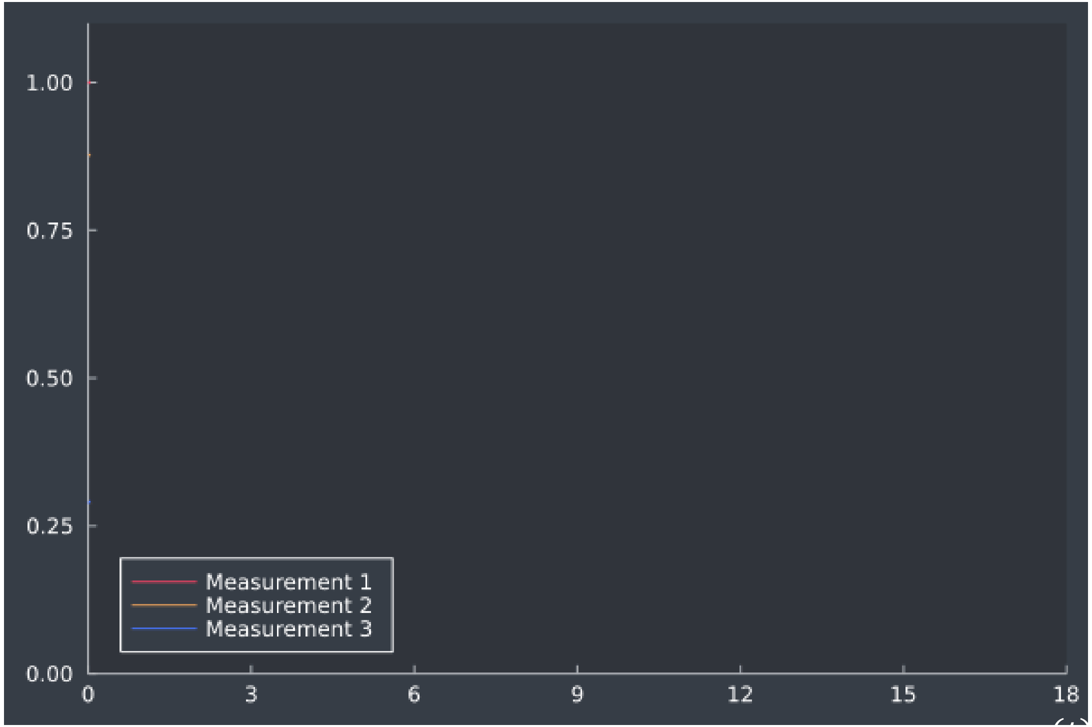


Human decisions are too slow

Automation first realised where urgently needed



Real-time security assessment of disturbances

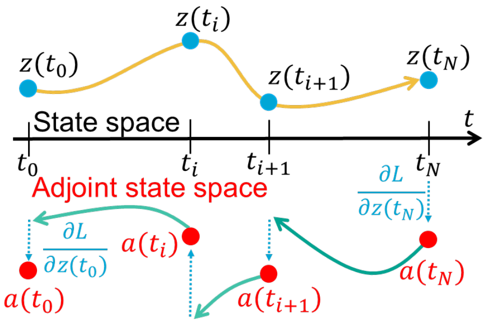


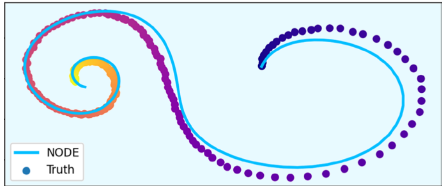
Phase angles [norm]

Time [s]

Mert Karaçelebi

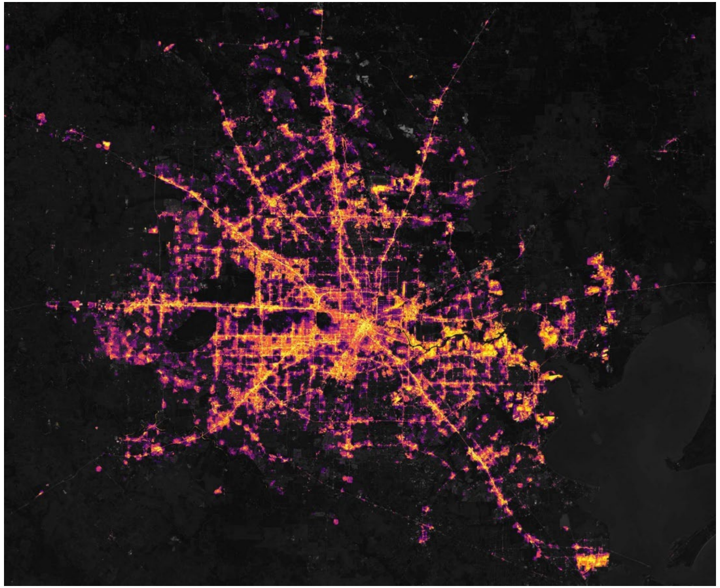
Neural ordinary differential equations





[1] Mert Karaçelebi, Jochen L. Cremer "Online Neural Dynamics Forecasting for Power System Security", *International Journal of Electrical Power & Energy Systems 2025*
[2] Mert Karaçelebi, Jochen L. Cremer, "Predicting Power System Frequency with Neural Ordinary Differential Equations", *12th Bulk Power System Dynamics and Control Symposium and Sustainable Energy, Grids and Networks Journal, 2025*

Why do system operators require reliability monitoring?



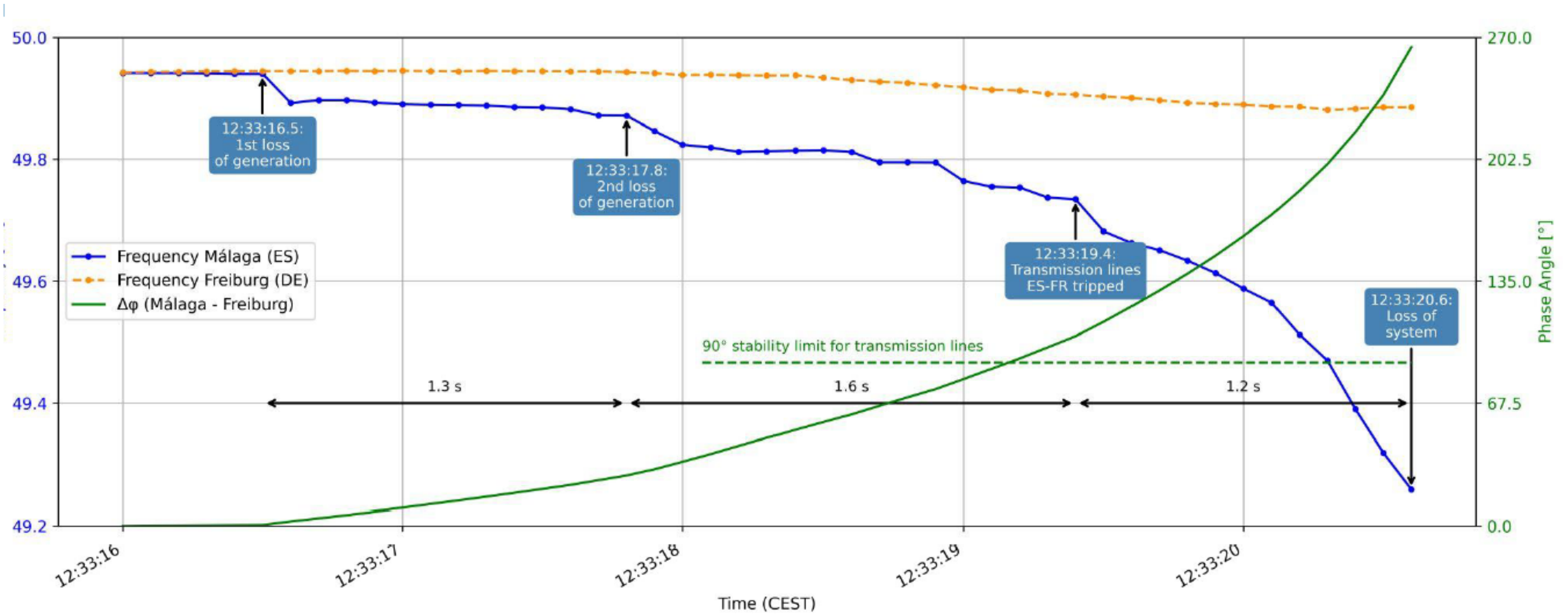
Houston, Texas 07 Feb 2021

Houston, Texas 16 Feb 2021

- Damages from the blackouts were estimated at **$195 billion [3]**
- Seconds away from a total power blackout in Texas

[3] 2021 Winter Storm Uri After-Action Review: Findings Report (PDF) (Report). City of Austin & Travis County. November 4, 2021. Archived (PDF) from the original on November 5, 2021. Retrieved November 5, 2021.

Power blackout 28 April 2025 Spain/Portugal

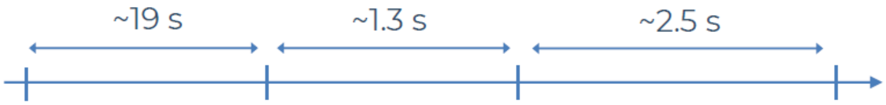


Source

Luis Badesa

N-2?

28th of April 2025 (CET)



Full Blackout

~12:20pm

FACT

Inter-area **oscillations** in Europe

(possibly related to later generation losses)

12:32:57

FACT

Generation loss

(size unknown)

12:33:16

FACT

Generation loss in the Southwest of Spain

(size unknown)

12:33:18

FACT

Generation loss in the Southwest of Spain

(size unknown)

12:33:20

FACT

Iberia becomes an **electric island**, and a "**massive disconnection of generation**" happens in Spain

https://badber.github.io/

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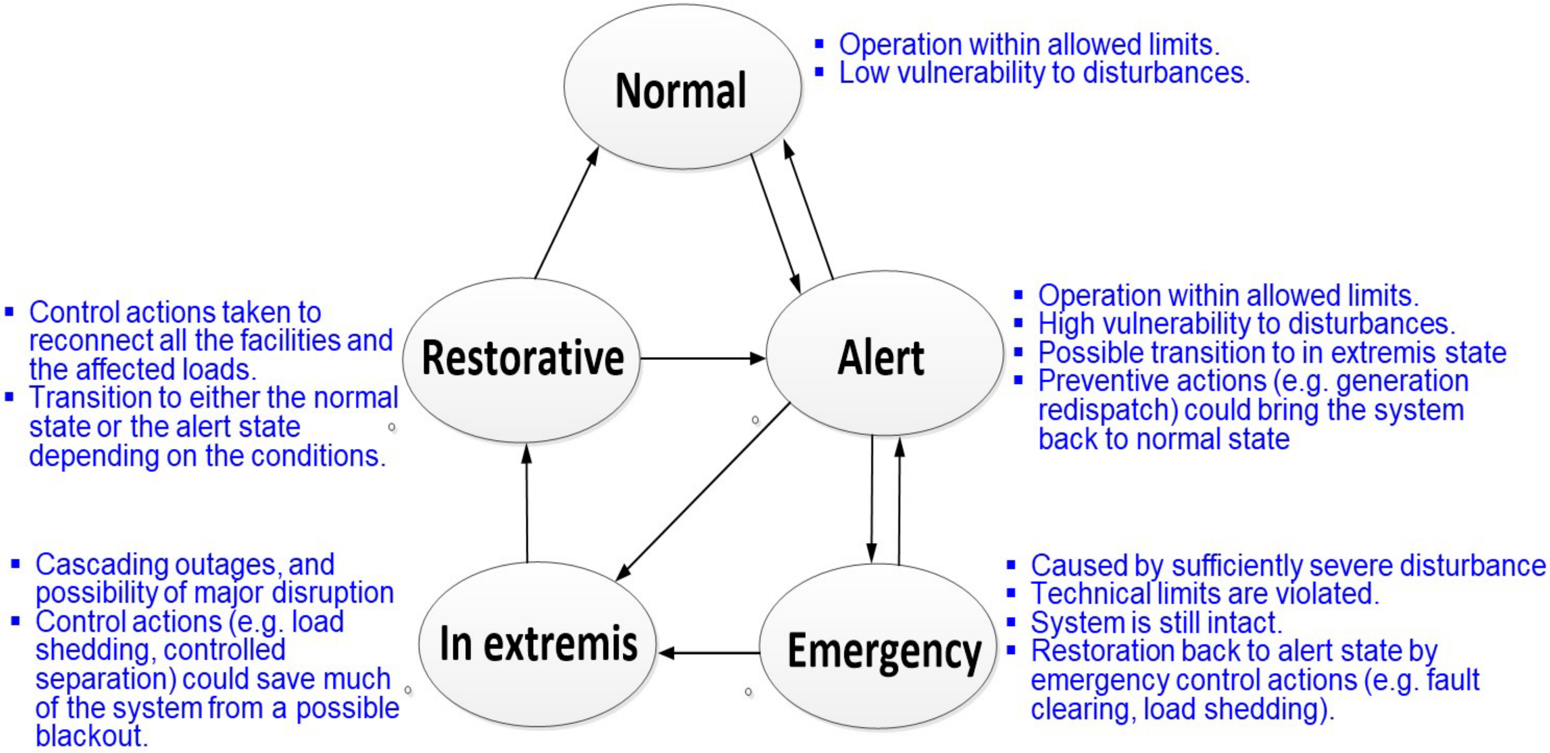
Power system reliability

"…is the probability that an electrical power system can perform a required function under given conditions for a given time interval."

[4] International Electrotechnical Commission, Electropedia: The worlds online electrotechnical vocabulary, http://www.electropedia.org/; 2016 [accessed 16 August 2018].

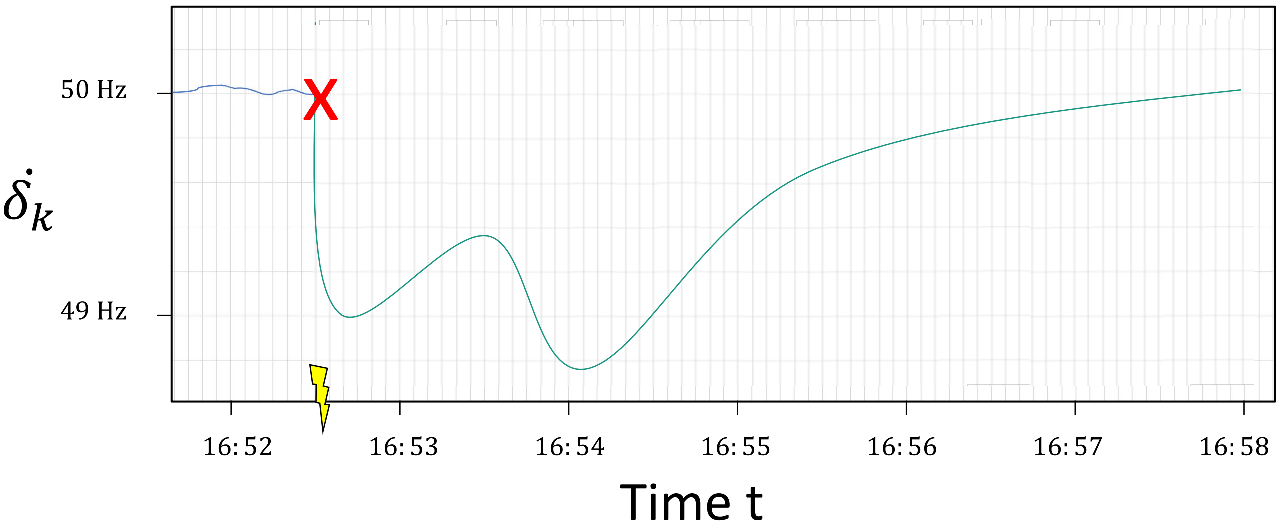
Operating states of power systems



[5] Power System Stability and Control (Kundur)

Conventional (offline) dynamic security assessment

Simulating time-response



Numerical integration

ODE system $\begin{cases} \dot{x} = f(x, t, x_0) \\ x_0 = (P_k^{16h}, Q_k^{16h}) \end{cases}$

Forward Euler

$$x_{k+1} = x_k + hf(x_k, t_k)$$

slow for large systems

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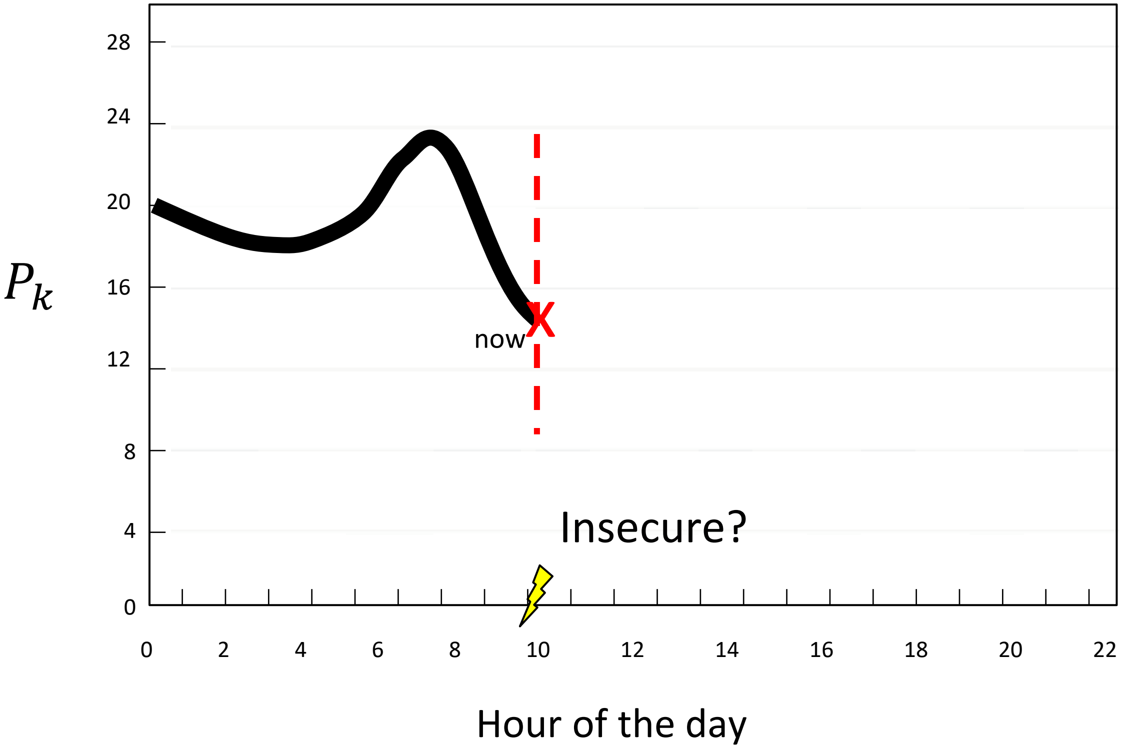
Real-time dynamic security assessment

Objective: predicting security in real-time

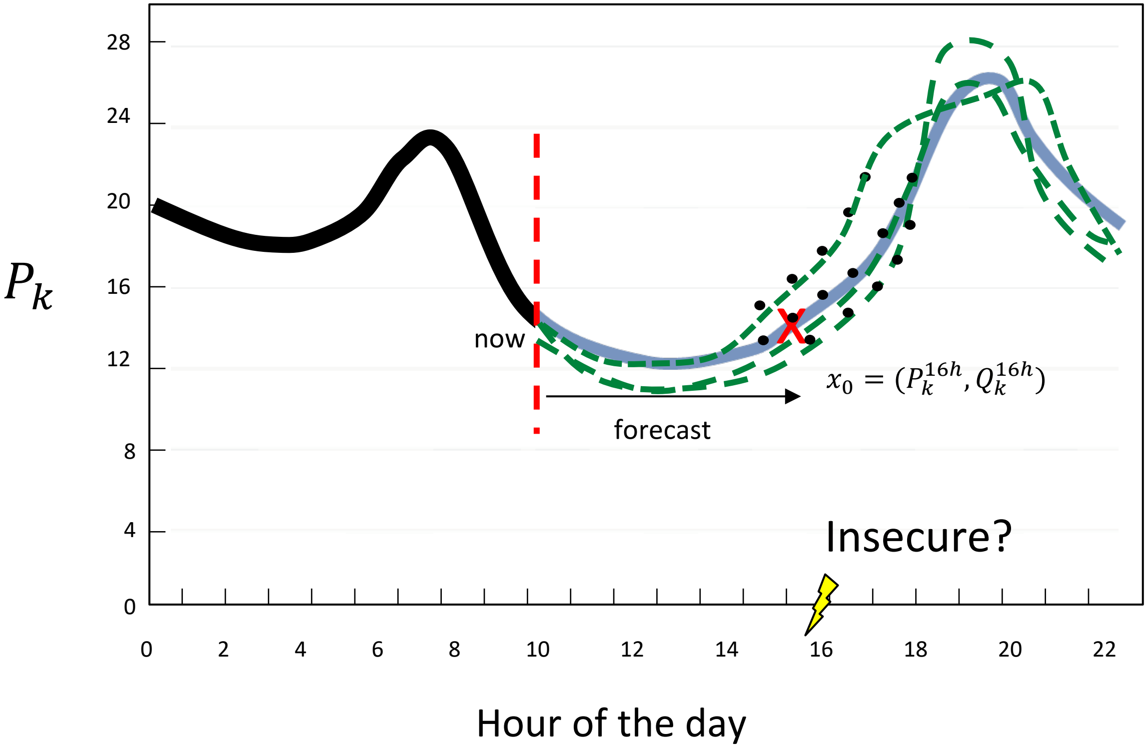
In response, use corrective actions in (near) real-time

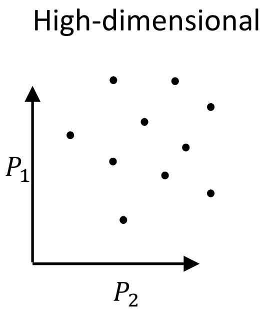


(Preventive) real-time dynamic security assessment

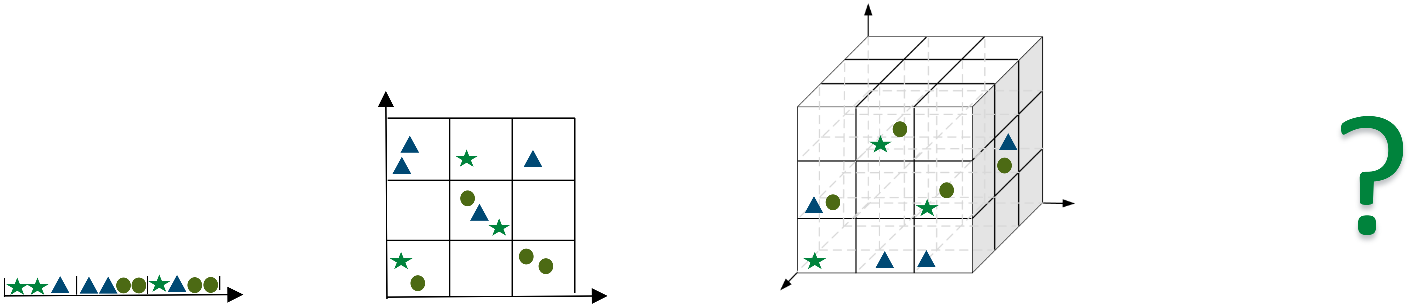
For N-1 security

Preventive actions





Curse of Dimensionality



1d: 3 regions

2d: 3^2 regions

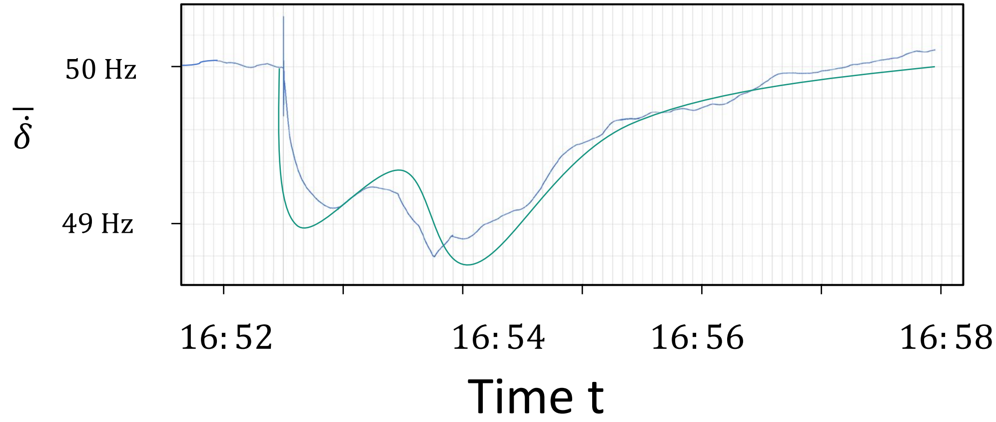
3d: 3^3 regions

1000d: hopeless

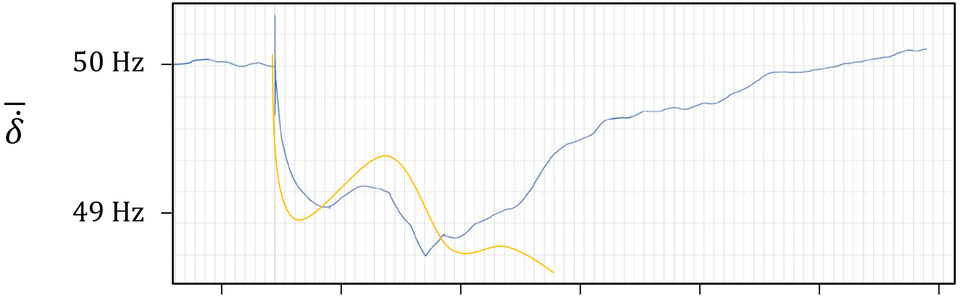
As dimensionality grows: fewer samples per region.

