Deep Learning for Power System Reliability Assessments

Liège Seminar, 09-05-2025

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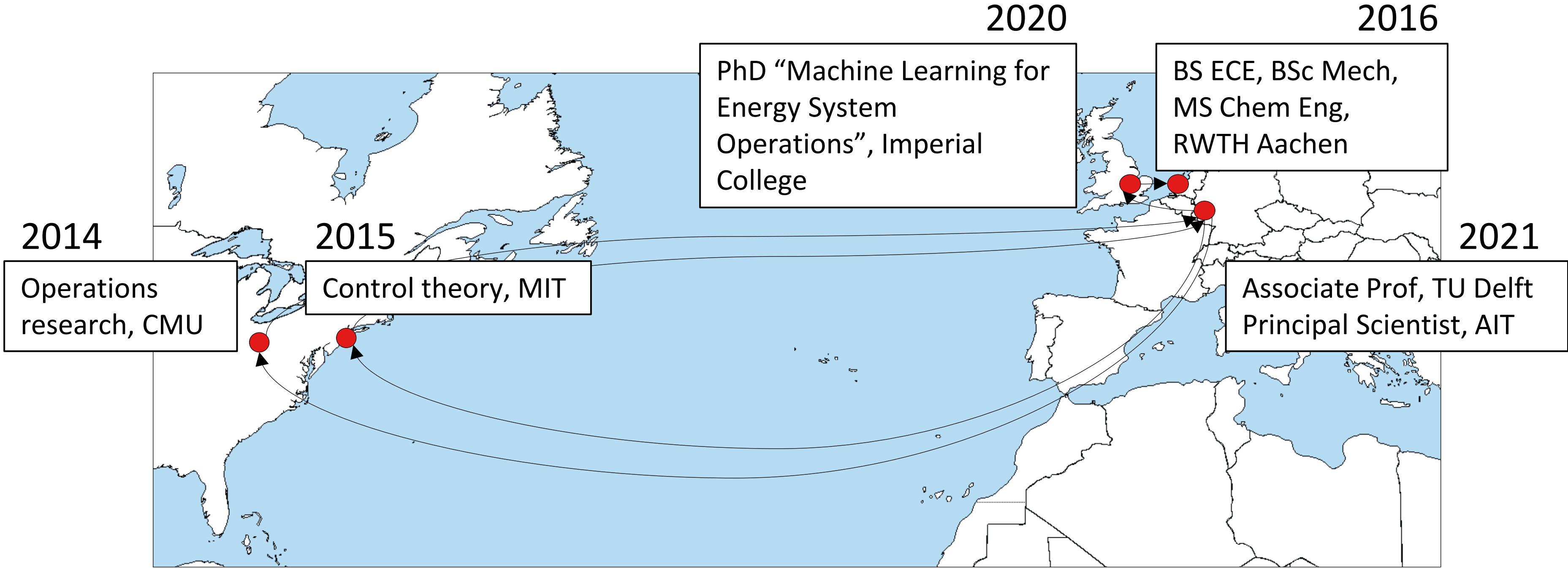
Associate Professor