[6] James, Gareth, et al. *An introduction to statistical learning*. Vol. 112. No. 1. New York: springer, 2013.

Security of power systems

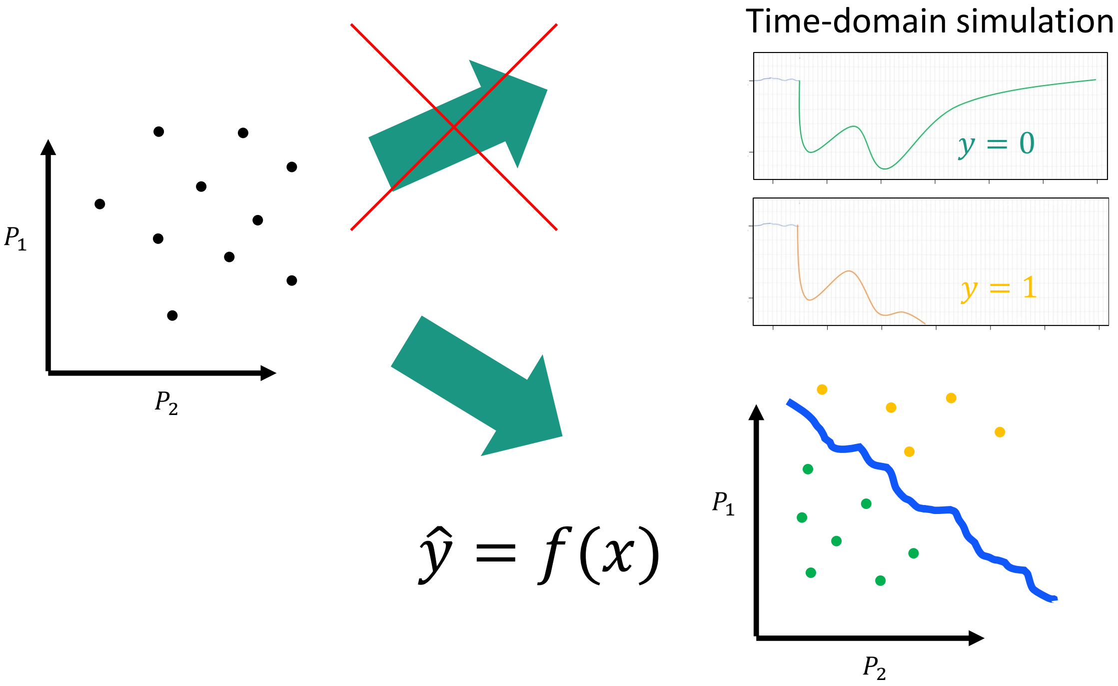


secure $y = 0$



insecure $y = 1$

Machine learning model to predict security



$$\hat{y} = f(x)$$

How to train and use f?

[7] Duchesne, L., Karangelos, E., & Wehenkel, L. (2020). Recent developments in machine learning for energy systems reliability management. *Proceedings of the IEEE*, *108*(9), 1656-1676.a

Challenges for reliability management

- More extreme weather events
- Higher grid load in the system
- Higher uncertainty
- Highly complex problem

Opportunities for reliability management with AI

- Availability of better models and data (weather, grid data, etc)
- New AI techniques
- Once trained, models are quick in ‘predicting’, but challenges also exist

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Supervised Learning for Surrogate Models


Federica Bellizio

Olayiwola Arowolo

Notation: Power system s, model m, parameter x

Objective: assess $m(x) \to y$ **very** fast and **often**

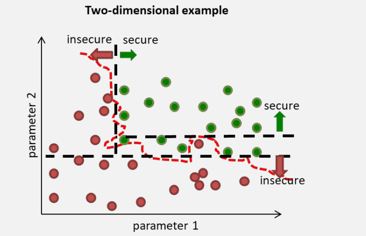
Surrogate approach

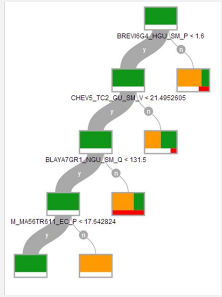
1. Generate a training dataset $\Omega^T = \{(x_i, y_i)\}_{i=1}^N$ where $y_i = m(x_i)$ from the full simulator
2. Train surrogate $f(x) \to \hat{y}$ with supervised loss $\sum_{i\in\Omega^T} \|y_i - \hat{y}_i\|$
3. Use $f(x_j)$ for new j $\notin \Omega^T$

Benefit: speed at inference

Applications

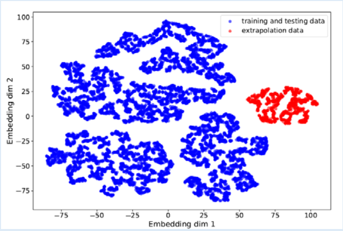
- Real-time dynamic security assessment ([8,9] and many others)





Challenges

- What if s and m changes? e.g., topology changes
- What if the model is inaccurate $s \neq m$? e.g., inverter-based controls
- Need large, representative training data



[8] Wehenkel, Louis, and Mania Pavella. "Decision trees and transient stability of electric power systems." *Automatica* 27.1 (1991): 115-134.
[9] Cremer, Jochen L., Ioannis Konstantelos, and Goran Strbac. "From optimization-based machine learning to interpretable security rules for operation." *IEEE Transactions on Power Systems* 34.5 (2019): 3826-3836.
[10] Olayiwola Arowolo, Jochen Stiasny, Jochen L. Cremer, "Exploring Extrapolation of Machine Learning Models for Power System Time Domain Simulation", *Bulk Power System Dynamics and Control Symposium, 2025*

Physics-Informed Learning

Objective: surrogate learning enhanced with physics knowledge from model m

Idea: Incorporate physics residual (e.g. from a PDE or simulator) to guide learning and improve generalization

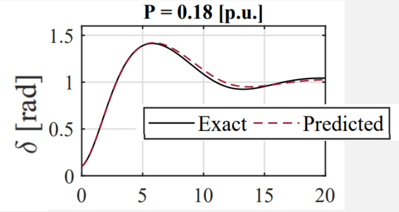
Physics-informed approach

1. Generate offline training dataset $\Omega^T = \{(x_i, y_i)\}_{i=1}^{N}$ with $y_i = m(x_i)$
2. Train surrogate $f(x) \rightarrow \hat{y}$ on composite loss $\sum_{i \in \Omega^T} \|y_i - \hat{y}_i\| + \mathcal{L}_{phys}\,(f(x_i), m)$
3. Use $f(x_j)$ for new j $\notin \Omega^T$

Benefits: Better generalisation performance with **fewer training samples**

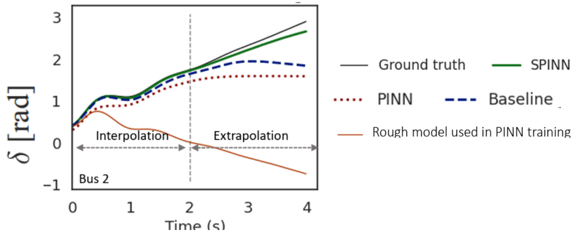
Applications

- Extrapolation in time-domain for dynamic analysis in power systems



Challenges

- Model inaccuracy $s \neq m$
- Changes in s or m
- Data sparsity
- Multi-loss scaling causes training instability
- Scaling issues to many physical loss terms in power systems



[11] Misyris, George S., Andreas Venzke, and Spyros Chatzivasileiadis. "Physics-informed neural networks for power systems." In *2020 IEEE power & energy society general meeting (PESGM)*, pp. 1-5. IEEE, 2020.
[12] Xie, Haiwei, Federica Bellizio, Jochen L. Cremer, and Goran Strbac. "Regularised Learning with Selected Physics for Power System Dynamics." In *2023 IEEE Belgrade PowerTech*, pp. 1-7. IEEE, 2023.

Weakly-Supervised (E2E) Learning

Objective: learn models $f(x)$ for downstream task even when exact labels $y_i = m(x_i)$ from the simulator m are unavailable, uncertain, or only indirectly defined.

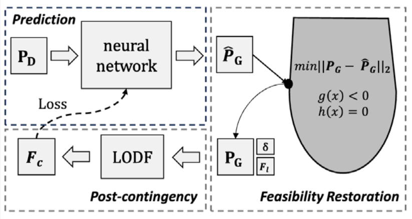
Approach

1. Generate many inputs $\Omega^T = \{(x_i)\}_{i=1}^N$
2. Model task loss $\sum_{i \in \Omega^T} \mathcal{L}(m(f(x_i))$
3. Use $f(x_j)$ for new j $\notin \Omega^T$

Benefits: learning for computationally expensive or ill-defined problems

Applications

- Learn to predict effective inputs to OPF[13]
- Replace conventional solvers with NN [14]
- Distribution system state estimation [15]
- N-k security-constrained OPF [16]



Challenges

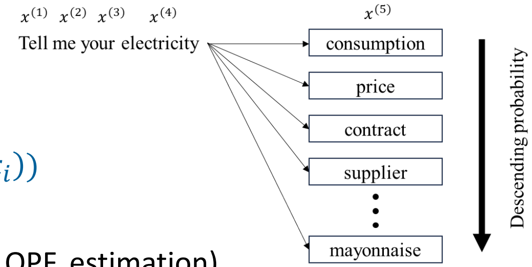
- Inexact supervision $s \neq m$ not so important as success defined by task-loss
- System shift in s or m
- Data coverage. Diverse samples are needed for generalization

[13] Donti, P., Amos, B., & Kolter, J. Z. (2017). Task-based end-to-end model learning in stochastic optimization. *Advances in neural information processing systems*, *30*.
[14] Donon, B., Liu, Z., Liu, W., Guyon, I., Marot, A., & Schoenauer, M. (2020). Deep statistical solvers. *Advances in Neural Information Processing Systems*, *33*, 7910-7921.
[15] Habib, B., Isufi, E., van Breda, W., Jongepier, A., & Cremer, J. L. (2023). Deep statistical solver for distribution system state estimation. *IEEE Transactions on Power Systems*, *39*(2), 4039-4050.
[16] Giraud, B. N., Rajaei, A., & Cremer, J. L. (2024). Constraint-driven deep learning for n-k security constrained optimal power flow. *Electric Power Systems Research*, *235*, 110692.

Self-Supervised Learning

Objective: Learn a **useful internal representation** from unlabeled data by solving a **pretext task** — no human-labeled or simulator-labeled outputs required.

Idea: instead of training on (x_i, y_i) train on auto-generated pseudo-labels or tasks constructed from structure x_i



Approach

1. Generate many inputs $\Omega^T = \{(x_i\ )\}_{i=1}^N$
2. Define self-supervised pretext loss $\mathcal{L}_{pretext}(f(x_i))$
3. Train encoder $\sum_{i \in \Omega^T} \mathcal{L}_{pretext}(f(x_i))$
4. Use $f(x)$ for downstream *task* (e.g. forecasting, OPF, estimation)

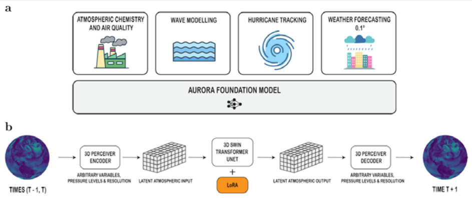
Benefits: Good initialization when little data, good transfer to downstream tasks

Challenges

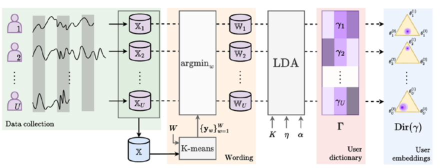
- Design pretext loss and model architectures with broad set of tasks, grid conditions, topologies
- Generate large data sets
- …

Applications

- Natural Language Processing
- Weather foundational models
- Earth system foundational models [17]



Load forecasting of users [18]



Grid foundation models (GFM) [19]

[17] Bodnar, C., Bruinsma, W. P., Lucic, A., Stanley, M., Vaughan, A., Brandstetter, J., ... & Perdikaris, P. (2024). A foundation model for the earth system. *arXiv preprint arXiv:2405.13063*.
[18] Bölat, Kutay, and Simon Tindemans. "GUIDE-VAE: Advancing Data Generation with User Information and Pattern Dictionaries." *arXiv preprint arXiv:2411.03936* (2024).
[19] Hamann, H. F., Gjorgiev, B., Brunschwiler, T., Martins, L. S., Puech, A., Varbella, A., ... & Sobolevsky, S. (2024). Foundation models for the electric power grid. Joule, 8(12), 3245-3258.

Graph Neural Networks

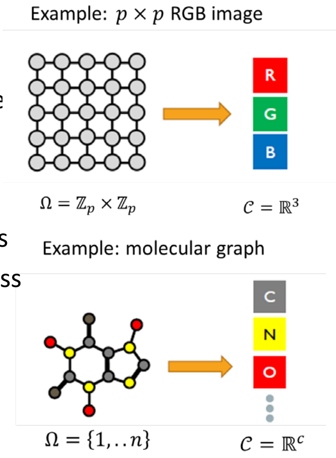
Objective: Improve generalization performance in learning tasks on network-structured systems (like power grids)

Idea: embedding graph topology directly into the model architecture as bias

Approach

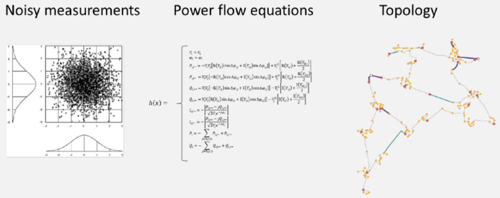
1. Construct graph $G = (V, \mathcal{E})$ with features on nodes and edges
2. Define f_{GNN} and learn with message passing on supervised loss $\sum_{i \in \Omega^T} \|y_i - \hat{y}_i\|$
3. Use $f(x_j)$ for new j $\notin \Omega^T$ or on unseen graphs G'

Benefits: Data efficient, generalisation to changes in topologies



Applications

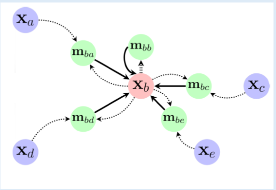
- Graph neural solvers [20] for ACOPF [21]
- Distribution system state estimation [22]



Challenges

- Model inaccuracy $s \neq m$
- Long-range dependencies are difficult to learn. *Power system topology is sparse*
- Challenging to learn for *global* problems (e.g. ACOPF)

Good to learn local relationships



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[20] Donon, B., Donnot, B., Guyon, I., & Marot, A. (2019, July). Graph neural solver for power systems. In *2019 international joint conference on neural networks (ijcnn)* (pp. 1-8). IEEE.
[21] Piloto, L., Liguori, S., Madjiheurem, S., Zgubic, M., Lovett, S., Tomlinson, H., ... & Witherspoon, S. (2024). Canos: A fast and scalable neural ac-opf solver robust to n-1 perturbations. *arXiv preprint arXiv:2403.17660*.
[22] B. Habib, E. Isufi, W. van Breda, A. Jongepier and J. L. Cremer, "Deep Statistical Solver for Distribution System State Estimation," in IEEE Transactions on Power Systems, vol. 39, no. 2, pp. 4039-4050, March 2024, doi: 10.1109/TPWRS.2023.3290358.

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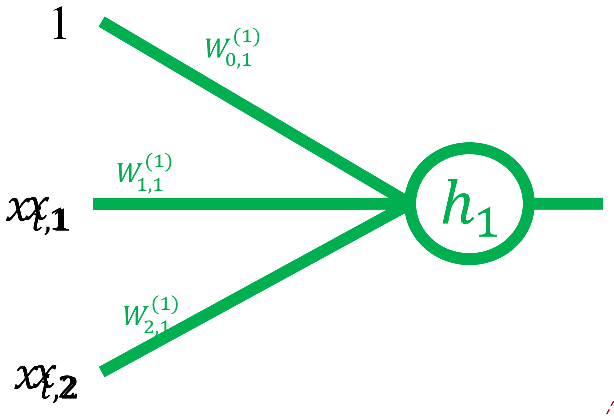
Neural networks

One neuron

Here simplified notation $x_{i,1}$ to x_1

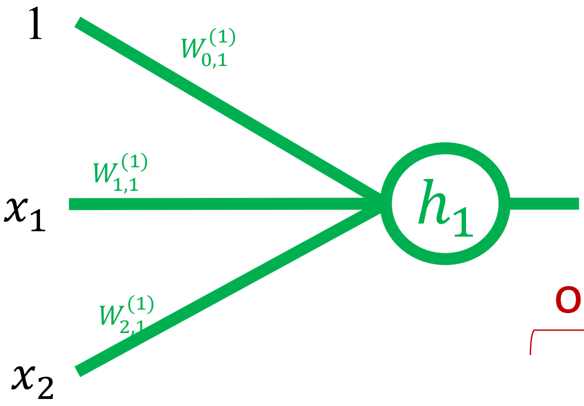


Activation function

$$h_1 = a(w_{0,1}^{(1)} + x_1 w_{1,1}^{(1)} + x_2 w_{2,1}^{(1)})$$

Neural networks

One neuron



$$h_1 = \overbrace{a(\overbrace{w_{0,1}^{(1)} + x_1 w_{1,1}^{(1)} + x_2 w_{2,1}^{(1)}}^{\text{in}_{h1}})}^{\text{out}_{h1}}$$

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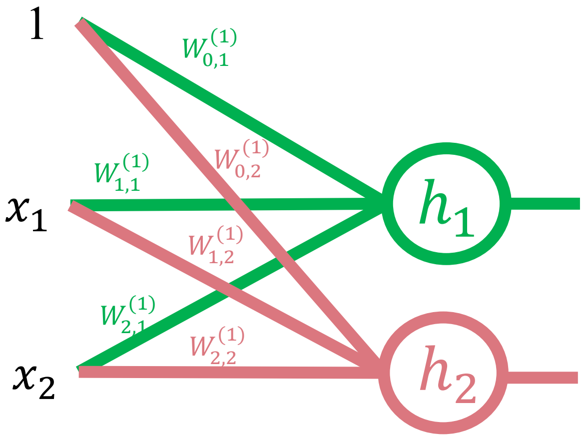
Compact model

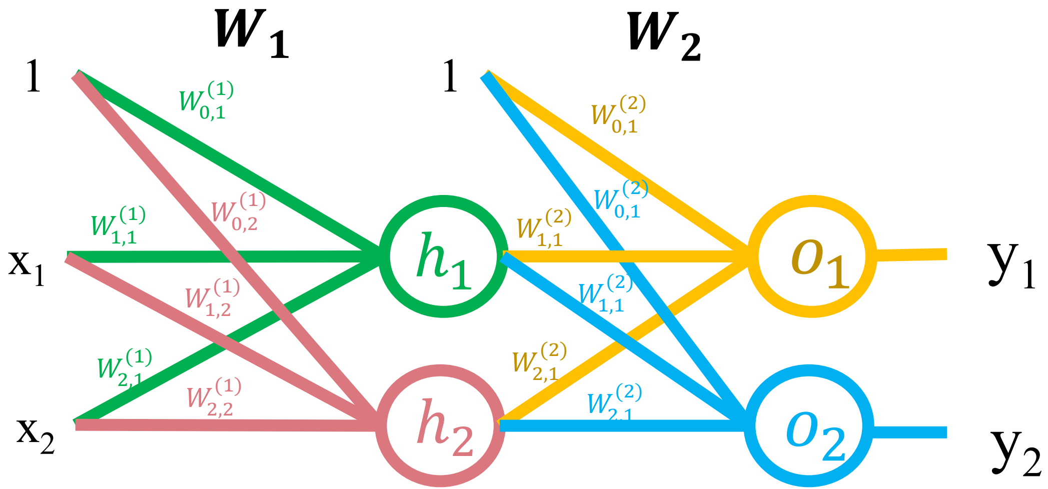


$$\mathring{\mathbf{a}}(\mathbf{W}_1^T \mathring{\mathbf{x}})$$

$$\boldsymbol{W}_1 = \begin{bmatrix} W_{0,1}^{(1)} & W_{0,2}^{(1)} \\ W_{1,1}^{(1)} & W_{1,2}^{(1)} \\ W_{2,1}^{(1)} & W_{2,2}^{(1)} \end{bmatrix}$$

$(N+1) \times u1$

Multiple layers



$\mathring{\mathbf{a}}(\mathbf{W}_1^T \mathring{\mathbf{x}})$ $\mathring{\mathbf{a}}(\mathbf{W}_2^T \mathring{\mathbf{a}}(\mathbf{W}_1^T \mathring{\mathbf{x}}))$

$$\boldsymbol{W_1} = \begin{bmatrix} W_{0,1}^{(1)} & W_{0,2}^{(1)} \\ W_{1,1}^{(1)} & W_{1,2}^{(1)} \\ W_{2,1}^{(1)} & W_{2,2}^{(1)} \end{bmatrix}$$

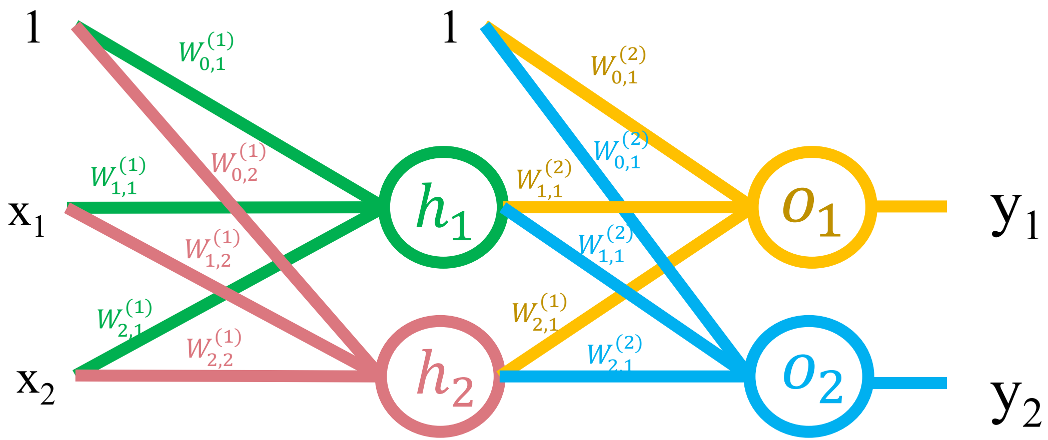
$(N+1) \times u1$

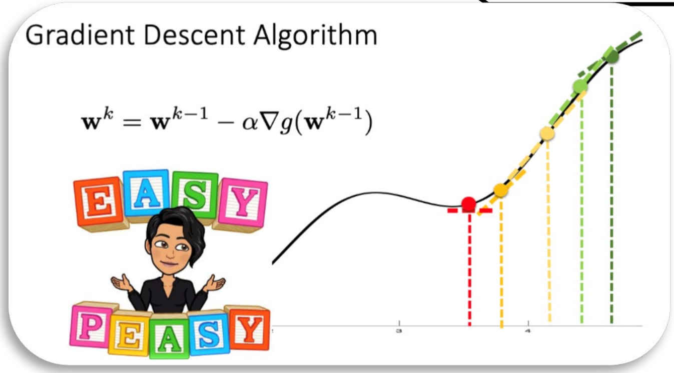
$$\boldsymbol{W_2} = \begin{bmatrix} W_{0,1}^{(2)} & W_{0,2}^{(2)} \\ W_{1,1}^{(2)} & W_{1,2}^{(2)} \\ W_{2,1}^{(2)} & W_{2,2}^{(2)} \end{bmatrix}$$

$(u1+1)$
$\times\ u2$

$$f(x) = \mathring{\mathbf{a}}(\mathbf{W}_2^T \mathring{\mathbf{a}}(\mathbf{W}_1^T \mathring{\mathbf{x}}))$$

Loss function





$$J = \frac{1}{|\Omega^{\mathrm{T}}|}\sum_{i\in\Omega^T}\left(\left(o_{i,1}-y_{i,1}\right)^2+\left(o_{i,2}-y_{i,2}\right)^2\right)$$

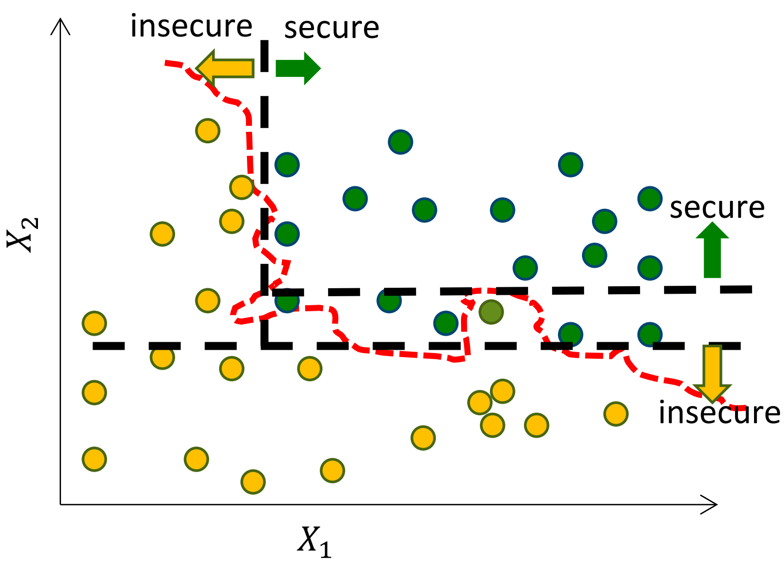
System operation

Experts are in charge to manually operate the power system based on **experience** and with **the support of tools**

Interpretable models

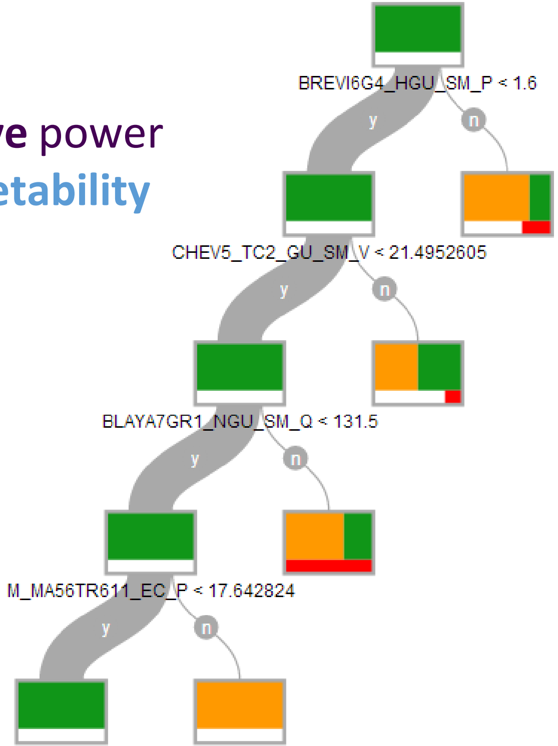
Decision Trees as a model?