TU Delft

Introduction



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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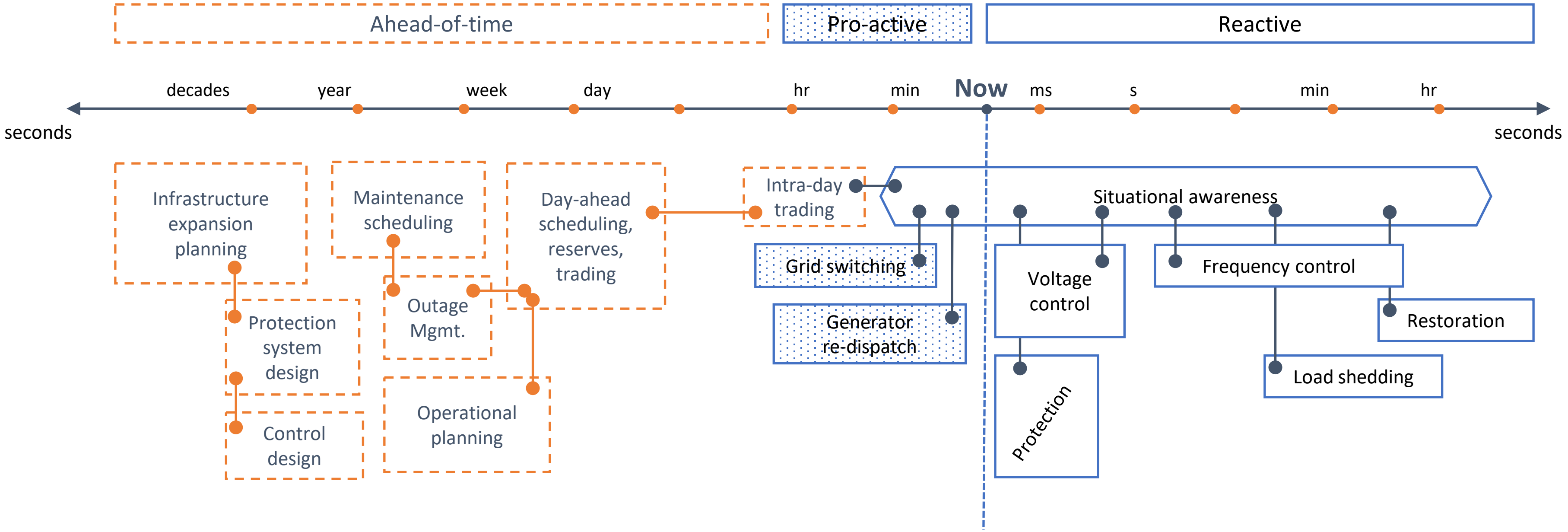
Outline

1. Introduction to reliability management
2. Machine learning approaches
3. Monitoring: Real-time dynamic security
4. Control: Weakly-supervised learning for N-k probabilistic, static security
5. Challenges applying ML to reliability

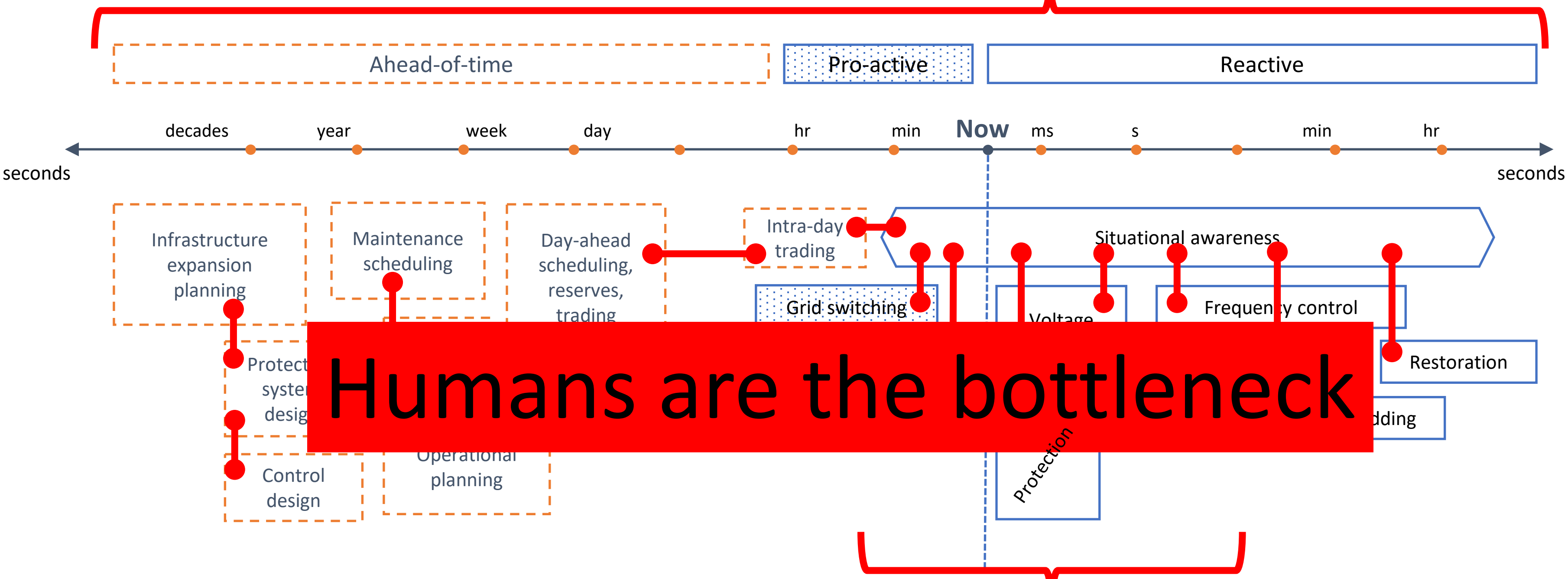
Experts are in charge to manually operate the power system based on **experience** and with **the support of tools**