Two-dimensional example

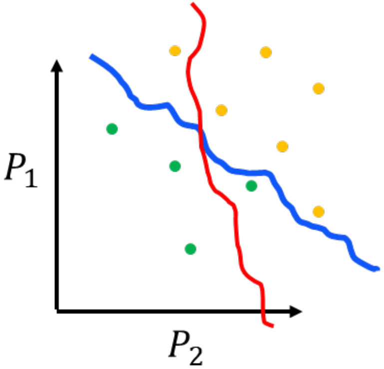


Decision trees:

- Limited **expressive** power
- Fantastic **interpretability**

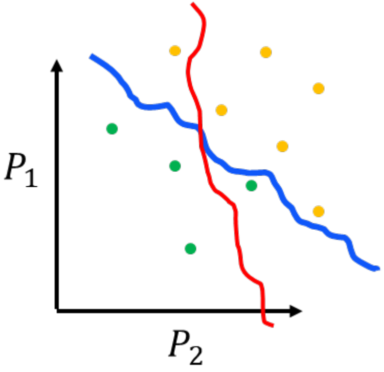


Metrics for classification



Predicted and actual security limits are different!

Metrics for classification

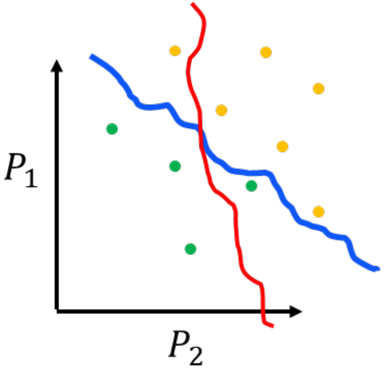


Predicted and actual security limits are different!

		Predicted Class: Positive	Predicted Class: Negative
True Class	Positive	TP	FN
	Negative	FP	TN

Confusion Matrix

Metrics for classification



Predicted and actual security limits are different!

Two types of accurate predictions:

TN: Is secure and we think it is secure (**GOOD**)

TP: Is insecure and we think it is insecure (**VERY GOOD!**)

True Class	Predicted Class: Positive	Predicted Class: Negative
Positive	TP	FN
Negative	FP	TN

Confusion Matrix

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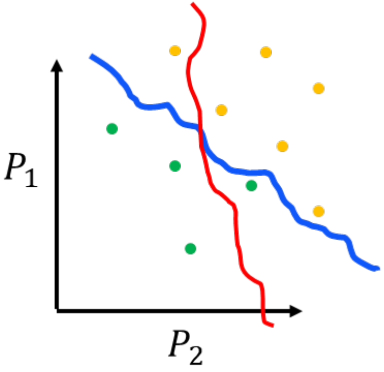
Metrics for classification



Predicted and actual security limits are different!

Predicted Class

		Positive	Negative
True Class	Positive	TP	FN
	Negative	FP	TN

Confusion Matrix

<u>**Two types of accurate predictions**</u>:

TN: Is secure and we think it is secure (**GOOD**)

TP: Is insecure and we think it is insecure (**VERY GOOD!**)

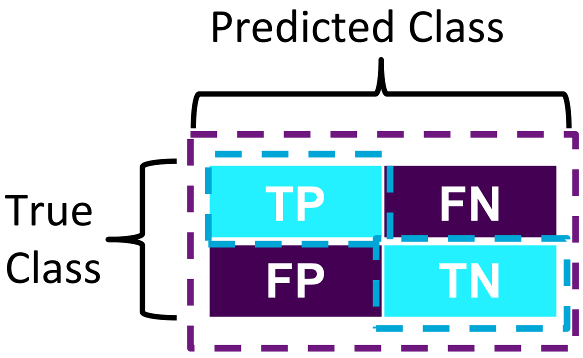
<u>**Two types of wrong predictions**</u>:

FP: Is secure but we think it is insecure (**BAD**)

FN: Is insecure but we think it is secure (**VERY BAD!**)

This can have a severe effect!

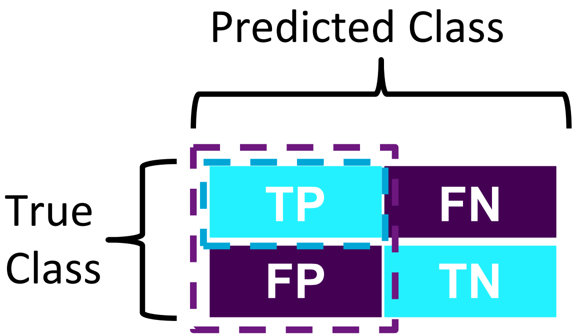
Metrics for classification



Ratio of correct predictions

$$\text{Accuracy} = \frac{N_{TP}+N_{TN}}{N_{FP}+N_{TP}+N_{FN}+N_{TN}}$$

Metrics for classification

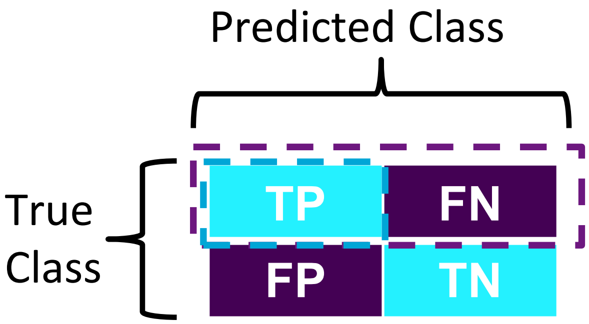


Ratio of correctly found insecure cases to predicted insecure predictions

$$\text{Accuracy} = \frac{N_{TP}+N_{TN}}{N_{FP}+N_{TP}+N_{FN}+N_{TN}}$$

$$\text{Precision} = \frac{N_{TP}}{N_{TP}+N_{FP}}$$

Metrics for classification



Ratio of correctly found insecure cases to all insecure cases

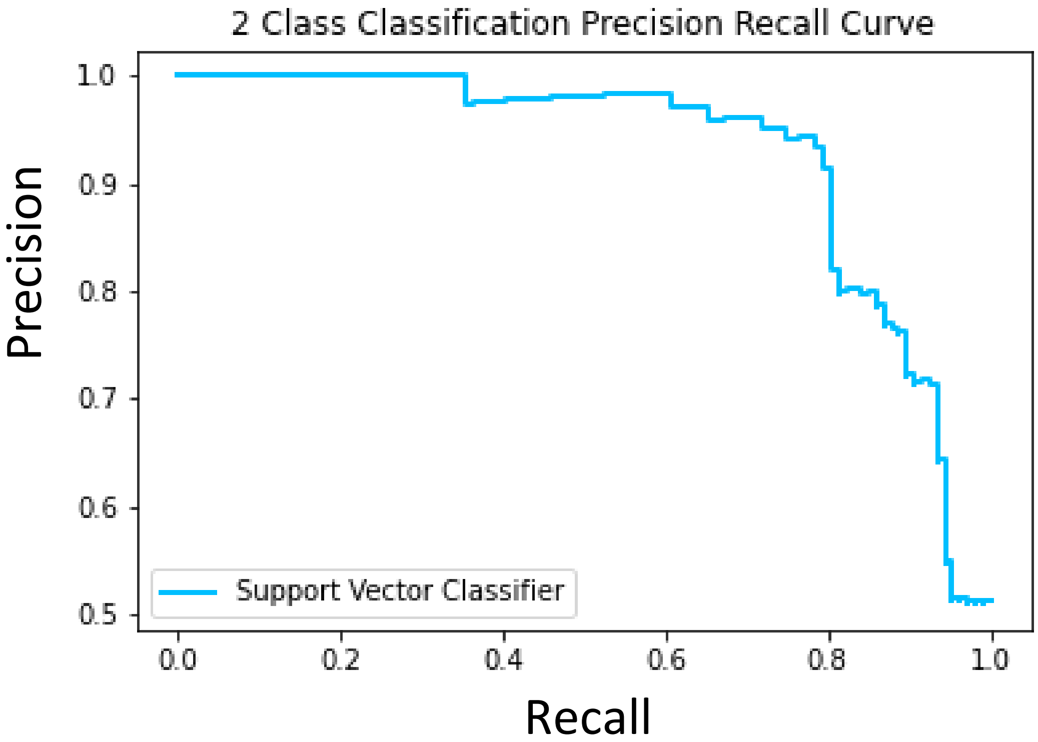
$$\text{Accuracy} = \frac{N_{TP}+N_{TN}}{N_{FP}+N_{TP}+N_{FN}+N_{TN}}$$

$$\text{Precision} = \frac{N_{TP}}{N_{TP}+N_{FP}}$$

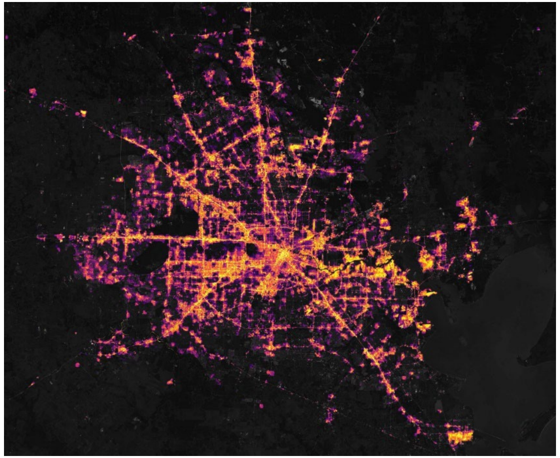
$$\text{Recall} = \frac{N_{TP}}{N_{TP}+N_{FN}}$$

Precision vs Recall

When do we observe the highest performance?



Blackout predictions: Precision or Recall?



Houston, Texas 07 Feb 2021

Houston, Texas 16 Feb 2021

$$\text{Precision} = \frac{N_{TP}}{N_{TP}+N_{FP}}$$

$$\text{Recall} = \frac{N_{TP}}{N_{TP}+N_{FN}}$$

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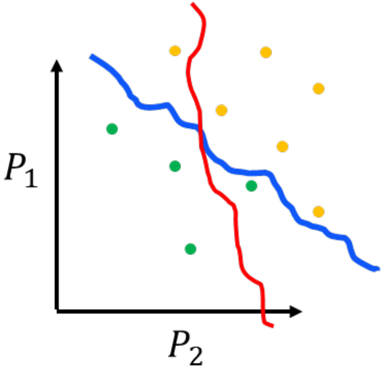
Cost skewness: $C_{FN} \gg C_{FP}$

Problem

- The two different false predictions have different costs.

- Damages from the blackouts were estimated at $195 billion
- Seconds away from a total power blackout in Texas

Metrics for classification



Predicted and actual security limits are different!

		Predicted Class: Positive	Predicted Class: Negative
True Class	Positive	0	C_{FN}
	Negative	C_{FP}	0

Two types of accurate predictions:

TN: Is secure and we think it is secure (**GOOD**)

TP: Is insecure and we think it is insecure (**VERY GOOD!**)

Two types of wrong predictions:

FP: Is secure but we think it is insecure (**BAD**)

FN: Is insecure but we think it is secure (**VERY BAD!**)

Two issues

- Cost-skewness: $C_{FN} \gg C_{FP}$
- Class imbalance: $\pi_{+} \ll \pi_{-}$

What a classifier can do

Classify points

- is x positive?

Rank points

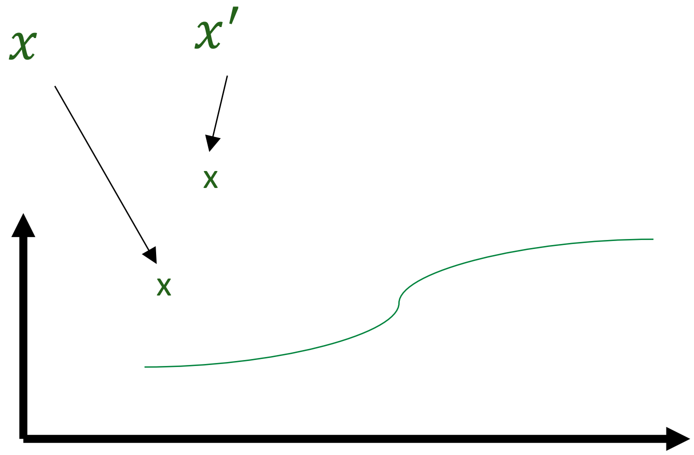
- Is x 'more positive' than x'?

Output a score $s(x)$

- 'How positive' is x?

Output a probability estimate $\hat{p}(x)$

- What is the (estimated) probability that x is positive?



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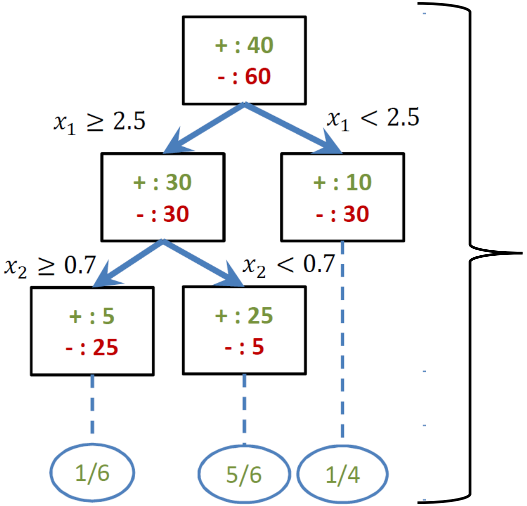
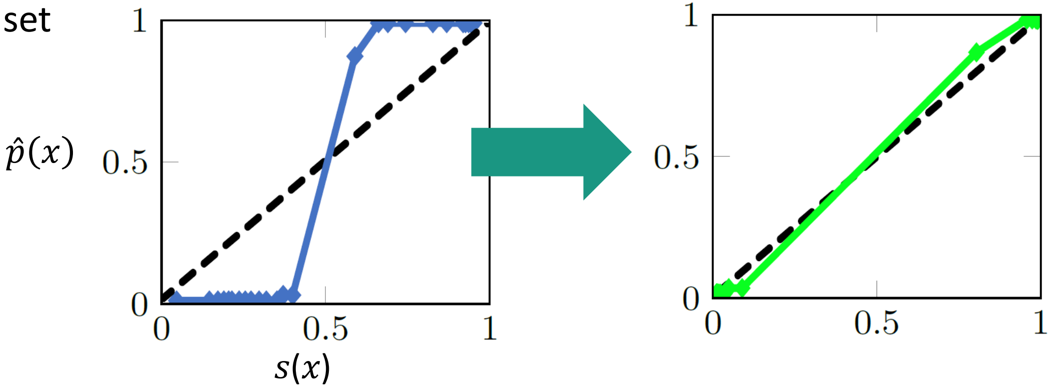
Probability estimation is not easy

- Scores $s(x) \in [0,1]$ as probability estimates $\hat{\boldsymbol{p}}(\boldsymbol{x})$? No!



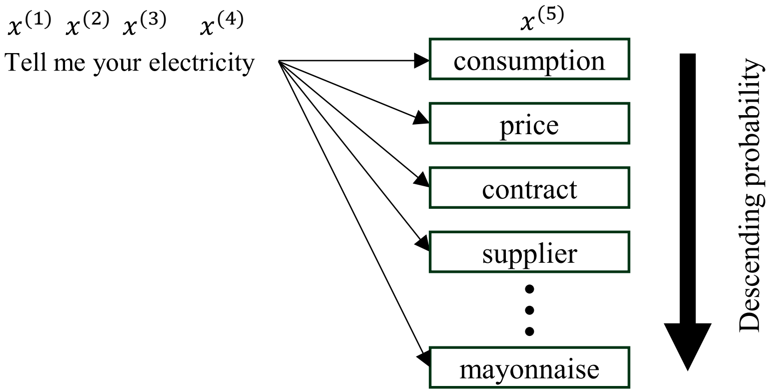
Based on training set

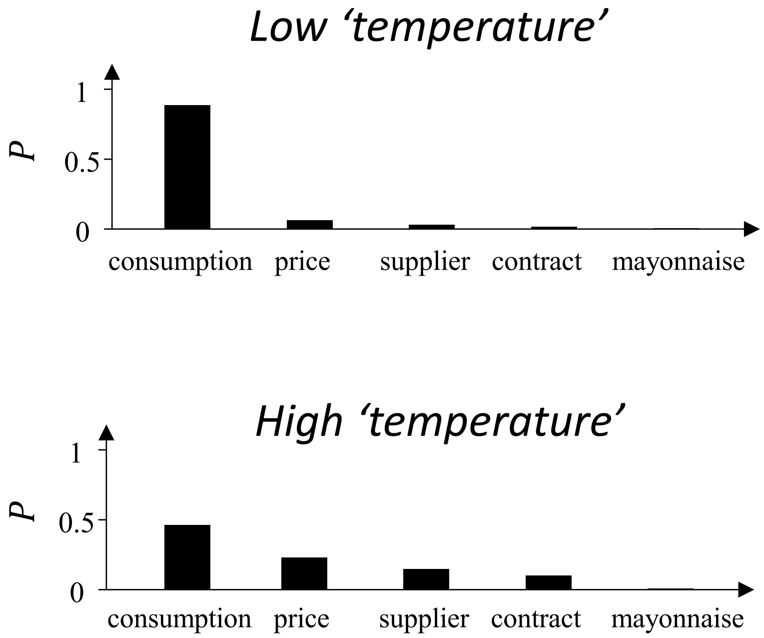
Platt scaling: Find $\hat{p}(x) = \frac{1}{1+e^{A\,s(x)+B}}$



[23] Nikolaou, N., Edakunni, N., Kull, M., Flach, P. and Brown, G., 2016. Cost-sensitive boosting algorithms: Do we really need them?. *Machine Learning*, *104*(2), pp.359-384.

Calibration in Large Language Models





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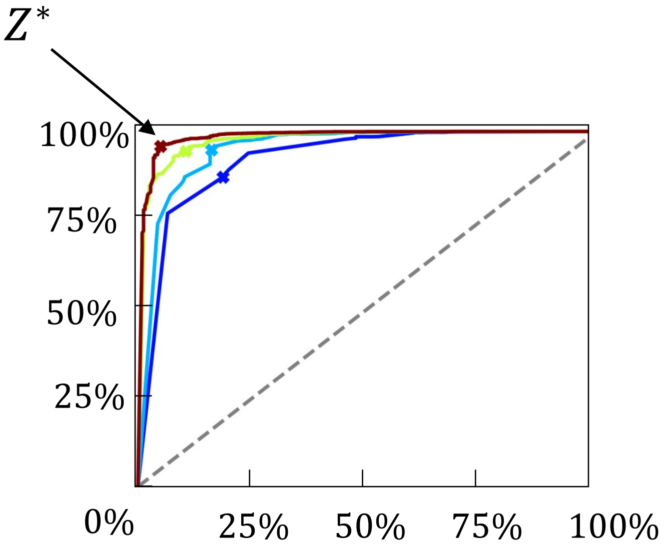
Cost-sensitive learning



$$TPR = \frac{TP}{\pi_+}$$

$$FPR = \frac{FP}{\pi_+}$$

$$Z^* = \frac{\Pi_- C_{FP}}{\Pi_- C_{FP} + \Pi_+ C_{FN}}$$

Probability of contingency

'Impact' of contingency

$\hat{\boldsymbol{p}}\,(\boldsymbol{x}) \geq \boldsymbol{Z}^*$ → predict secure

$\hat{\boldsymbol{p}}\,(\boldsymbol{x}) < \boldsymbol{Z}^*$ → predict insecure

[24] Jochen Cremer, Goran Strbac, "A Machine-learning based Probabilistic Perspective on Dynamic Security Assessment, *International Journal of Electrical Power and Energy Systems, 2021*

The risk of relying on machine learning

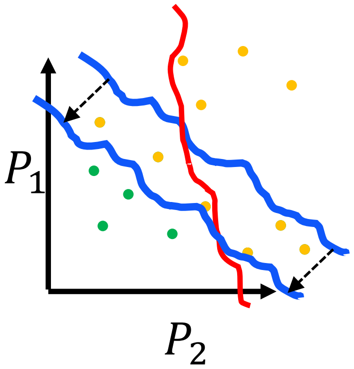
Step 1: Compute risks when predicting x_i as secure $\hat{y}_i = 1$ and insecure $\hat{y}_i$ =0

$$R_{\text{secure}} = p_i p_c \hat{\boldsymbol{p}}(\boldsymbol{x_i}) \boldsymbol{C_{FN}}$$

$$R_{\text{insecure}} = p_i(1 - p_c)(1 - \hat{\boldsymbol{p}}(\boldsymbol{x_i}))\boldsymbol{C_{FP}}$$

Step 2: Predict with lowest residual risk

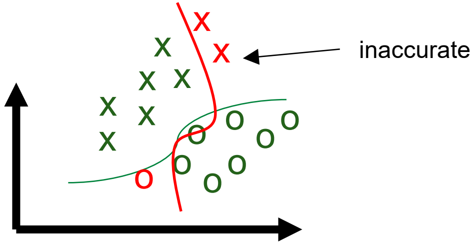
$$R_{\text{secure}} \bigvee R_{\text{insecure}}$$



[24] Jochen Cremer, Goran Strbac, “A Machine-learning based Probabilistic Perspective on Dynamic Security Assessment, *International Journal of Electrical Power and Energy Systems, 2021*

Minimize risks by hybrid approach

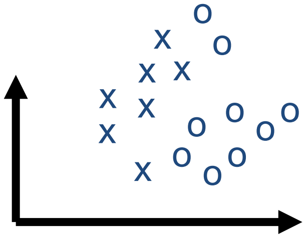
Machine Learning



- Fast
- Sometimes inaccurate

+

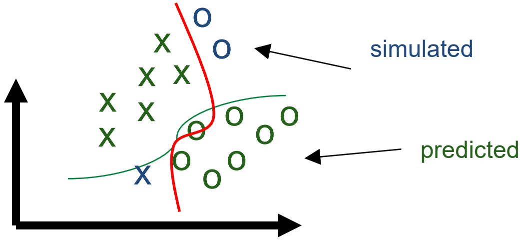
Simulator



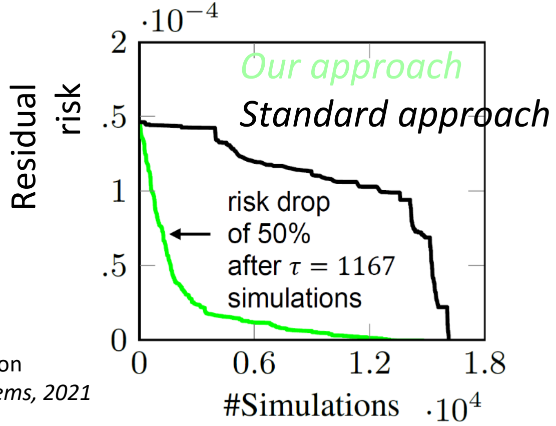
- Slow
- Always accurate

=

Probabilistic approach



Case study: French system



[24] Jochen Cremer, Goran Strbac, "A Machine-learning based Probabilistic Perspective on Dynamic Security Assessment, *International Journal of Electrical Power and Energy Systems, 2021*

Outline

Reliability management and data in control rooms

1. Introduction to reliability management
2. Machine learning approaches
3. Security assessment with cost-sensitive supervised learning

Learning models for secure system operation

4. Learning with domain knowledge
5. State estimation with graph neural networks
6. Weakly-supervised learning for secure operation
7. Challenges applying ML to reliability

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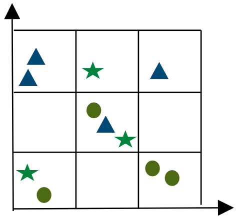
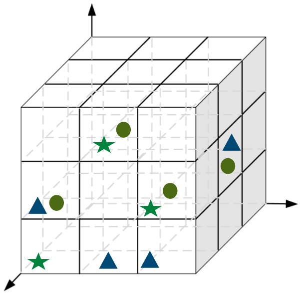
How to address curse of dimensionality?

1d: 3 regions



2d: 3^2 regions



3d: 3^3 regions

?

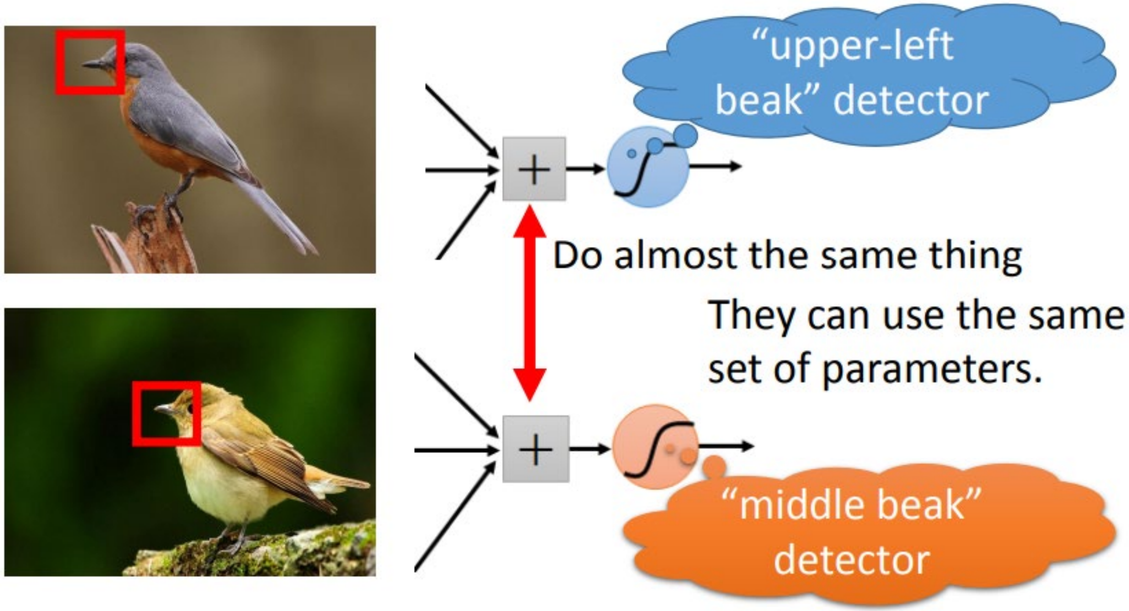
1000d: hopeless

As dimensionality grows: fewer samples per region.

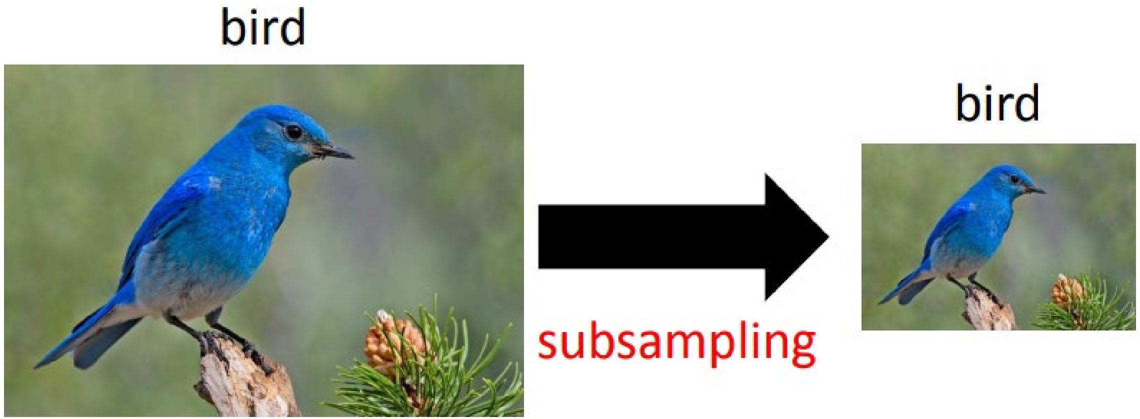
AI can well predict with images

Property 1: Some patterns are much smaller than the whole image. A neuron does not have to see the whole image to discover the pattern.

Property 2: The same patterns appear in different regions. (translated invariance)



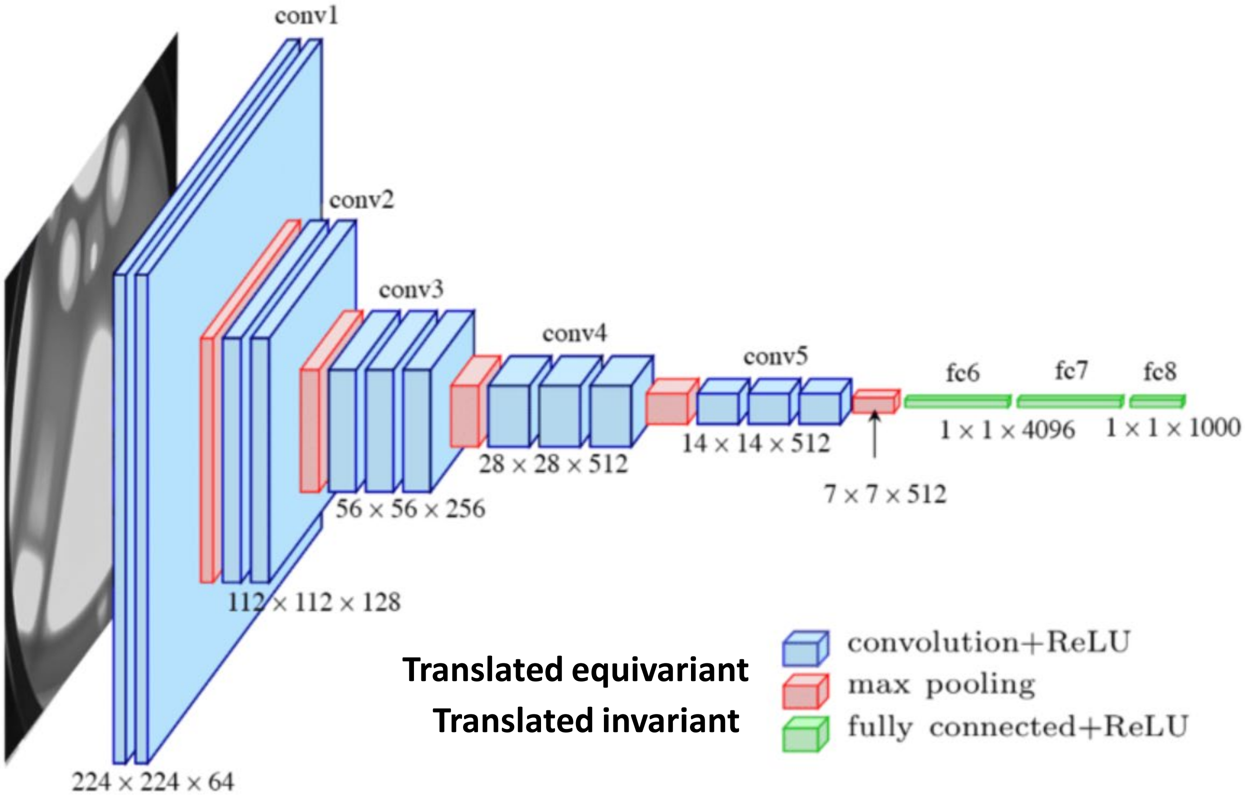
Property 3: Subsampling the pixels will not change the object. (Subsampling invariance)



We can subsample the pixels to make image smaller

→ Less parameters for the network to process the image

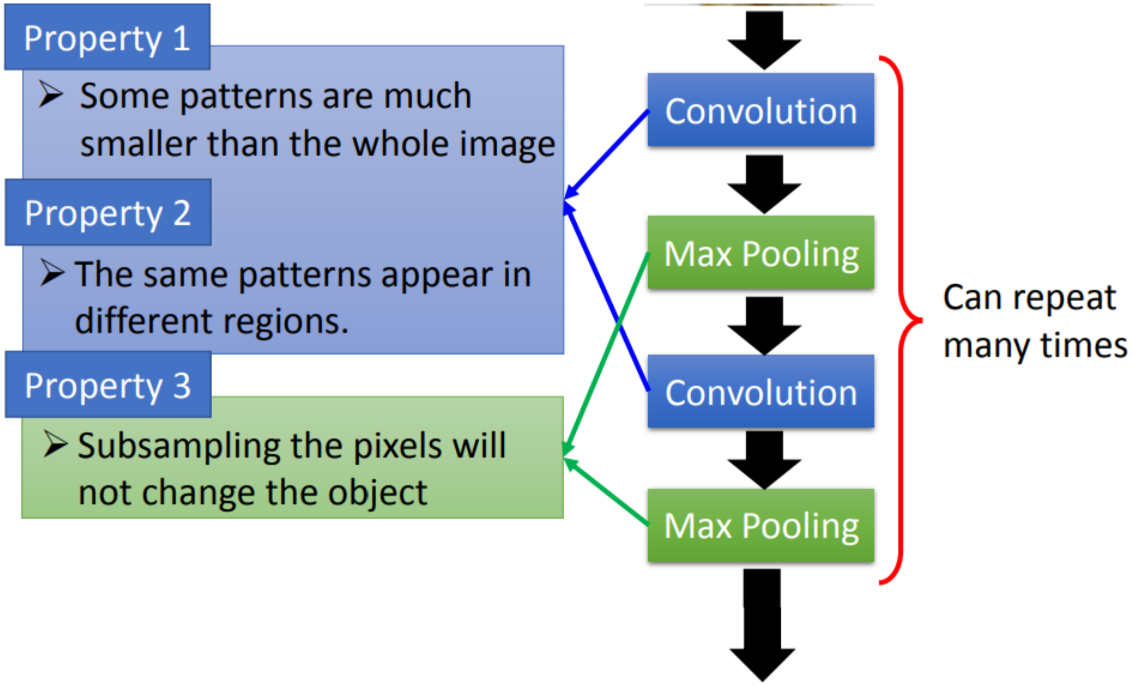
How can CNN make this happen?



Translated equivariant

Translated invariant

How can CNN make this happen?



CNN— Convolution layer

Stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
0	0	0	0	1	0
1	1	1	0	1	0
0	0	0	0	1	0

6×6 image

Those are the network parameters to be learned.

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

Matrix

3	-1	-3	-1
-2	2	-1	-3
-2	-4	0	1
-1	0	-2	-1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

Matrix

Property 1 Each filter detects a small pattern (3 x 3).

CNN— Convolution layer

Stride=1

0	1	0	0	0	1
0	1	0	0	1	0
0	0	0	1	0	0
0	0	0	1	0	0
1	1	1	0	1	0
0	0	0	0	0	1

6×6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

Matrix

0	1	-2	-1
-1	1	-1	-3
-1	-4	0	-1
-1	-1	-3	3

Property 2

The same patterns appear in different regions can be detected.

CNN— Max Pooling

Property 3

Subsampling the pixels will not change the object

6×6 image

convolution

3	-1	-3	-1
-2	2	-1	-3
-2	-4	0	1
-1	0	-2	-1

0	1	-2	-1
-1	1	-1	-3
-1	-4	0	-1
-1	-1	-3	3

Max pooling

3	-1
0	1

New images but smaller

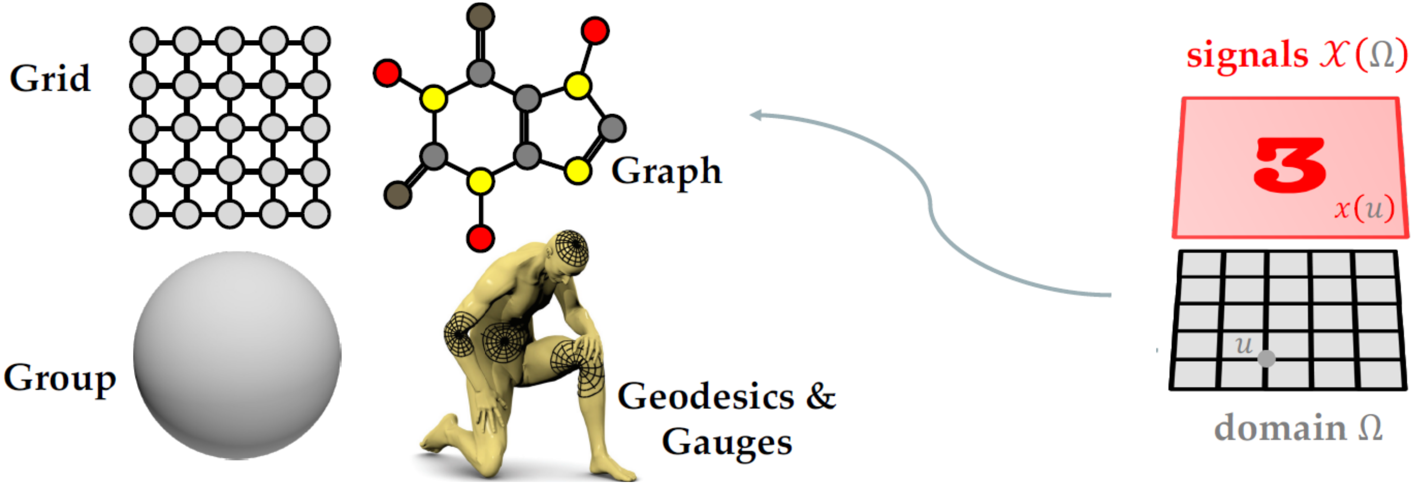
1	-1
-1	3

Not much image-like data in power system operation and planning…

Geometric deep learning (GDL)

In GDL, data are **signals** x on **geometric domains** Ω

- The domain Ω is a set, possibly with additional structure
- A signal x on Ω is a function $\chi(\Omega, C) = \{x: \Omega \rightarrow C\}$
- C is a vector space whose dimensions are called channels



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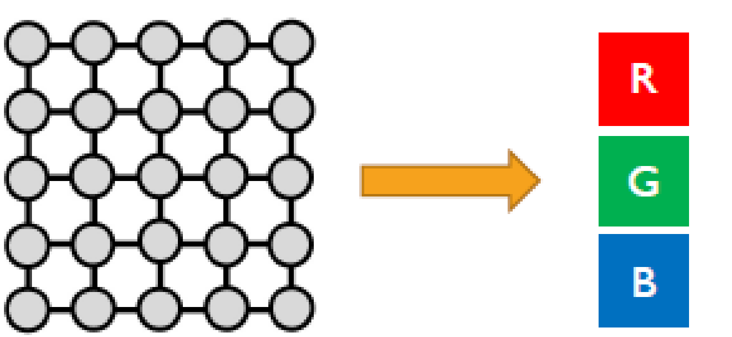
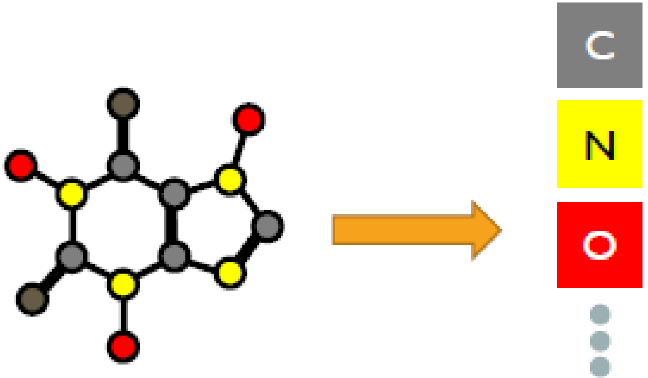
[25] Bronstein, M. M., Bruna, J., Cohen, T., & Veličković, P. (2021). Geometric deep learning: Grids, groups, graphs, geodesics, and gauges. *arXiv preprint arXiv:2104.13478*.

Graph Neural Networks (GNNs)



$\Omega = \mathbb{Z}_n \times \mathbb{Z}_n$ $\mathcal{C} = \mathbb{R}^3$

Example: $n \times n$ RGB image

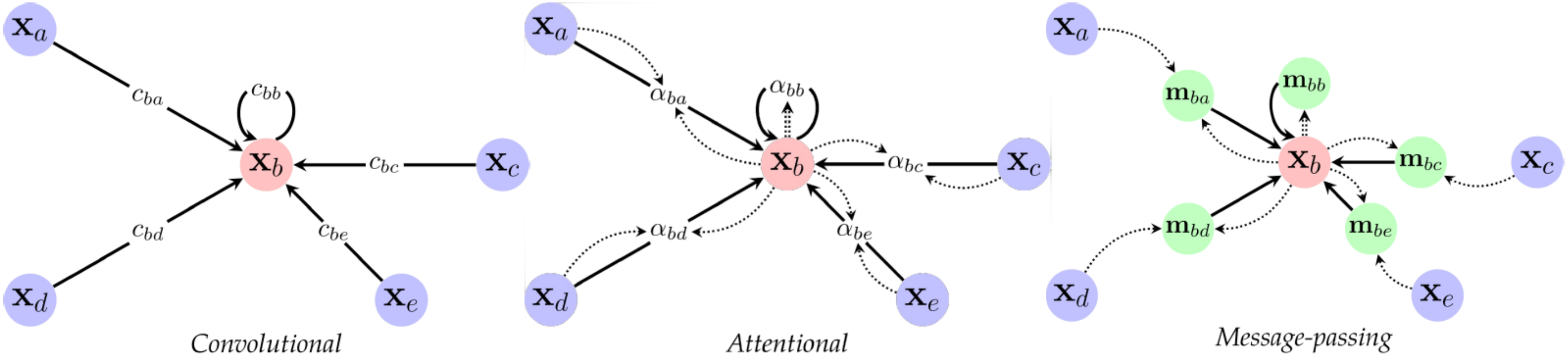


$\Omega = \{1, \ldots, n\}$ $\mathcal{C} = \mathbb{R}^m$

Example: molecular graph

[25] Bronstein, M. M., Bruna, J., Cohen, T., & Veličković, P. (2021). Geometric deep learning: Grids, groups, graphs, geodesics, and gauges. *arXiv preprint arXiv:2104.13478*.

The three ‘flavours’ of GNN layers



$$\mathbf{h}_i = \phi\left(\mathbf{x}_i, \bigoplus_{j \in \mathcal{N}_i} c_{ij}\psi(\mathbf{x}_j)\right)$$

$$\mathbf{h}_i = \phi\left(\mathbf{x}_i, \bigoplus_{j \in \mathcal{N}_i} a(\mathbf{x}_i, \mathbf{x}_j)\psi(\mathbf{x}_j)\right)$$

$$\mathbf{h}_i = \phi\left(\mathbf{x}_i, \bigoplus_{j \in \mathcal{N}_i} \psi(\mathbf{x}_i, \mathbf{x}_j)\right)$$

Increasing order of generality: $convolutional \subseteq attentional \subseteq message - passing$

Outline

Reliability management and data in control rooms

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Distribution system state estimation

- Measurements $z \in \mathbb{R}^m$ with noise $\varepsilon \in \mathbb{R}^m$
- System state $x \in \mathbb{R}^{2n}$
- State estimation $f(z) \rightarrow x$
- Challenge: partial observable, scarce measurements $m \ll n$

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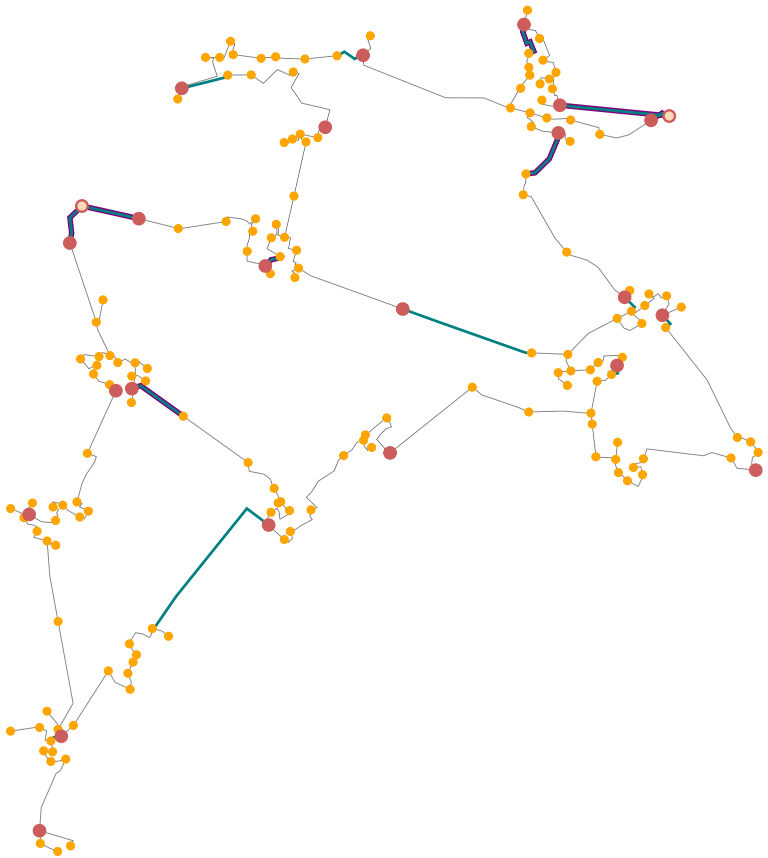
[26] A. Primadianto and C. -N. Lu, "A Review on Distribution System State Estimation," in *IEEE Transactions on Power Systems*, vol. 32, no. 5, pp. 3875-3883, Sept. 2017, doi: 10.1109/TPWRS.2016.2632156.