A complex process



What's the issue?

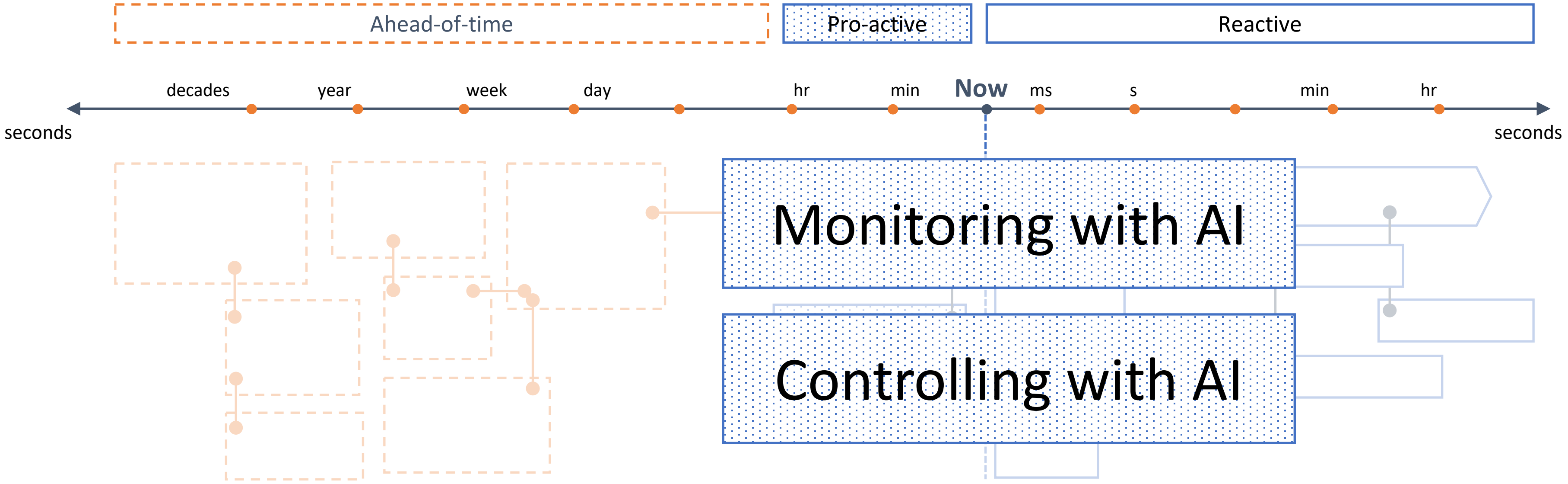
Interdependencies challenge manual rules



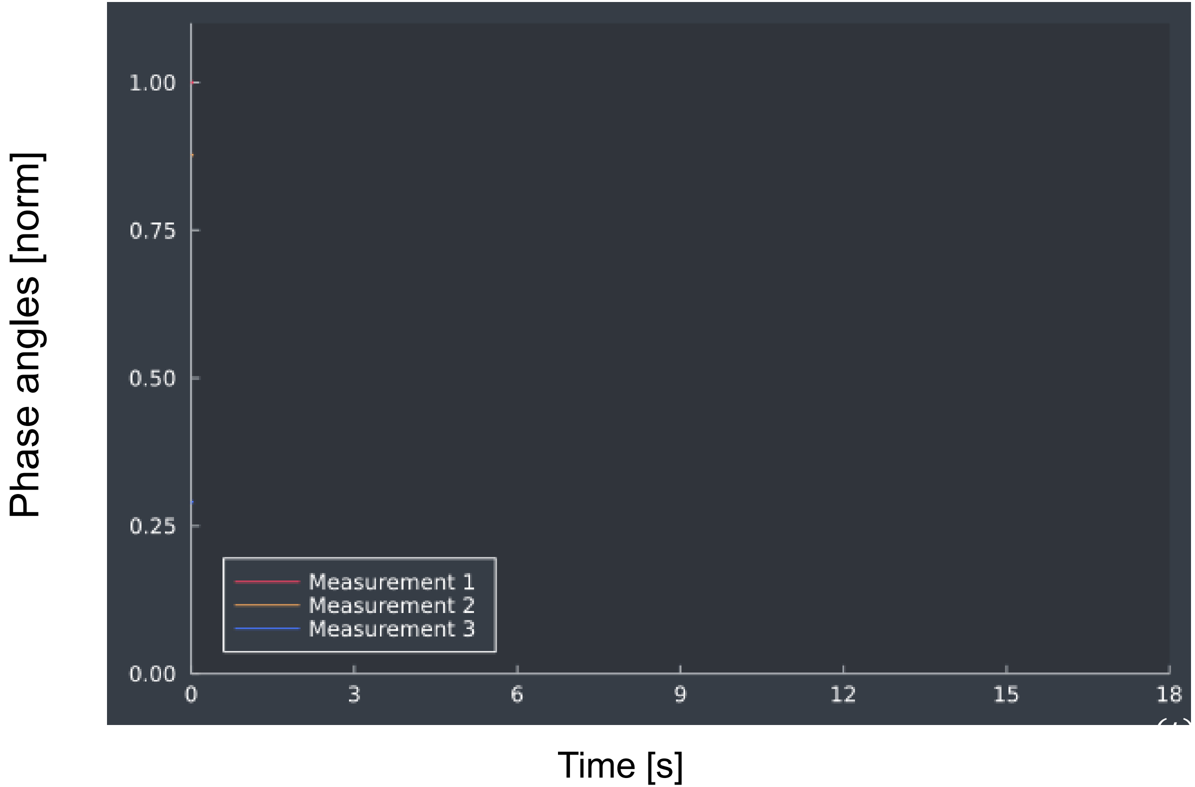
Humans are the bottleneck

Human decisions are too slow

Automation first realised where urgently needed

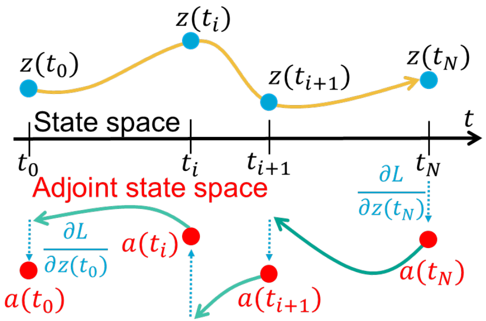


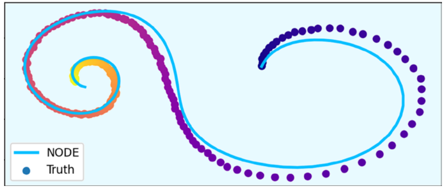
Real-time security assessment of disturbances