Distribution system (MV)



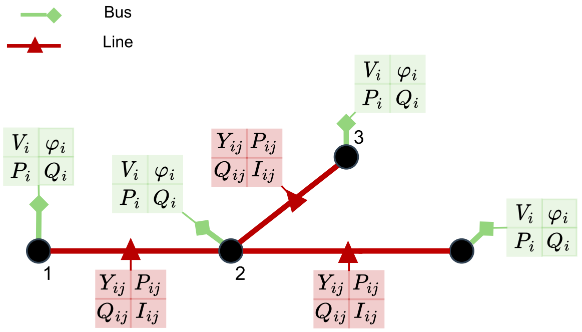
- Trafo
- Lines
- MV/LV buses
- HV buses
- Power flow measurement
- Voltage measurements

Model of the power flow

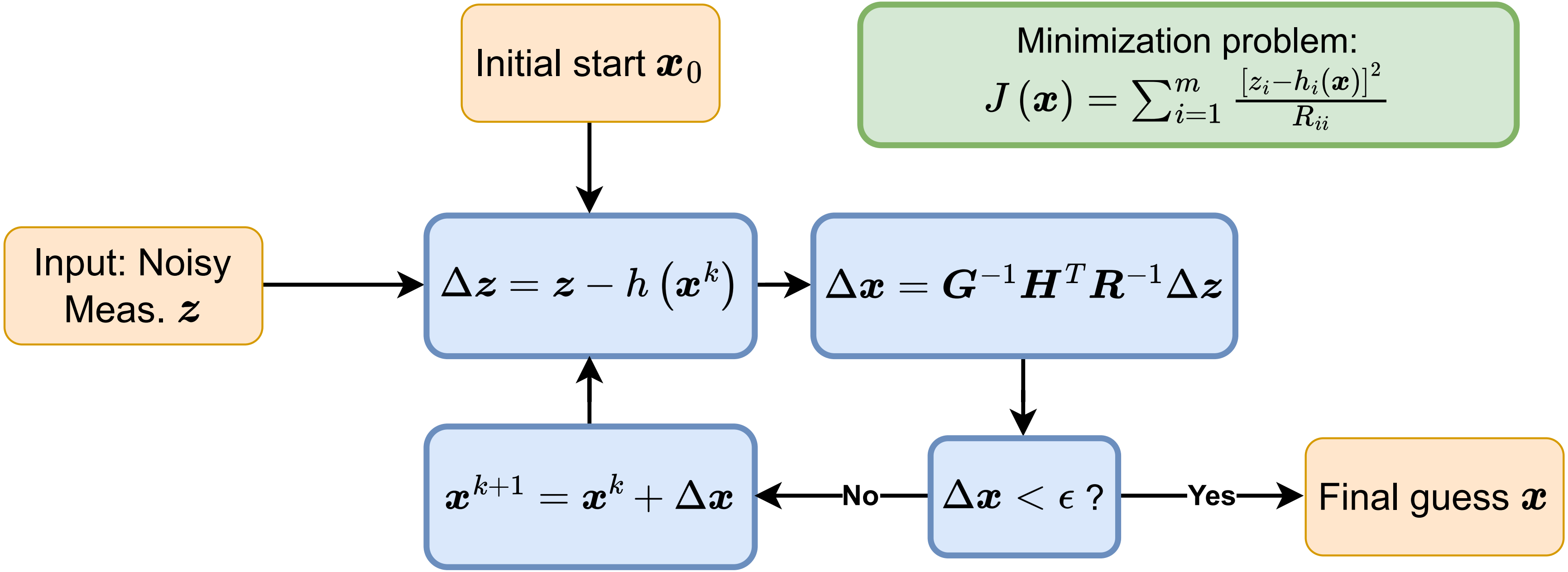
$$x = [V, \varphi]$$

$$z = h(x) + \varepsilon$$

$$h(x) = \begin{cases} V_i = V_i \\ \varphi_i = \varphi_i \\ P_{ij\rightarrow} = -V_i V_j [\mathbb{R}(Y_{ij}) \cos \Delta\varphi_{ij} + \mathbb{I}(Y_{ij}) \sin \Delta\varphi_{ij}] + V_i^2 \left[\mathbb{R}(Y_{ij}) + \frac{\mathbb{R}(Y_{sij})}{2}\right] \\ P_{ij\leftarrow} = V_i V_j [-\mathbb{R}(Y_{ij}) \cos \Delta\varphi_{ij} + \mathbb{I}(Y_{ij}) \sin \Delta\varphi_{ij}] + V_j^2 \left[\mathbb{R}(Y_{ij}) + \frac{\mathbb{R}(Y_{sij})}{2}\right] \\ Q_{ij\rightarrow} = V_i V_j [-\mathbb{R}(Y_{ij}) \sin \Delta\varphi_{ij} + \mathbb{I}(Y_{ij}) \cos \Delta\varphi_{ij}] - V_i^2 \left[\mathbb{I}(Y_{ij}) + \frac{\mathbb{I}(Y_{sij})}{2}\right] \\ Q_{ij\leftarrow} = V_i V_j [\mathbb{R}(Y_{ij}) \sin \Delta\varphi_{ij} + \mathbb{I}(Y_{ij}) \cos \Delta\varphi_{ij}] - V_j^2 \left[\mathbb{I}(Y_{ij}) + \frac{\mathbb{I}(Y_{sij})}{2}\right] \\ I_{ij\rightarrow} = -\left|\frac{P_{ij\rightarrow} - jQ_{ij\rightarrow}}{\sqrt{3} V_i e^{-j\varphi_i}}\right| \\ I_{ij\leftarrow} = -\left|\frac{P_{ij\leftarrow} - jQ_{ij\leftarrow}}{\sqrt{3} V_j e^{-j\varphi_j}}\right| \\ P_i = -\sum_{j \in N_x(i)} P_{ij\leftarrow} + P_{ij\rightarrow} \\ Q_i = -\sum_{j \in N_x(i)} Q_{ij\leftarrow} + Q_{ij\rightarrow} \end{cases}$$



Weighted least squares method



How accurate is x?
Convergence?

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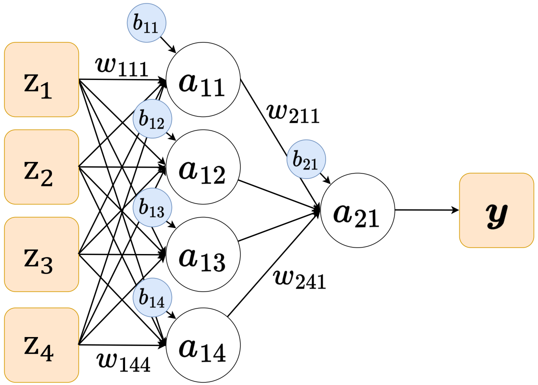
Statistical learning

- Training set $\Omega^T = \{(z_1, y_1), (z_2, y_2) \dots (z_t, y_t)\}$ with t samples

- Inference problem is to find a function $f: Z \to Y$ such that $f(z) \sim y$

- Common loss function $\mathrm{L}(f(z), y)$ for regression is the square loss

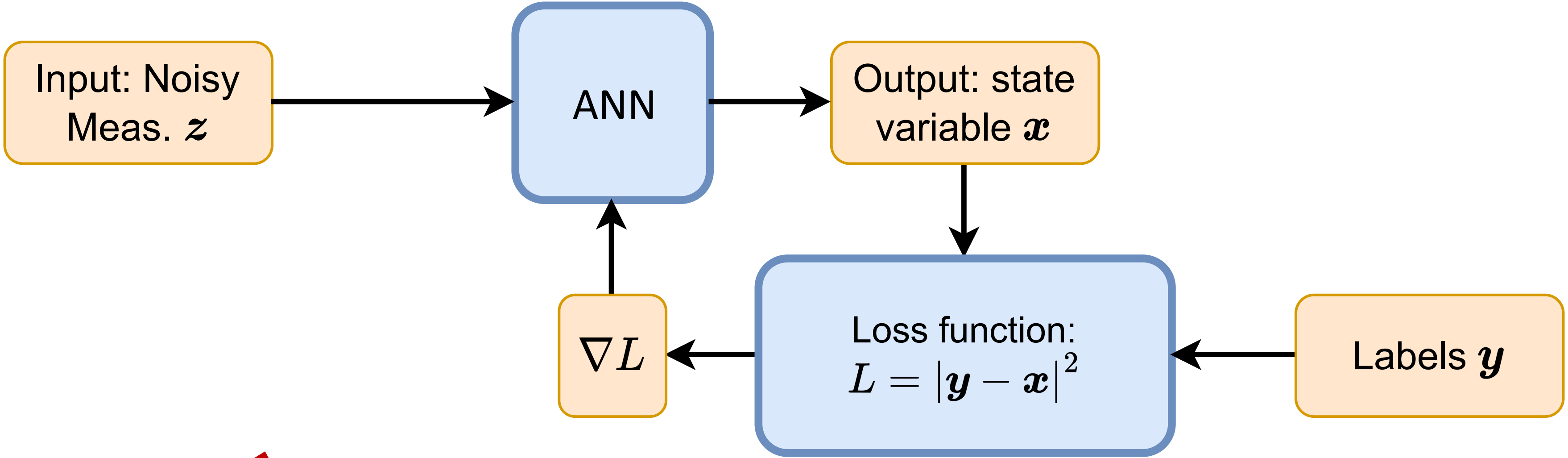
Artificial Neural Network (ANN)



$f_\theta: Z \to Y$

Note: this notation differs to conventional statistical learning where x is feature

Supervised learning for state estimation



- Labels are not known
- Newton's method generates label with "errors" $\hat{y} = y + \gamma^N$

Weakly-supervised learning

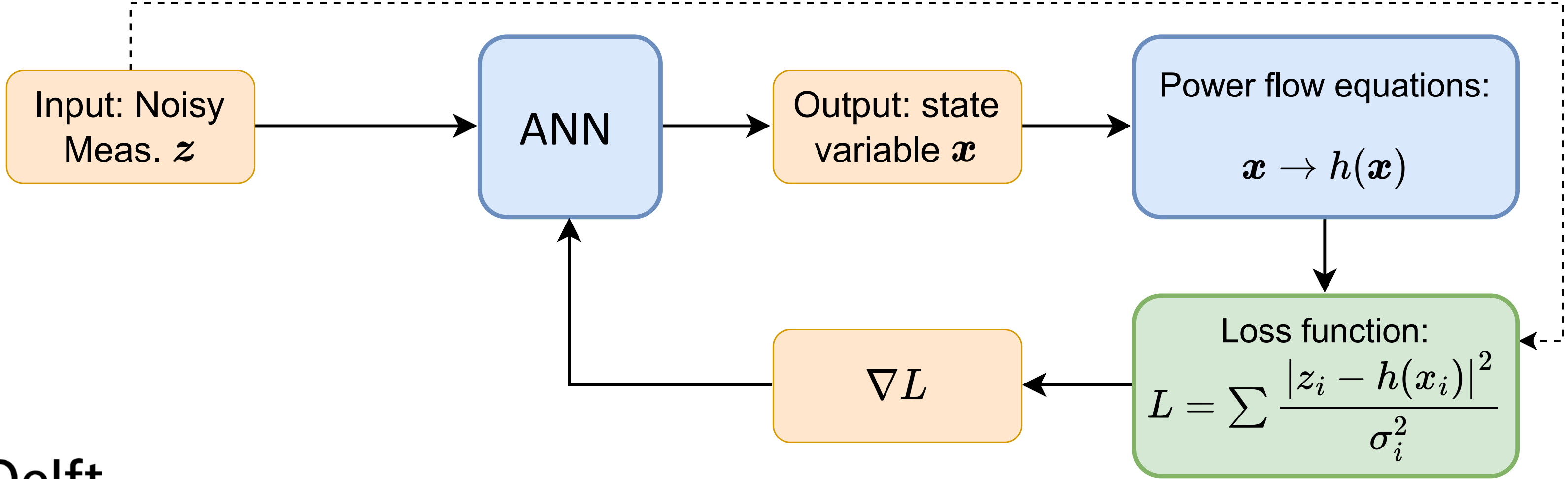
- Inaccurate input and output
- Learn with inaccurate labels $\Omega^T = \{(z_1, \hat{y}_1), (z_2, \hat{y}_2) \dots (z_t, \hat{y}_t)\}$
- Design a loss function $\mathrm{L}(f(z), \hat{y})$
- Objective: learning $f: Z \rightarrow Y$ such that $f(z) \sim y$

[27] Y. -F. Li, L. -Z. Guo and Z. -H. Zhou, "Towards Safe Weakly Supervised Learning," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 1, pp. 334-346, 1 Jan. 2021, doi: 10.1109/TPAMI.2019.2922396.

Weakly-supervised learning for state estimation

Benjamin Habib

- ANN $f(z) \rightarrow x$
- Measurement function using power flow equations $\mathrm{h}(\mathrm{x}) \rightarrow \hat{z}$



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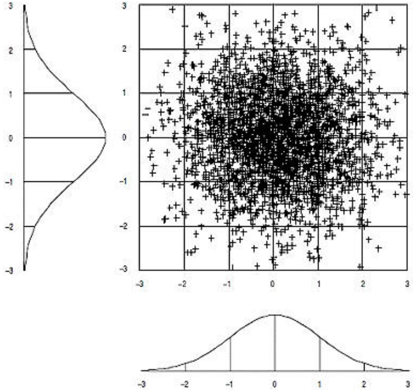
[22] B. Habib, E. Isufi, W. v. Breda, A. Jongepier and Jochen L. Cremer, ”Deep Statistical Solver for Distribution System State Estimation, ” *IEEE Transactions on Power Systems, 2023, doi: 10.1109/TPWRS.2023.3290358*.

Respect the structure of the domain

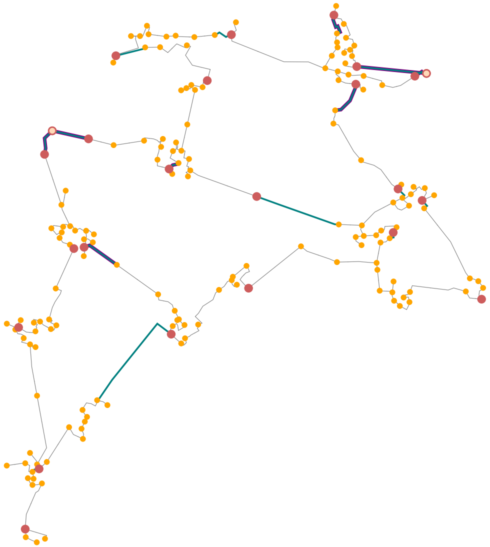
Noisy measurements



Power flow equations

$$h(x) = \begin{cases} V_i = V_i \\ \varphi_i = \varphi_i \\ P_{ij\rightarrow} = -V_i V_j \left[\mathbb{R}(Y_{ij}) \cos \Delta\varphi_{ij} + \mathbb{I}(Y_{ij}) \sin \Delta\varphi_{ij}\right]\big] + V_i^2 \left[\mathbb{R}(Y_{ij}) + \frac{\mathbb{R}(Y_{sij})}{2}\right] \\ P_{ij\leftarrow} = V_i V_j \left[-\mathbb{R}(Y_{ij}) \cos \Delta\varphi_{ij} + \mathbb{I}(Y_{ij}) \sin \Delta\varphi_{ij}\right]\big] + V_j^2 \left[\mathbb{R}(Y_{ij}) + \frac{\mathbb{R}(Y_{sij})}{2}\right] \\ Q_{ij\rightarrow} = V_i V_j \left[-\mathbb{R}(Y_{ij}) \sin \Delta\varphi_{ij} + \mathbb{I}(Y_{ij}) \cos \Delta\varphi_{ij}\right]\big] - V_i^2 \left[\mathbb{I}(Y_{ij}) + \frac{\mathbb{I}(Y_{sij})}{2}\right] \\ Q_{ij\leftarrow} = V_i V_j \left[\mathbb{R}(Y_{ij}) \sin \Delta\varphi_{ij} + \mathbb{I}(Y_{ij}) \cos \Delta\varphi_{ij}\right]\big] - V_j^2 \left[\mathbb{I}(Y_{ij}) + \frac{\mathbb{I}(Y_{sij})}{2}\right] \\ I_{ij\rightarrow} = -\left|\frac{P_{ij\rightarrow} - jQ_{ij\rightarrow}}{\sqrt{3} V_i e^{-j\varphi_i}}\right| \\ I_{ij\leftarrow} = -\left|\frac{P_{ij\leftarrow} - jQ_{ij\leftarrow}}{\sqrt{3} V_j e^{-j\varphi_j}}\right| \\ P_i = -\sum_{j \in N_x(i)} P_{ij\leftarrow} + P_{ij\rightarrow} \\ Q_i = -\sum_{j \in N_x(i)} Q_{ij\leftarrow} + Q_{ij\rightarrow} \end{cases}$$

Topology



[22] B. Habib, E. Isufi, W. v. Breda, A. Jongepier and Jochen L. Cremer, "Deep Statistical Solver for Distribution System State Estimation," *IEEE Transactions on Power Systems, 2023, doi: 10.1109/TPWRS.2023.3290358*.

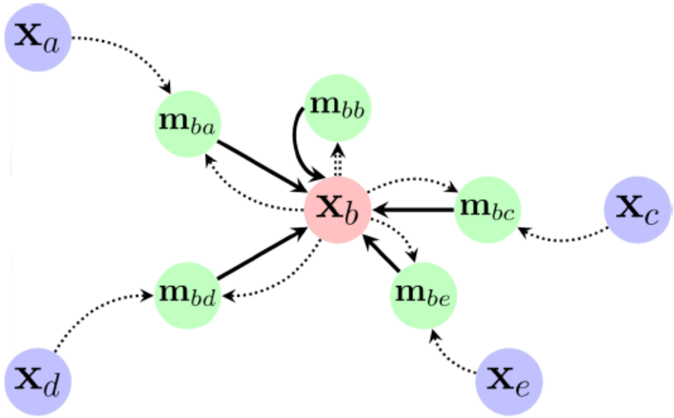
Locality on graphs: Neighbourhoods

- Consider graph $G = (V, E)$ where $E \subseteq V \times V$
- Adjacency matrix A with

$$a_{ij} = \begin{cases} 1, & (i,j) \in E \\ 0, & (i,j) \notin E \end{cases}$$

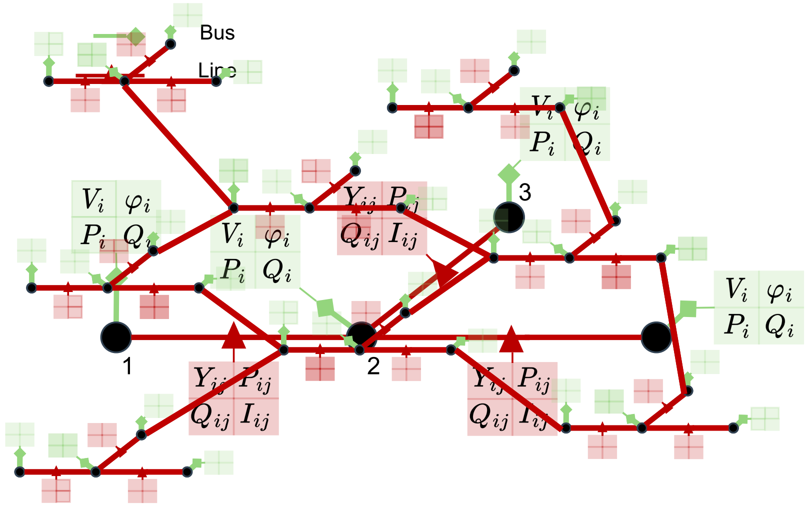
- (1-hop) neighbourhood $N_i = \{j: (i,j) \in E \cup (j,i) \in E\}$ for a node i
- Neighbourhood features $\boldsymbol{X}_{N_i} = \{\{x_j : j \in N_i\}\}$
- Local function, $\phi(x_i, \boldsymbol{X}_{N_i})$, operating over them.

Convolutional layers & message passing



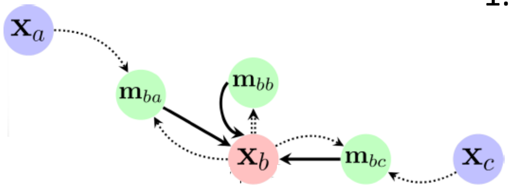
$$\eta_i = \phi\left(x_i, \bigoplus_{j \in N_i} \psi(x_i, x_j)\right)$$

State estimation



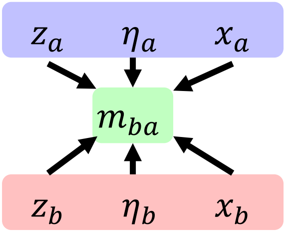
[28] Battaglia, P. W., Hamrick, J. B., Bapst, V., Sanchez-Gonzalez, A., Zambaldi, V., Malinowski, M., ... & Pascanu, R. (2018). Relational inductive biases, deep learning, and graph networks. *arXiv e-prints*, arXiv-1806.

Deep statistical solver



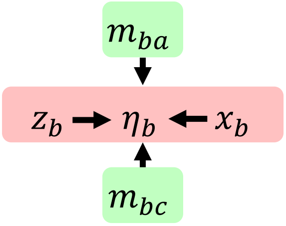
0. Initialize $x = x^0, \eta = \eta^0$

1. update edges



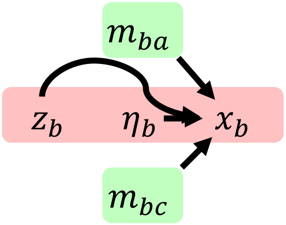
$$m_{ba} \leftarrow m_{ba} + \Delta t \times [\phi_\theta^{ba}(t, z_a, \eta_a, x_a) + \phi_\theta^{ba}(t, z_b, \eta_b, x_b)]$$

2. update vertices



$$\eta_b \leftarrow \eta_b + \Delta t \times \phi_\theta^b(t, z_b, \eta_b, x_b, m_{ba}, m_{bc}, m_{bb})$$

3. update label



$$x_b \leftarrow x_b + \Delta t \times \phi_\theta^{bx}(t, z_b, \eta_b, x_b, m_{ba}, m_{bc}, m_{bb})$$

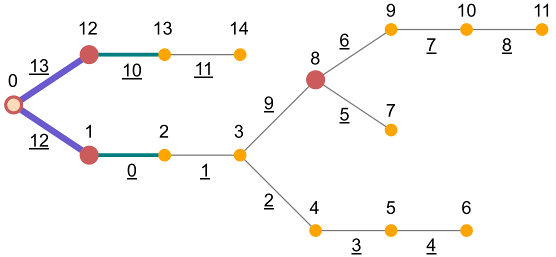
Perform $t = 1, \ldots T$

[14] Balthazar Donon, Liu, Z., Liu, W., Guyon, I., Marot, A., & Schoenauer, M. (2020). Deep statistical solvers. *Advances in Neural Information Processing Systems*, *33*, 7910-7921.

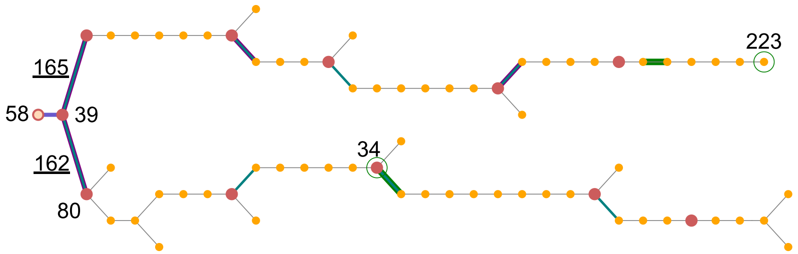
Benjamin Habib

Case study: power systems

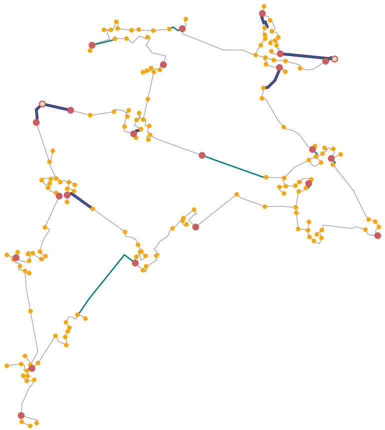
14-bus CIGRE MV grid from



70-bus Oberrhein MV sub-grid from



179-bus Oberrhein MV grid from



- Trafo
- Lines
- MV/LV buses
- HV buses
- Power flow measurement
- Voltage measurements
- Focus bus

[22] B. Habib, E. Isufi, W. v. Breda, A. Jongepier and J. L. Cremer, "Deep Statistical Solver for Distribution System State Estimation," in IEEE Transactions on Power Systems, doi: 10.1109/TPWRS.2023.3290358.

Case study settings

Data generation

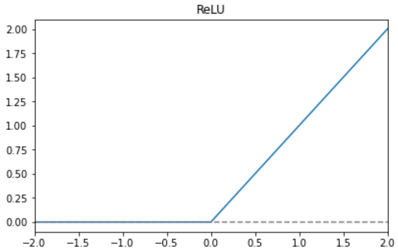
- 8640 days, with each 24 hours, +/- 15% around Gaussian on loads
- Balanced system, pandapower, AC power flow
- Measurement noise
  - $0.5\% - 2\%$ for the voltage and current measurement
  - $1\% - 5\%$ for the active and reactive power measurement
  - Pseudomeasurement were generic load profiles
- Baselines
  - Weighted least square (WLS)
  - Feedforward Neural Network (FFNN)
  - supervised DSS^2

Model & hyperparameters

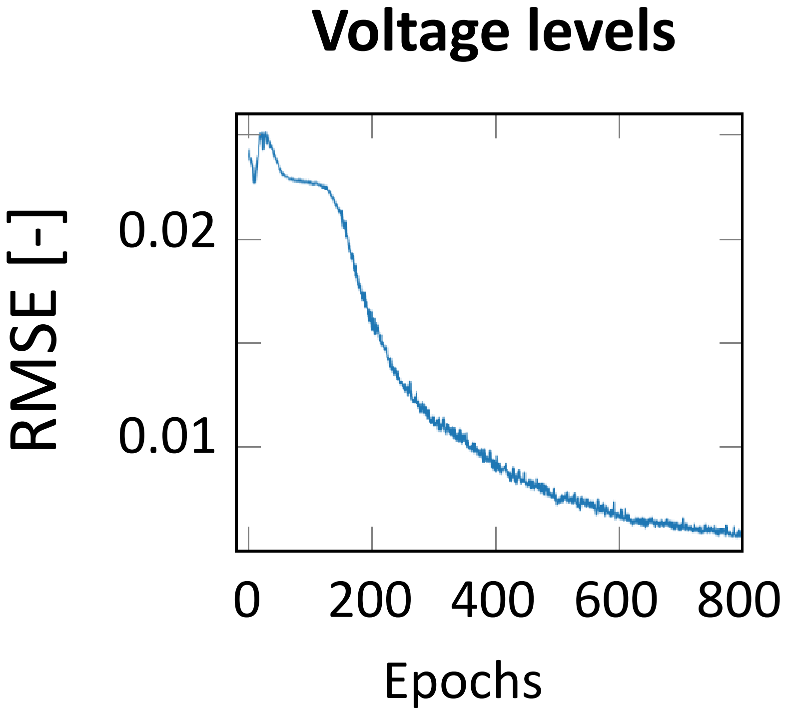
- Hyper-Heterogeneous Multi GNN
- Training 80%, validation 10%, testing 10%
- Grid search on learning rate λ, layer dimensions d, and layer numbers

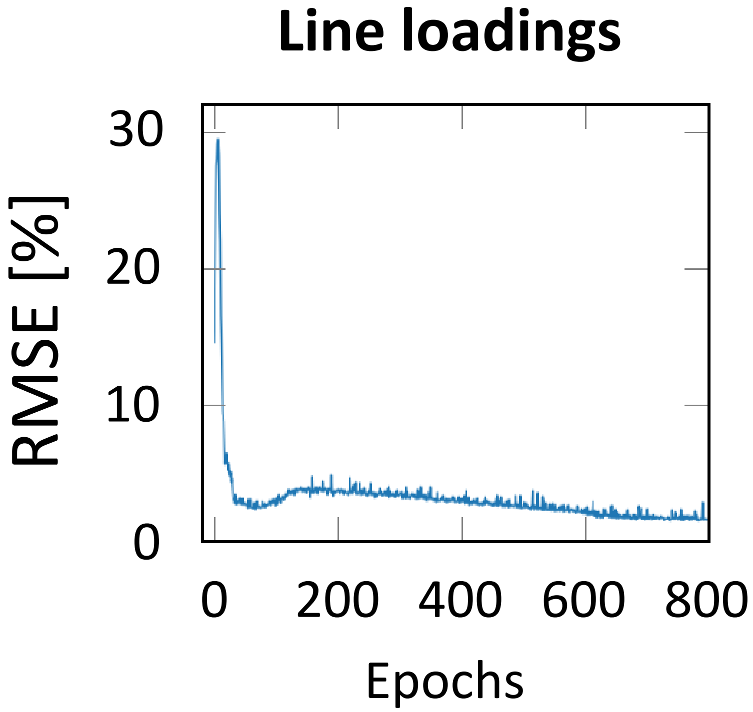
Assume stable system

$$L(\boldsymbol{z}, \boldsymbol{x}) = \sum_{i \in m} \frac{|z_i - h_i(\boldsymbol{x})|^2}{R_{ii}} + \lambda[\text{ReLU}(V - 1.05) + \text{ReLU}(0.95 - V)$$
$$+ \text{ReLU}(\text{ loading } - 100) + \text{ReLU}(\varphi - 0.25) + \text{ReLU}(-0.25 - \varphi)]$$



Training performance 14-bus system

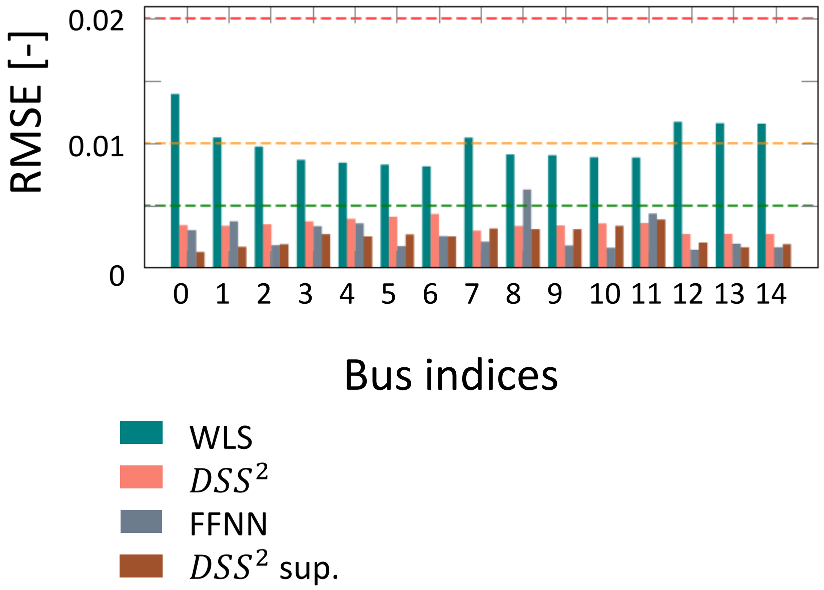




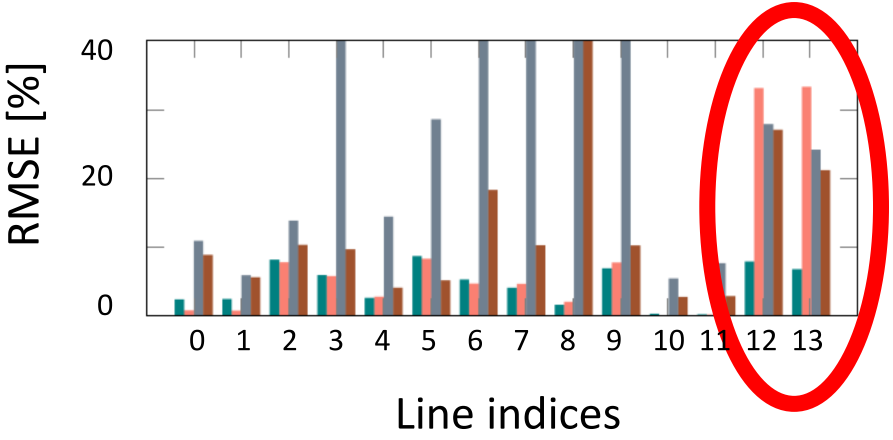
[22] B. Habib, E. Isufi, W. v. Breda, A. Jongepier and Jochen L. Cremer, ”Deep Statistical Solver for Distribution System State Estimation, ” *IEEE Transactions on Power Systems, 2023, doi: 10.1109/TPWRS.2023.3290358*.

State estimation 14-bus system

Voltage levels



Line loadings



Model inaccuracies: assumed transformer = lines!

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[22] B. Habib, E. Isufi, W. v. Breda, A. Jongepier and Jochen L. Cremer, "Deep Statistical Solver for Distribution System State Estimation, " *IEEE Transactions on Power Systems, 2023, doi: 10.1109/TPWRS.2023.3290358.*

Accuracy

	14-bus system			
Metric \ approach	WLS	ANN	sup DSS^2	DSS^2
Voltage RMSE $[10^{-3}]$	10	3	**3**	3
Line loading RMSE [%]	**3**	42	13	4
Trafos loading RMSE [%]	**5**	39	14	8

* with increased convergence rate
** with higher tolerance and more iterations

[22] B. Habib, E. Isufi, W. v. Breda, A. Jongepier and Jochen L. Cremer, "Deep Statistical Solver for Distribution System State Estimation," *IEEE Transactions on Power Systems, 2023, doi: 10.1109/TPWRS.2023.3290358.*

Convergence

	14-bus system				70-bus Oberrhein			179-bus Oberrhein	
Metric \ approach	WLS	ANN	sup DSS^2	DSS^2	WLS	WLS*	DSS^2	WLS**	DSS^2
Voltage RMSE $[10^{-3}]$	10	3	3	3	31	6	2	10	2
Line loading RMSE [%]	3	42	13	4	17	15	2	6	3
Trafos loading RMSE [%]	5	39	14	8	39	24	3	4	4
Convergence [%]	100	100	100	100	25	100	100	53	100

- WLS did not converge in some instances (25%-50%)
- DSS^2 always 'converges' (produces a label)

* with increased convergence rate
** with higher tolerance and more iterations

[22] B. Habib, E. Isufi, W. v. Breda, A. Jongepier and Jochen L. Cremer, "Deep Statistical Solver for Distribution System State Estimation, " *IEEE Transactions on Power Systems, 2023, doi: 10.1109/TPWRS.2023.3290358.*

Computational ‘prediction’ time [ms]

	14-bus system				70-bus Oberrhein			179-bus Oberrhein	
Metric \ approach	WLS	ANN	sup DSS^2	DSS^2	WLS	WLS*	DSS^2	WLS**	DSS^2
Voltage RMSE $[10^{-3}]$	10	3	3	3	31	6	2	10	2
Line loading RMSE [%]	3	42	13	4	17	15	2	6	3
Trafos loading RMSE [%]	5	39	14	8	39	24	3	4	4
Convergence [%]	100	100	100	100	25	100	100	53	100
Computational time $[ms]$	86	**4**	5	6	123	161	**26**	1212	**58**

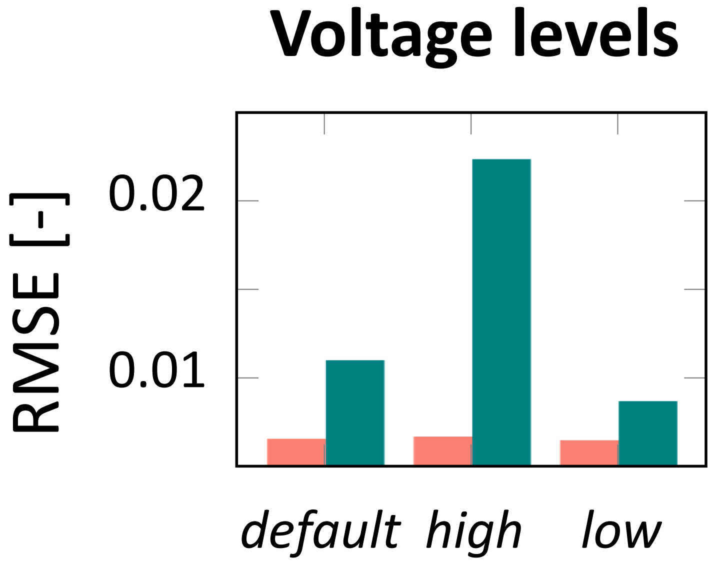
~10 ~2

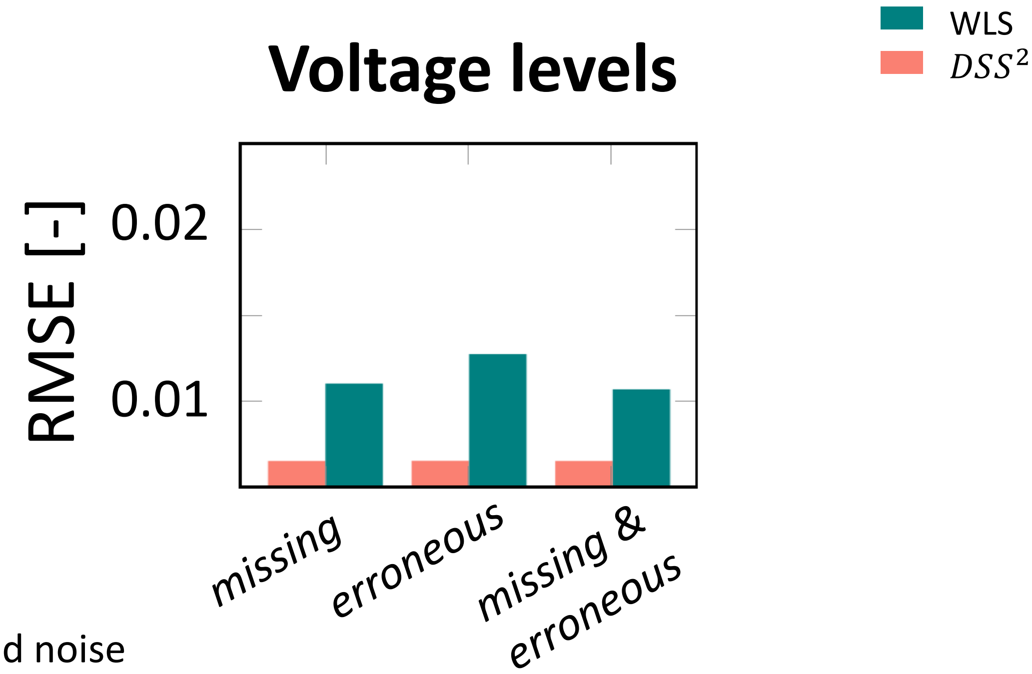
- WLS increases significantly with system size
- DSS^2 increases moderately with system size

* with increased convergence rate
** with higher tolerance and more iterations

[22] B. Habib, E. Isufi, W. v. Breda, A. Jongepier and Jochen L. Cremer, ”Deep Statistical Solver for Distribution System State Estimation, ” *IEEE Transactions on Power Systems, 2023, doi: 10.1109/TPWRS.2023.3290358.*

Noise and missing, erroneous data

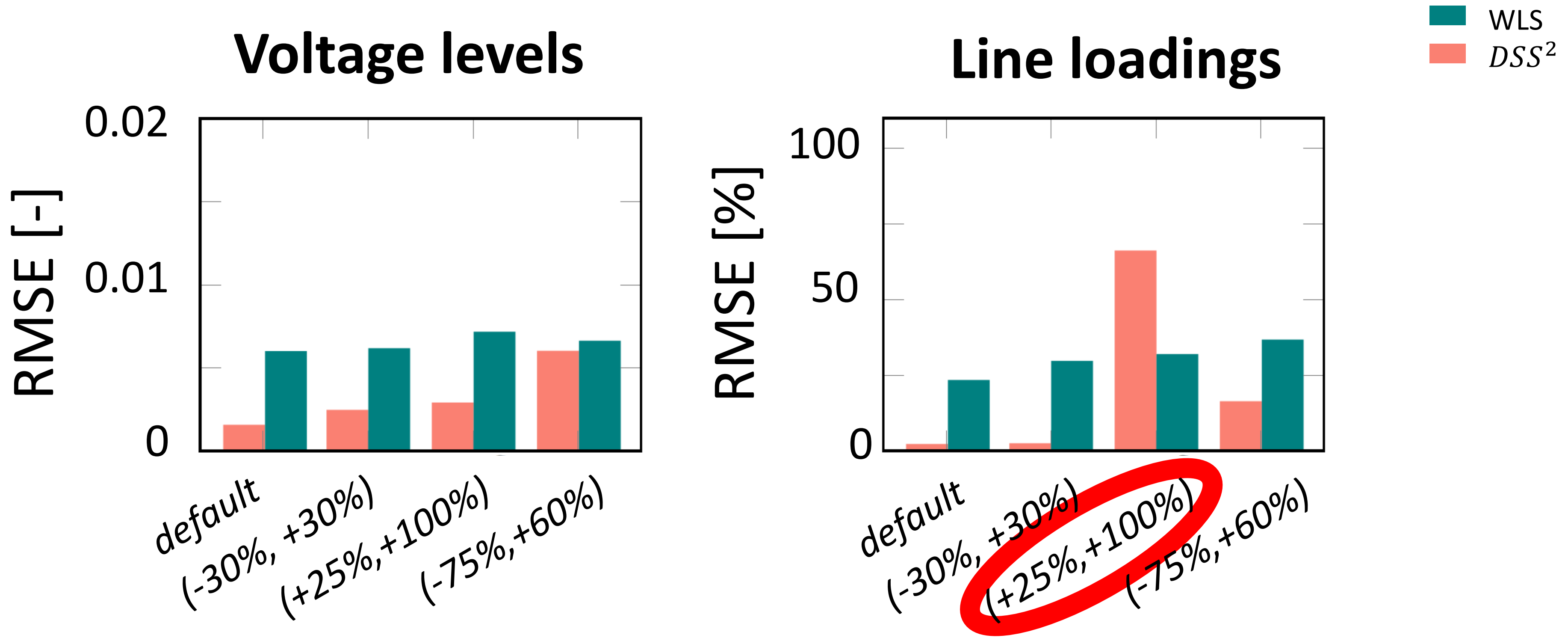




- DSS^2 successfully cancelled noise
- DSS^2 was not trained to handle such events
- GNN architecture increased the interpolation capabilities by incorporating the data symmetries w.r.t. the underlying graph

[22] B. Habib, E. Isufi, W. v. Breda, A. Jongepier and Jochen L. Cremer, "Deep Statistical Solver for Distribution System State Estimation, " *IEEE Transactions on Power Systems, 2023, doi: 10.1109/TPWRS.2023.3290358.*

Increase in (generation, load)



Limitation: high load levels

[22] B. Habib, E. Isufi, W. v. Breda, A. Jongepier and Jochen L. Cremer, "Deep Statistical Solver for Distribution System State Estimation," *IEEE Transactions on Power Systems, 2023, doi: 10.1109/TPWRS.2023.3290358.*

Outline

Reliability management and data in control rooms

1. Introduction to reliability management
2. Machine learning approaches
3. Security assessment with cost-sensitive supervised learning

Learning models for secure system operation

4. Learning with domain knowledge
5. State estimation with graph neural networks
6. Weakly-supervised learning for secure operation
7. Challenges applying ML to reliability

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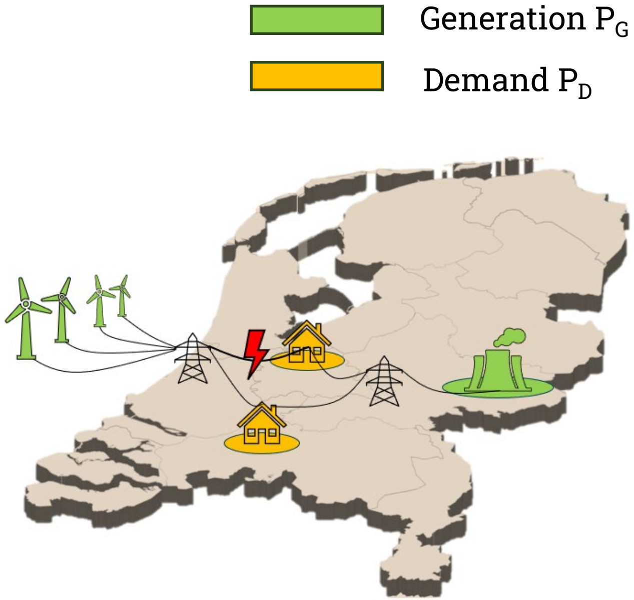
Problem overview

- Growing grid complexity
  - ➢ Challenging to maintain N-1 security
- Increasing number of unforeseen weather events
- Need for N-k considerations to increase reliability

- **Problem:** Conventional approaches don’t scale well with the number of simultaneous outages k



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Security constrained optimal power flow (SCOPF)

Objective:	minimize cost	$\min_{n \in \Omega^G} \Sigma\, c_n P_{G_n}$
Constraints:	In = out	$\boldsymbol{B} \cdot \boldsymbol{\delta} = \boldsymbol{P_G} - \boldsymbol{P_D}$
	Generator limits	$P_{G_n}^{min} < P_{G_n} < P_{G_n}^{max}\ \forall n \in \Omega^G$
	Line flow limits	$F_l^{min} < F_l < F_l^{max}\ \forall l \in \Omega^L$
Contingency Constraints:	Line flow limits	$F_l^{min} < F_l^c < F_l^{max}\ \forall l \in \Omega^L, \forall c \in \Omega^C$

Combinatorial complexity

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Conventional approaches

Outaged line

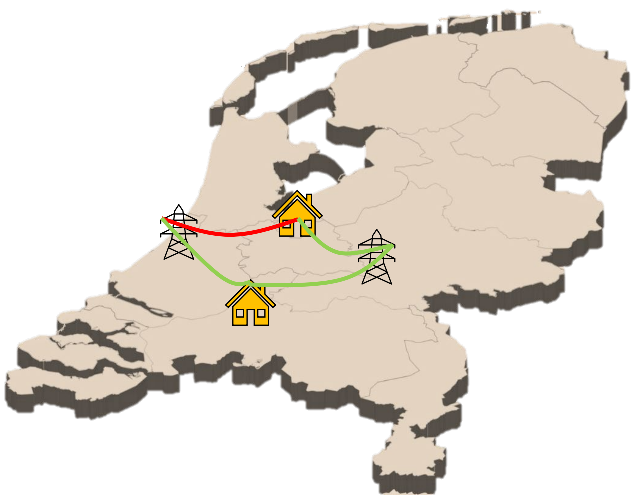
Line flow changes

Solving a **large optimization** problem can be slow

- Benders decomposition
- Column and constraint generation algorithm with robust optimization
- Line outage distribution factors (**LODF**)

Machine learning approaches often rely on **labeled** training data

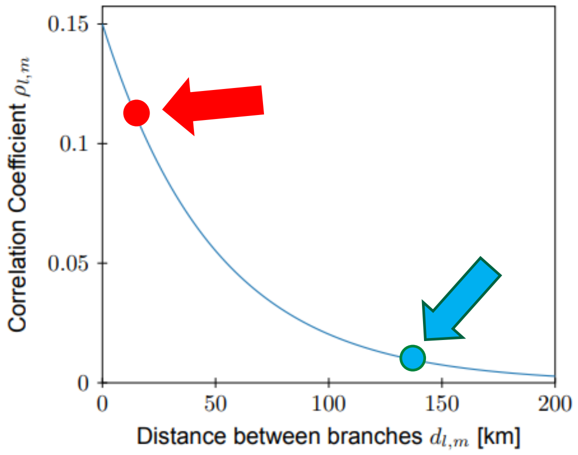
- Intractable for increasing k

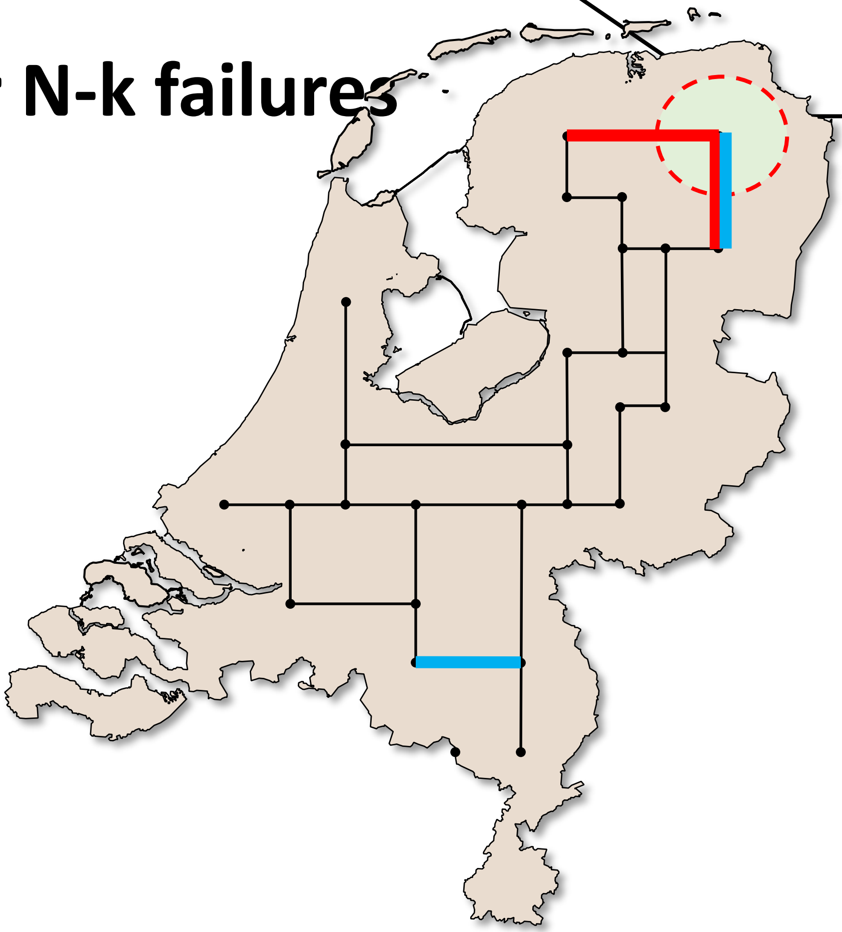


$$F^c = F^0 + LODF_{N-k} \times F^0$$

Probabilistic security for N-k failures

- Compute probabilities of all contingencies
- Spatial correlation between line outages
- Compute joint probabilities using a copula analysis





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Proposed constraint-driven approach

Main advantages

- Weakly-supervised -> so **no labeled data** needed
- Never actually solve an SCOPF

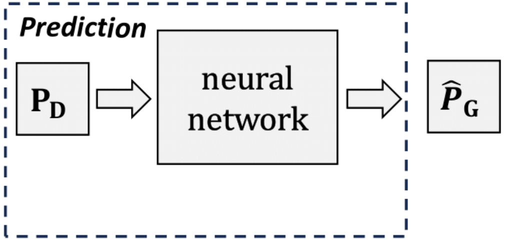
Contributions

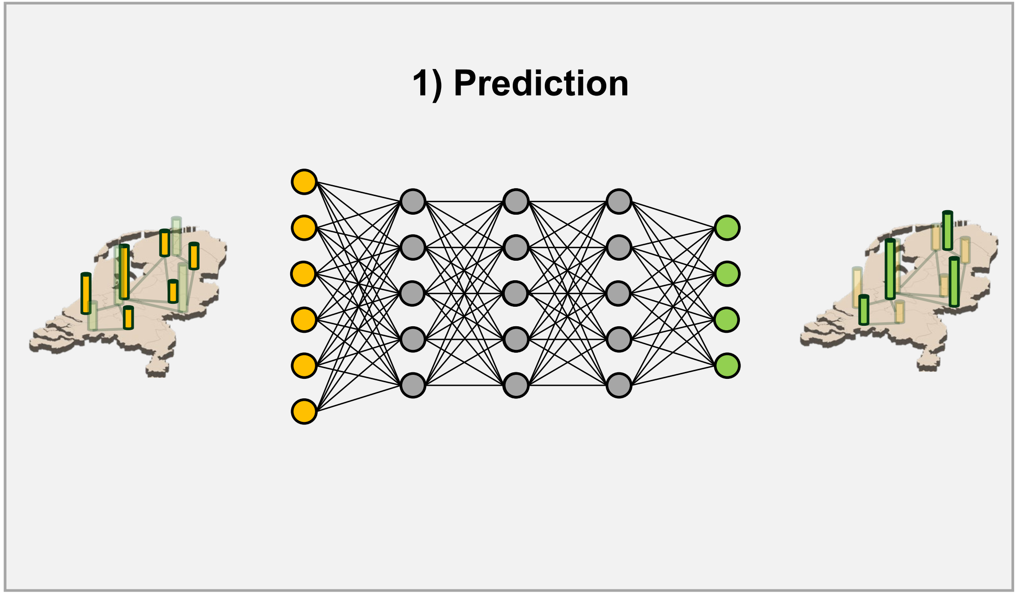
- The deterministic constraint-driven approach to approximate N-k SCOPFs, considering all line contingencies using LODFs.
- The computational graph memory reduction for fast and efficient implementation.
- The probabilistic security assessment to formulate a N-k risk-based security criterion, providing an alternative to the current deterministic N-1 security criterion.

LODF = line outage distribution factor
SCOPF = security constrainted optimal power flow

[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

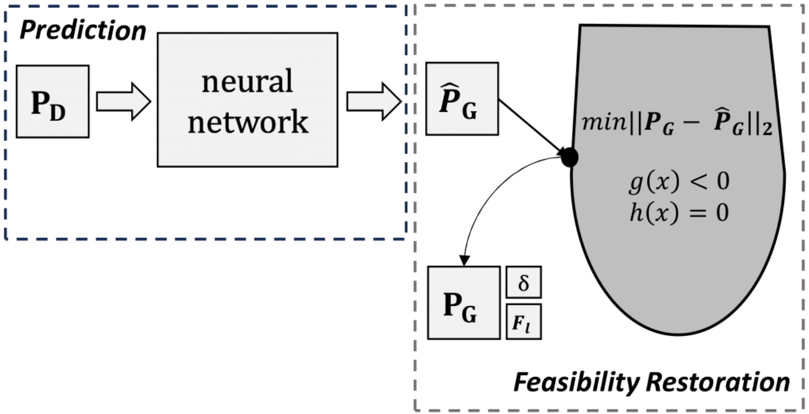
Proposed constraint-driven approach





[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Proposed constraint-driven approach



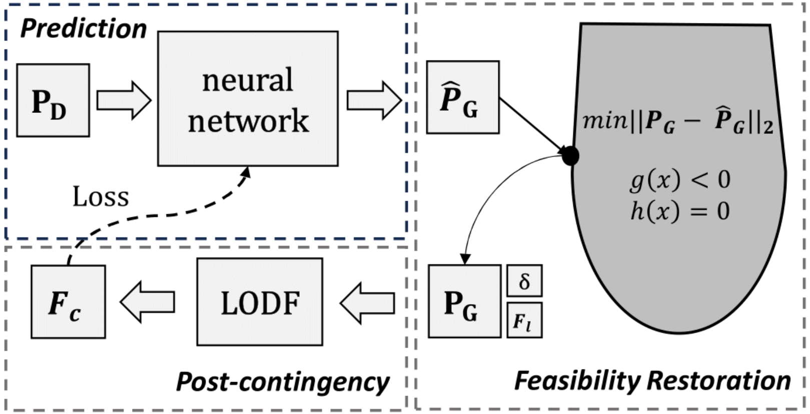
2) Feasibility Restoration

- With $\hat{P}_{G_n}$ compute predicted line flow $\hat{F}_l^0$
- Prediction might **violate** DC PF equations
- Map prediction to feasible region constrained by DC PF equations

DC PF = DC power flow

[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Proposed constraint-driven approach



3) Post-contingency

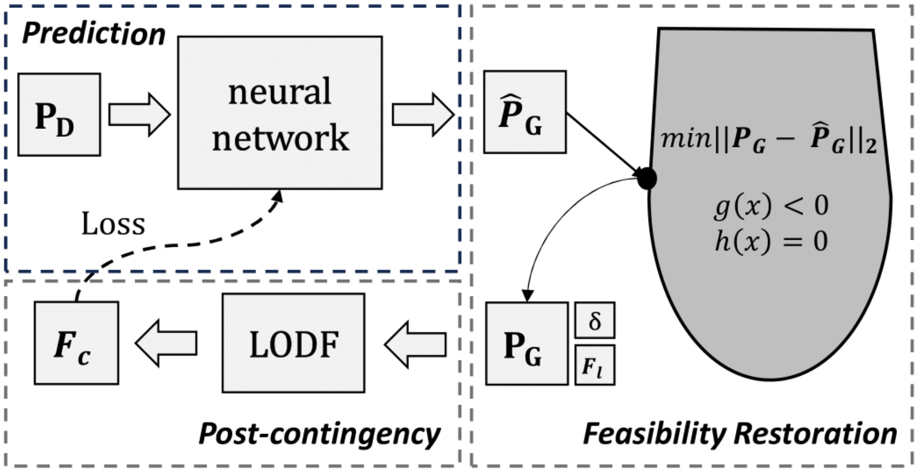
$$\boldsymbol{F^c = F^0 + LODF_{N-k} \times F^0}$$

$$F_l^{min} < F_l^c < F_l^{max}\ \forall l \in \Omega^L, \forall c \in \Omega^C$$

LODF = line outage distribution factor

[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Proposed constraint-driven approach



1) Dispatch cost — $\lambda_c \sum \boldsymbol{P_G c_G}$

2) Line flow violation pre-contingency — $\lambda_0 \left\| ReLU(|\boldsymbol{\hat{F}^0}| - \boldsymbol{F^{max}}) \right\|_1$

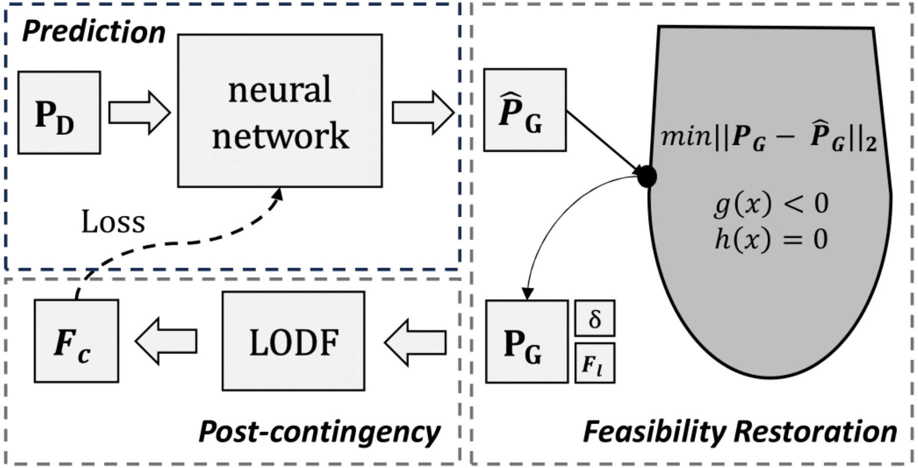
3) Line flow violation post-contingency — $\lambda_1 \| ReLU(|\boldsymbol{F^c}| - \boldsymbol{F^{max}}) \|_1$

4) Power imbalance — $\lambda_2 \left\| \sum \boldsymbol{\hat{P}_G} - \sum \boldsymbol{P_D} \right\|_1$

$$Loss = \lambda_c \sum \boldsymbol{P_G c_G} + \lambda_0 \left\| ReLU(|\boldsymbol{\hat{F}^0}| - \boldsymbol{F^{max}}) \right\|_1 + \lambda_1 \| ReLU(|\boldsymbol{F^c}| - \boldsymbol{F^{max}}) \|_1 + \lambda_2 \left\| \sum \boldsymbol{\hat{P}_G} - \sum \boldsymbol{P_D} \right\|_1$$

[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Proposed constraint-driven approach



1) Dispatch cost $\lambda_c \sum P_G c_G$

2) Line flow violation pre-contingency $\lambda_0 \left\| ReLU(|\hat{F}^0| - F^{max}) \right\|_1$

3) Line flow violation post-contingency $\lambda_1 \| \pi_{N-k} \cdot ReLU(|F^c| - F^{max}) \|_1$

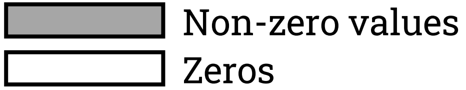
4) Power imbalance $\lambda_2 \left\| \sum \hat{P}_G - \sum P_D \right\|_1$

$$Loss = \lambda_c \sum P_G c_G + \lambda_0 \left\| ReLU(|\hat{F}^0| - F^{max}) \right\|_1 + \lambda_1 \| \pi_{N-k} \cdot ReLU(|F^c| - F^{max}) \|_1 + \lambda_2 \left\| \sum \hat{P}_G - \sum P_D \right\|_1$$

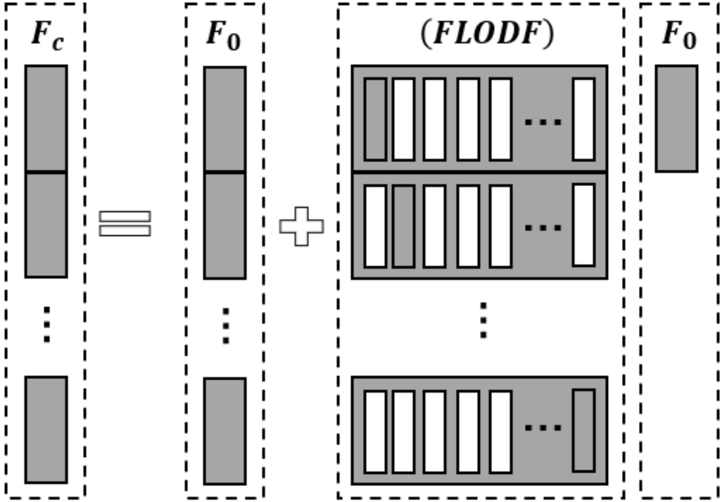
π_{N-k} = matrix of contingency probabilities

[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Sparsity LODF matrix



$$F^c = F^0 + LODF_{N-k} \times F^0$$



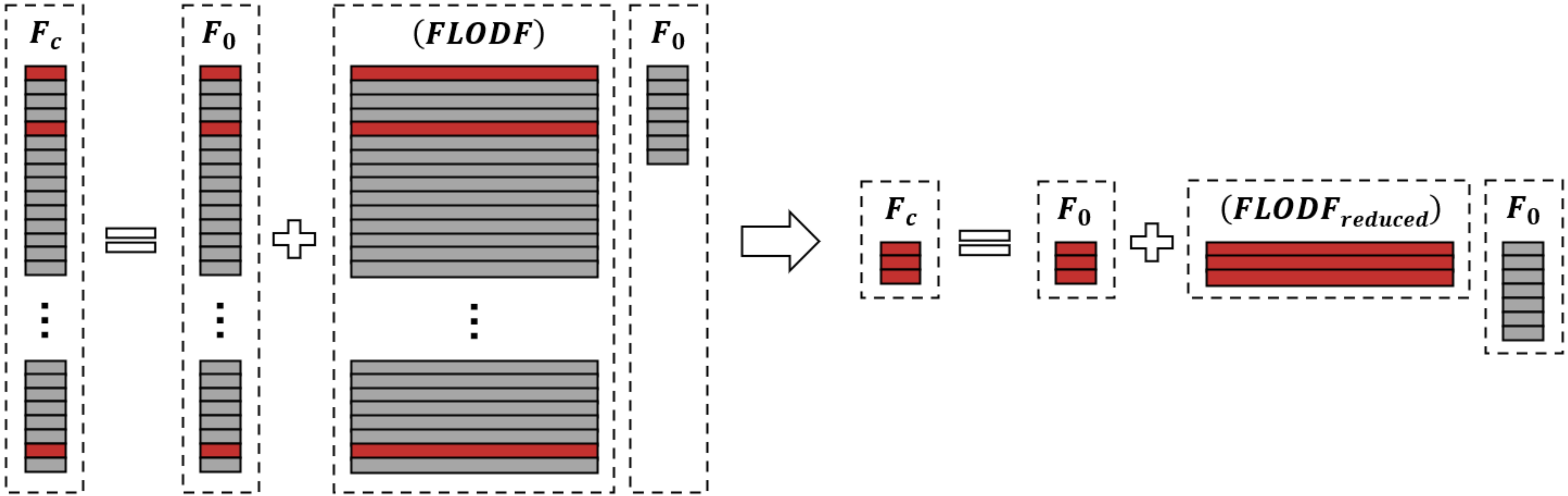
FLODF = 'Full LODF'

k	1	2	3
39-bus sparsity [%]	98.5	97.6	97.5
118-bus sparsity [%]	99.6	99.3	99.0

LODF = line outage distribution factor

[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

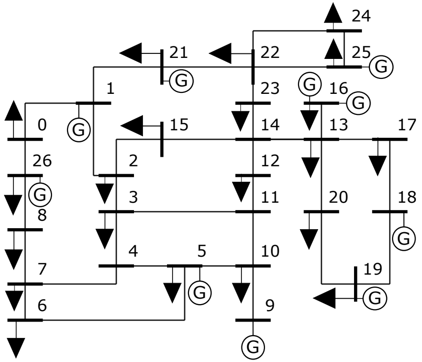
Reducing the graph

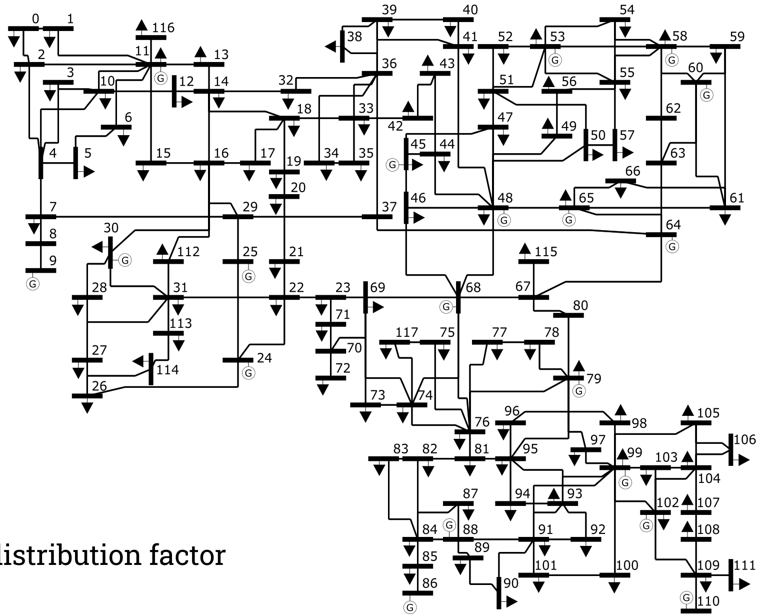


[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Case studies

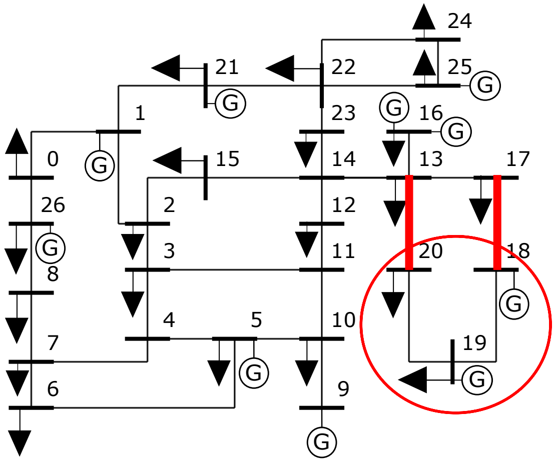
- IEEE 39-bus and 118-bus test systems
- k = {1,2,3}
- Baseline: iterative contingency screening with LODFs
- Code: https://github.com/TU-Delft-AI-Energy-Lab/Constraint-Driven-SCOPF

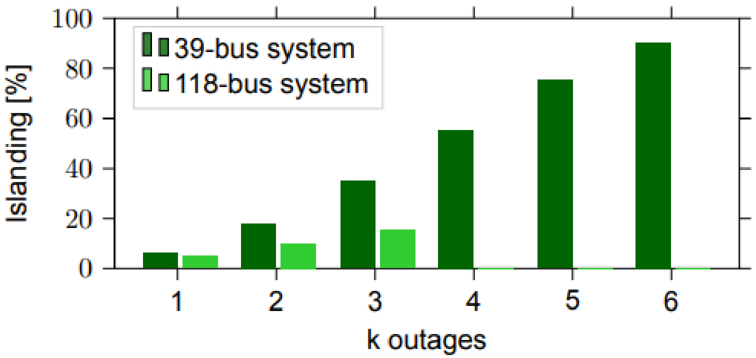




LODF = line outage distribution factor

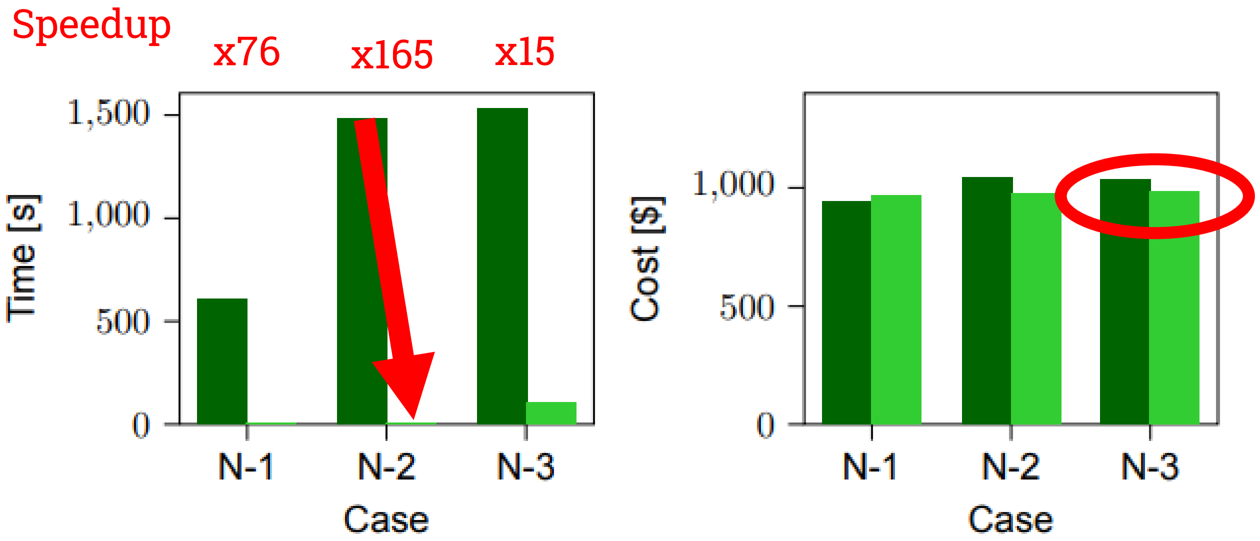
Islanding





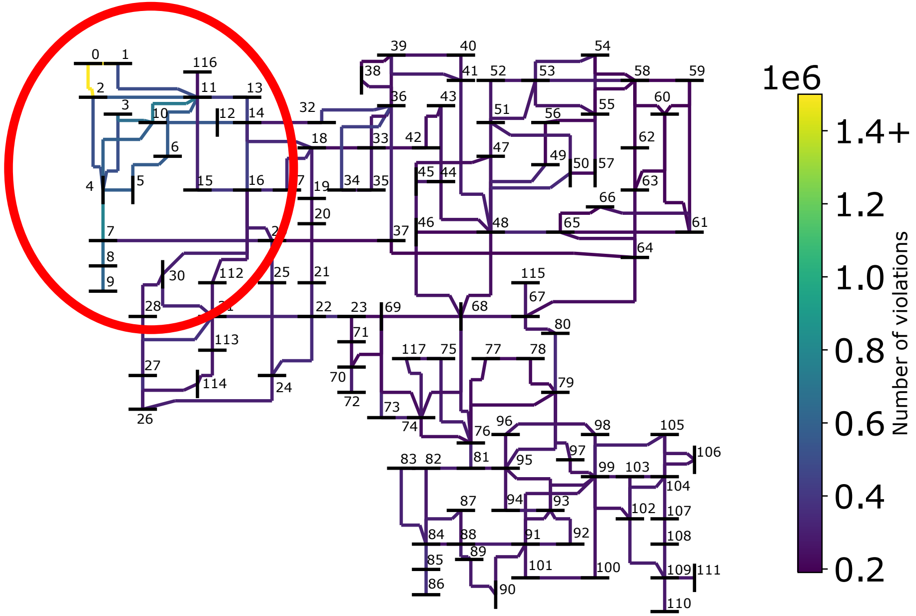
Removing islanding cases

Performance 118-bus system

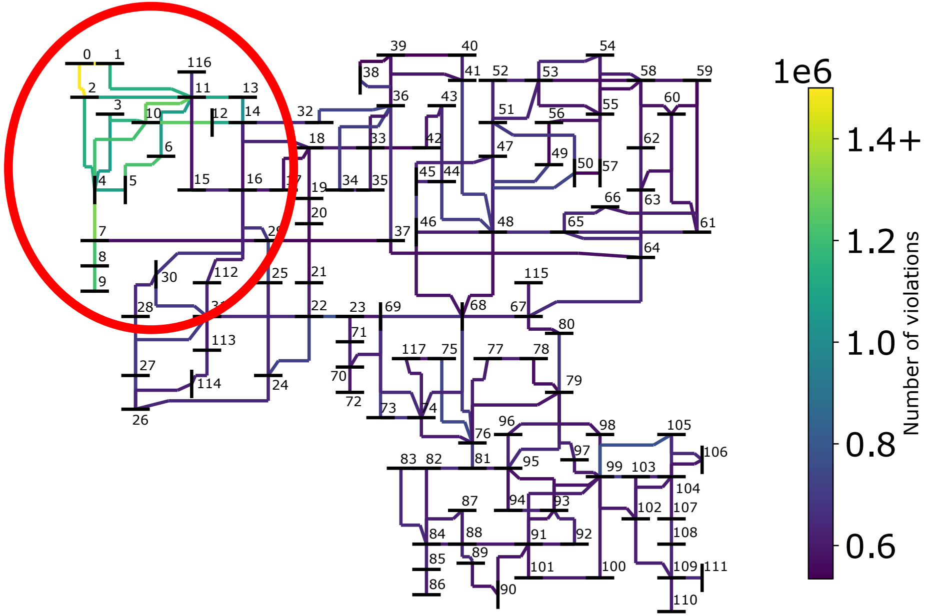


[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

N-3 proposed approach



N-3 baseline



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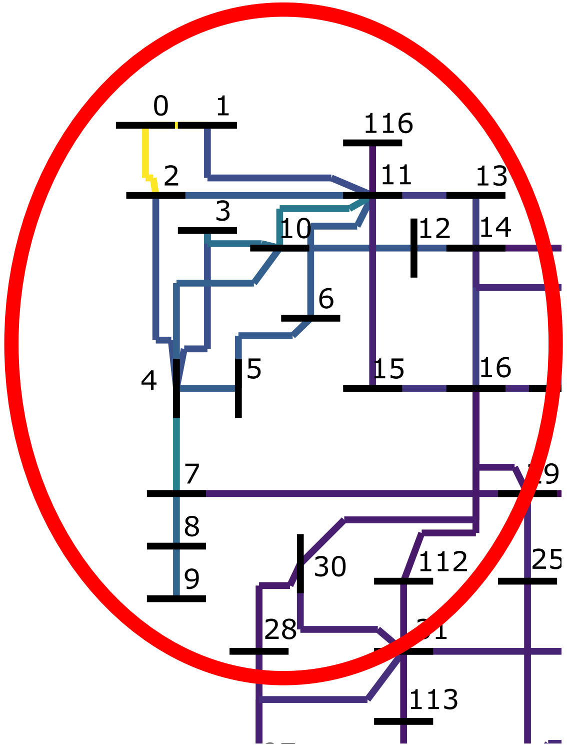
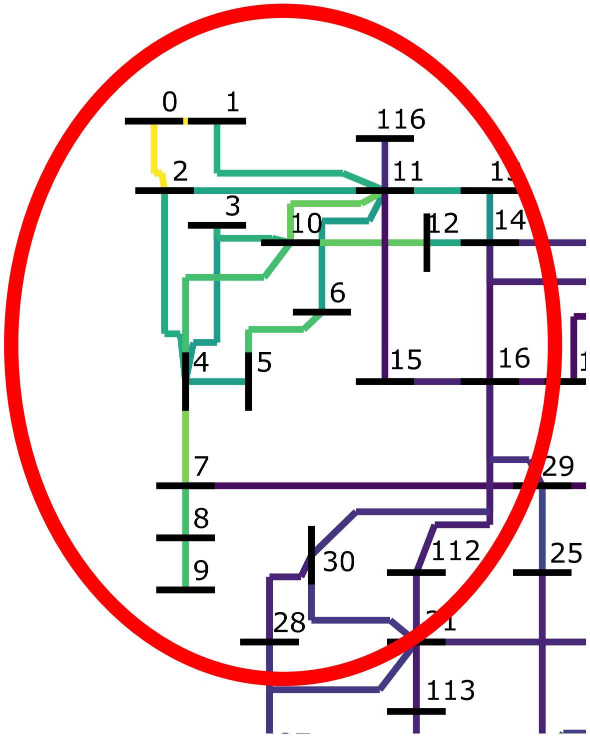
[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

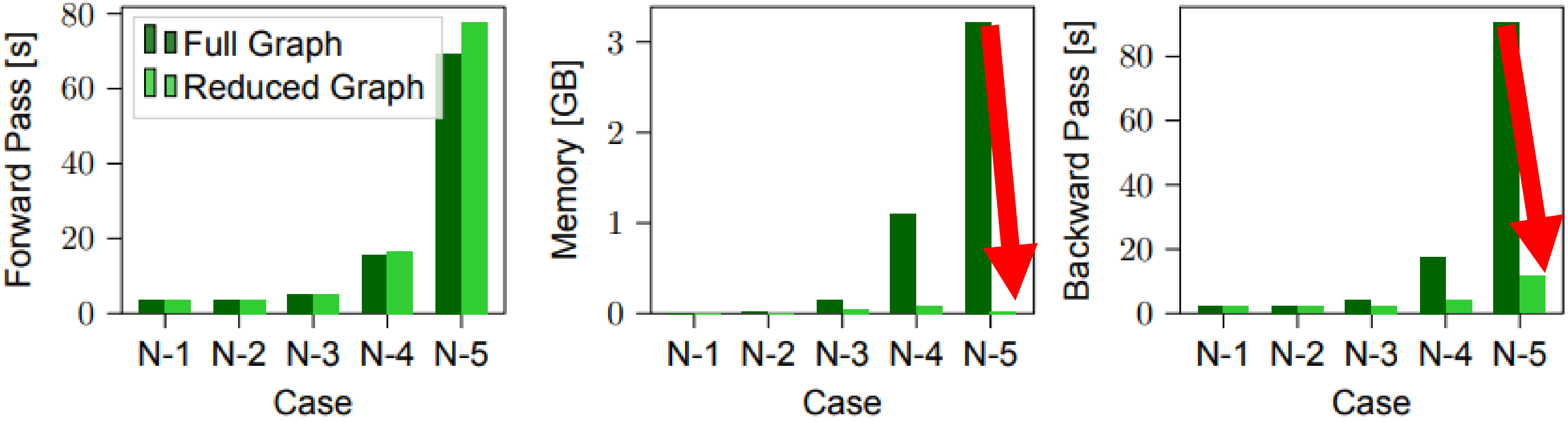
N-3 proposed approach





[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Reducing computational graph



Reduction in memory

Reduction in computation time

[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Outline

Reliability management and data in control rooms

1. Introduction to reliability management
2. Machine learning approaches
3. Security assessment with cost-sensitive supervised learning

Learning models for secure system operation

4. Learning with domain knowledge
5. State estimation with graph neural networks
6. Weakly-supervised learning for secure operation
7. Challenges applying ML to reliability

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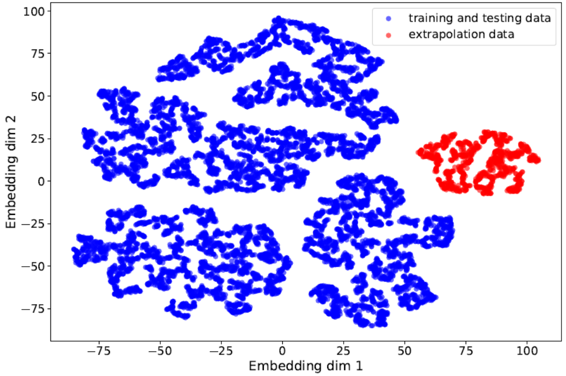
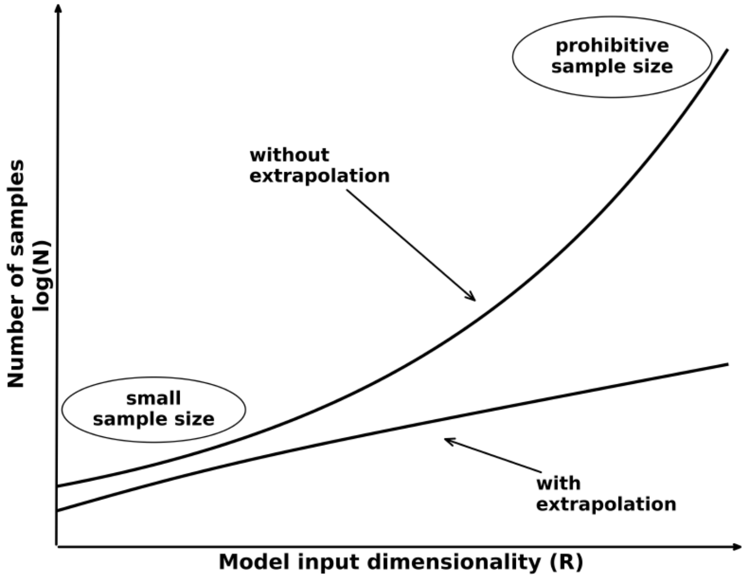
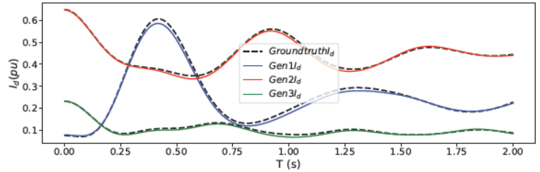
Generalisation to changes in s or m

The model performs well not just on training data, but on ***unseen scenarios*** *— new grid states, topologies, contingencies, or time horizons.*



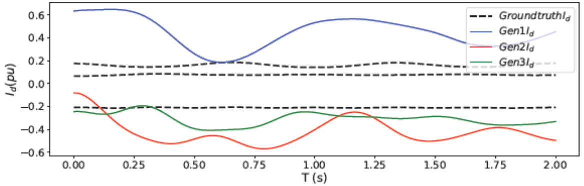


Extrapolation in continuous domain



(a) I_d current trajectory

Extrapolation in nonlinear domain (discrete)

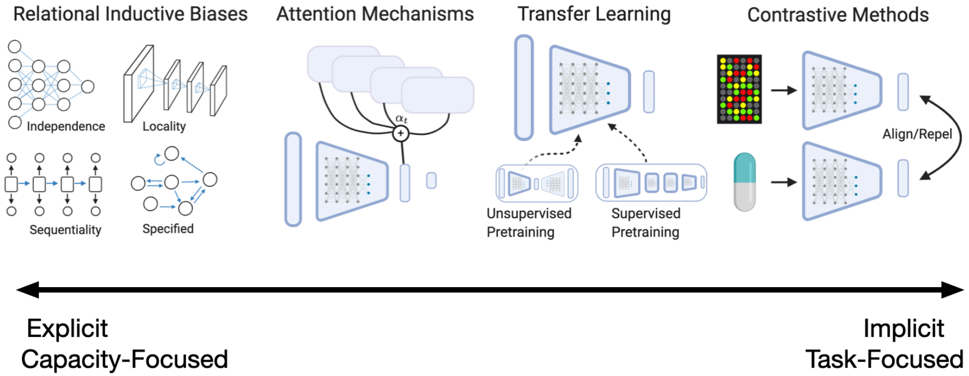


(a) I_d current trajectory

[10] Olayiwola Arowolo, Jochen Stiasny, Jochen Cremer, "Exploring the Extrapolation Performance of Machine Learning Models for Power System Time Domain Simulations", *12th Bulk Power System Dynamics and Control Symposium and Sustainable Energy, Grids and Networks Journal, 2025*

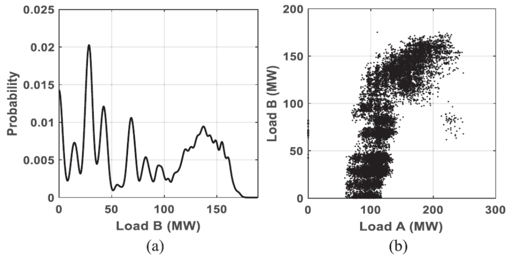
Challenge: Data-efficiency

- **Data efficiency is critical**
- Embedding **inductive bias** and learning **task-aware representations** helps supervised models generalise better — even with limited labels.

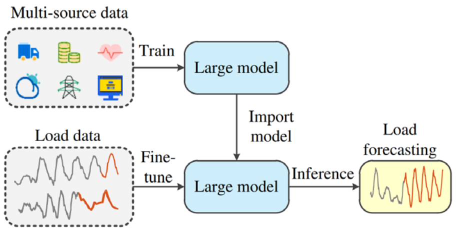


Sampling synthetic data & use real-data

Snapshot sampling



Time-series foundational models

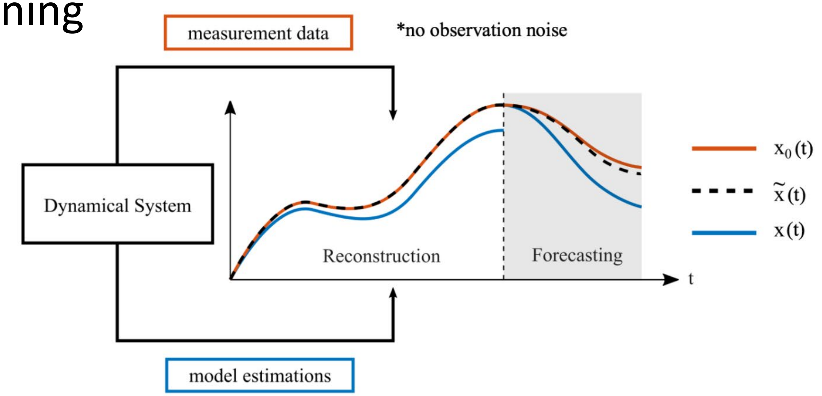


[29] https://sgfin.github.io/2020/06/22/Induction-Intro/
[30] Konstantelos, I., Sun, M., Tindemans, S. H., Issad, S., Panciatici, P., & Strbac, G. (2018). Using vine copulas to generate representative system states for machine learning. IEEE Transactions on Power Systems, 34(1), 225-235.
[31] Al-Amin Bugaje, Jochen L. Cremer, Goran Strbac, “Split-based Sequential Sampling for Realtime Security Assessment”, *International Journal of Electrical Power & Energy Systems, 2022*
[32] A. Venzke, D.K. Molzahn, S. Chatzivasileiadis,(2019). Efficient Creation of Datasets for Data-Driven Power System Applications, arXiv:1910.01794
[33] Liao, W., Wang, S., Yang, D., Yang, Z., Fang, J., Rehtanz, C., & Porté-Agel, F. (2025). TimeGPT in load forecasting: A large time series model perspective. *Applied Energy*, *379*, 124973.

Model inaccuracy $s \neq m$ (data quality issues)

"All models are wrong, but some are useful", George E. P. Box

- Example challenges
  - Distribution: Inaccurate transformer-tap positions
  - Transmission: Converter-based control models are unkown
- Possible techniques: Parameter estimation to develop probabilistic and deterministic models, discrepancy learning



[34] Ebers, M. R., Steele, K. M., & Kutz, J. N. (2024). Discrepancy modeling framework: Learning missing physics, modeling systematic residuals, and disambiguating between deterministic and random effects. *SIAM Journal on Applied Dynamical Systems*, *23*(1), 440-469.

Conclusions

- For many decades, AI has been investigated for power system reliability -> demonstrating promising ideas

- Promising: New techniques, availability of data, models, industry R&D commitments

Open research challenges

- Handling changes in data, and model inaccuracy -> Adaptive GNNs
- Curse of dimensionality -> Self-supervised learning
- Addressing risks, confidence, and trust in ML models
- A large amount of data is needed
- Integrating various concepts

Thank you

Speaker

Jochen Cremer

Associate Professor IEPG, TU Delft

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Personal www.jochen-cremer.com

Email: j.l.cremer@tudelft.nl

Code: https://github.com/TU-Delft-AI-Energy-Lab

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References & code

Weakly supervised learning for power systems (**Example code:** https://github.com/TU-Delft-AI-Energy-Lab/Deep-Statistical-Solver-for-Distribution-System-State-Estimation)

- Bastien Giraud, Ali Rajaei, Jochen L. Cremer "Constraint-Driven Deep Learning for N-k Security Constrained Optimal Power Flow", *Electric Power System Research and 2024 IEEE Power System Computation Conference [**Code**:* https://github.com/TU-Delft-AI-Energy-Lab/Constraint-Driven-SCOPF]

- B. Habib, E. Isufi, W. v. Breda, A. Jongepier and Jochen L. Cremer, "Deep Statistical Solver for Distribution System State Estimation, " *IEEE Transactions on Power Systems, 2023, doi: 10.1109/TPWRS.2023.3290358*.

Cost-sensitive learning

- Dariush Wahdany, Carlo Schmitt, Jochen L. Cremer, "More than Accuracy: End-To-End Wind Power Forecasting that Optimises the Energy System", *Electric Power System Research, 2023*
- A. Bugaje, J. L. Cremer, M. Sun, G. Strbac, "Selecting DT Models for Security Assessment using ROC- and Cost-Curves", *Energy and AI*, 2021: 100110.
- J. L. Cremer, G. Strbac, "A Machine-learning based Probabilistic Perspective on Dynamic Security Assessment" *International Journal of Electrical Power & Energy System, 2020*

Interpretable models (**Example code:** https://github.com/JochenC/From-optimization-based-machine-learning-to-interpretable-security-rules-for-operation)

- J. L. Cremer, I. Konstantelos, G. Strbac, "From Optimization-based Machine Learning to Interpretable Security Rules for Operation", *IEEE Transactions on Power Systems, 2019*
- J. L. Cremer, I. Konstantelos, S. H. Tindemans, G. Strbac, "Data-driven Power System Operation: Exploring the Balance between Cost and Risk", *IEEE Transactions on Power Systems, 2018*

Fast training of models

- Mert Karaçelebi, Jochen L. Cremer "Online Neural Dynamics Forecasting for Power System Security", *International Journal of Electrical Power & Energy Systems 2025*
- Mert Karaçelebi, Jochen L. Cremer, "Predicting Power System Frequency with Neural Ordinary Differential Equations", *12th Bulk Power System Dynamics and Control Symposium and Sustainable Energy, Grids and Networks Journal, 2025*

Generalisation challenge:

- Olayiwola Arowolo, Jochen Stiasny, Jochen Cremer, "Exploring the Extrapolation Performance of Machine Learning Models for Power System Time Domain Simulations", *12th Bulk Power System Dynamics and Control Symposium and Sustainable Energy, Grids and Networks Journal, 2025*

Thank you for your attention

Jochen Cremer
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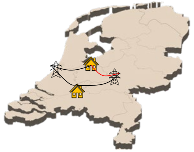
Reliability Indicators

Loss of load expectation (LOLE)

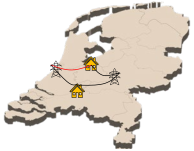
- Expected amount of time demand can not be supplied [h/y]
- ∑ (Outage duration x probability)

Expected energy not supplied (EENS)

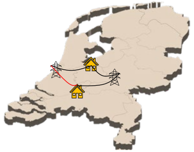
- Amount of energy expected not to be supplied during that period [MWh/y]
- ∑ (Energy not supplied x probability)



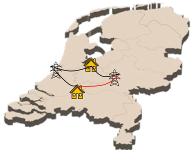
$t_1 * \pi_1 = 2$ h/y
$E_1 * \pi_1 = 3$ MWh/y



$t_1 * \pi_1 = 0$ h/y
$E_1 * \pi_1 = 0$ MWh/y



$t_1 * \pi_1 = 0$ h/y
$E_1 * \pi_1 = 0$ MWh/y



$t_1 * \pi_1 = 3$ h/y
$E_1 * \pi_1 = 4$ MWh/y

+

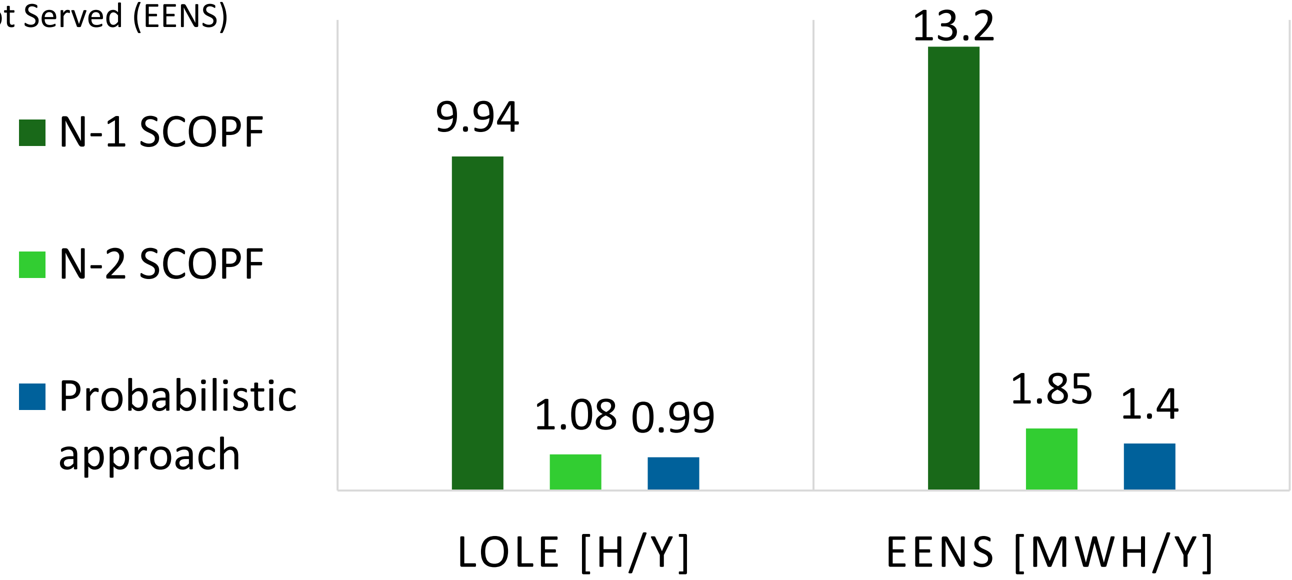
LOLE = 5 h/y
EENS = 7 MWh/y

Probabilistic security assessment

Proposed probabilistic security enhances reliability

Compare reliability indices

- Loss of Load Expected (LOLE)
- Expected Energy not Served (EENS)



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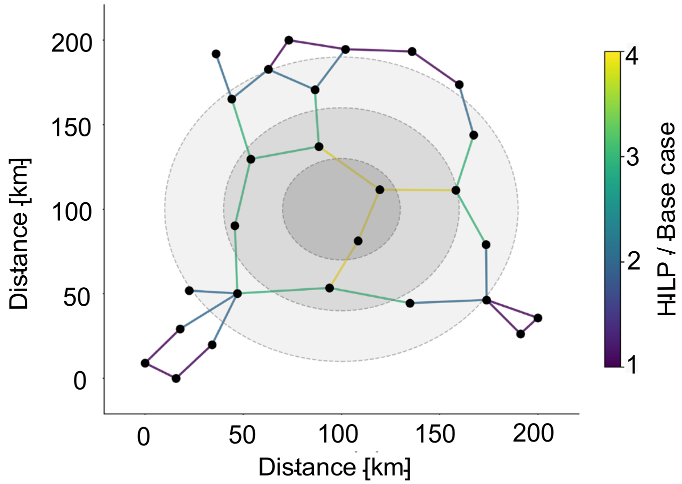
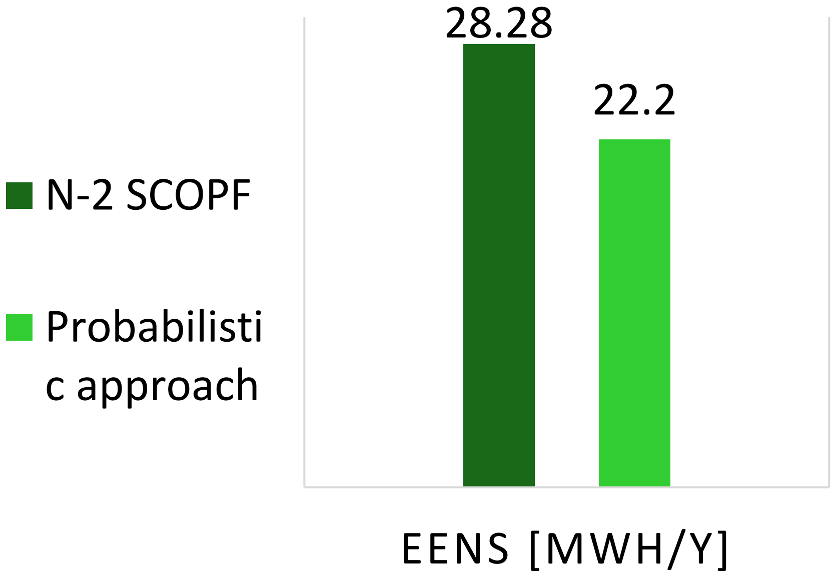
[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Extreme event

- Individual probabilities change due to an earthquake
- Recompute joint probabilities
- Recompute reliability indices



Potential for increased resiliency



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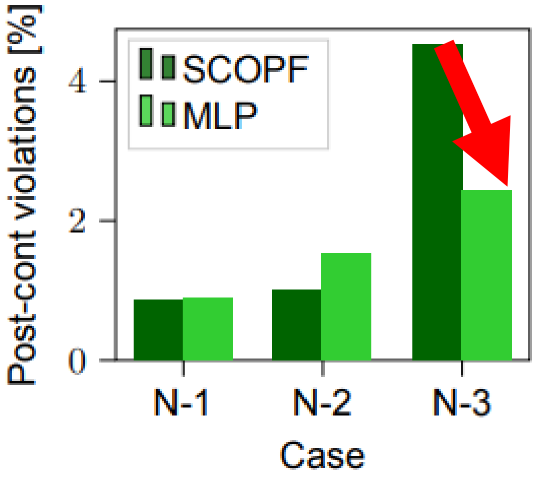
Performance 118-bus system

Proposed approach
Baseline

- Evaluate ability to identify line violations
- **Only** consider single, double or triple line outages
- Post-cont violations [%] indicates the percentage of samples where line violations occur



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