Mert Karaçelebi

<u>Neural</u> ordinary differential equations

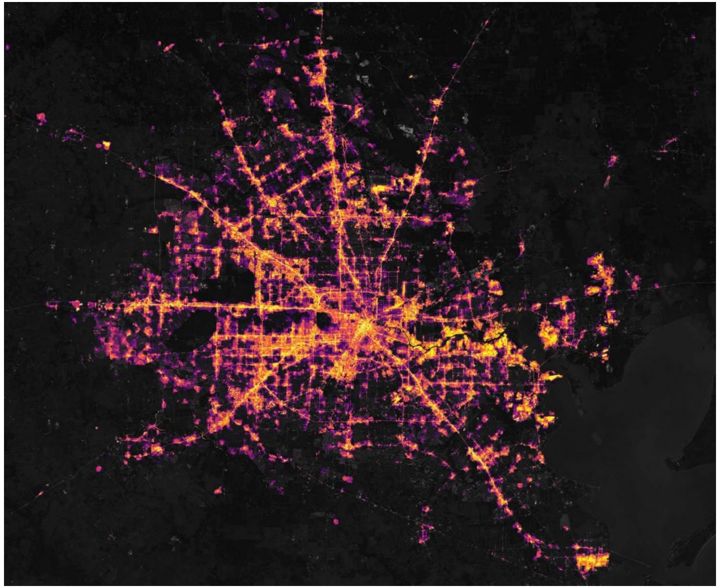




[1] Mert Karaçelebi, Jochen L. Cremer "Online Neural Dynamics Forecasting for Power System Security", *International Journal of Electrical Power & Energy Systems 2025*

[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?



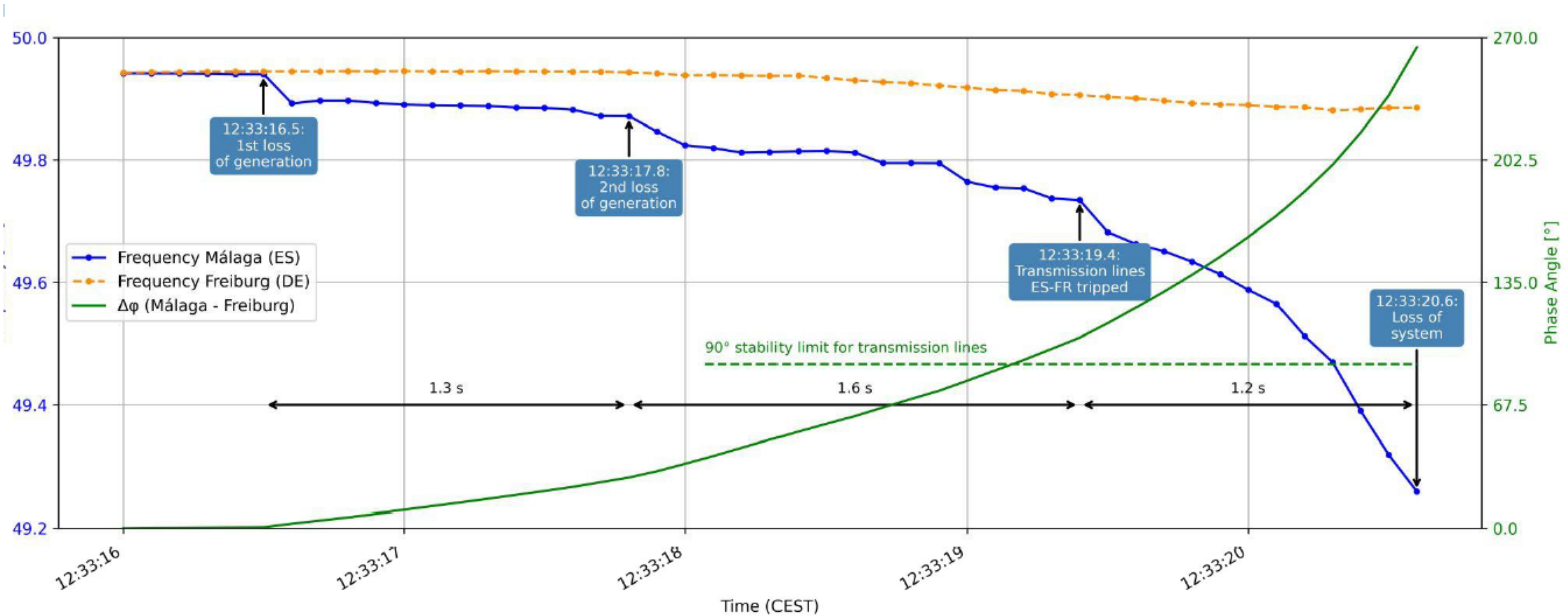
Houston, Texas 07 Feb 2021

Houston, Texas 16 Feb 2021

- Damages from the blackouts were estimated at **$195 billion [1]**
- 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



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Source

N-2?

28th of April 2025 (CET)

~19 s | ~1.3 s | ~2.5 s

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 become an **electric island**, and a "**massive disconnectio of generatior** happens in Spain

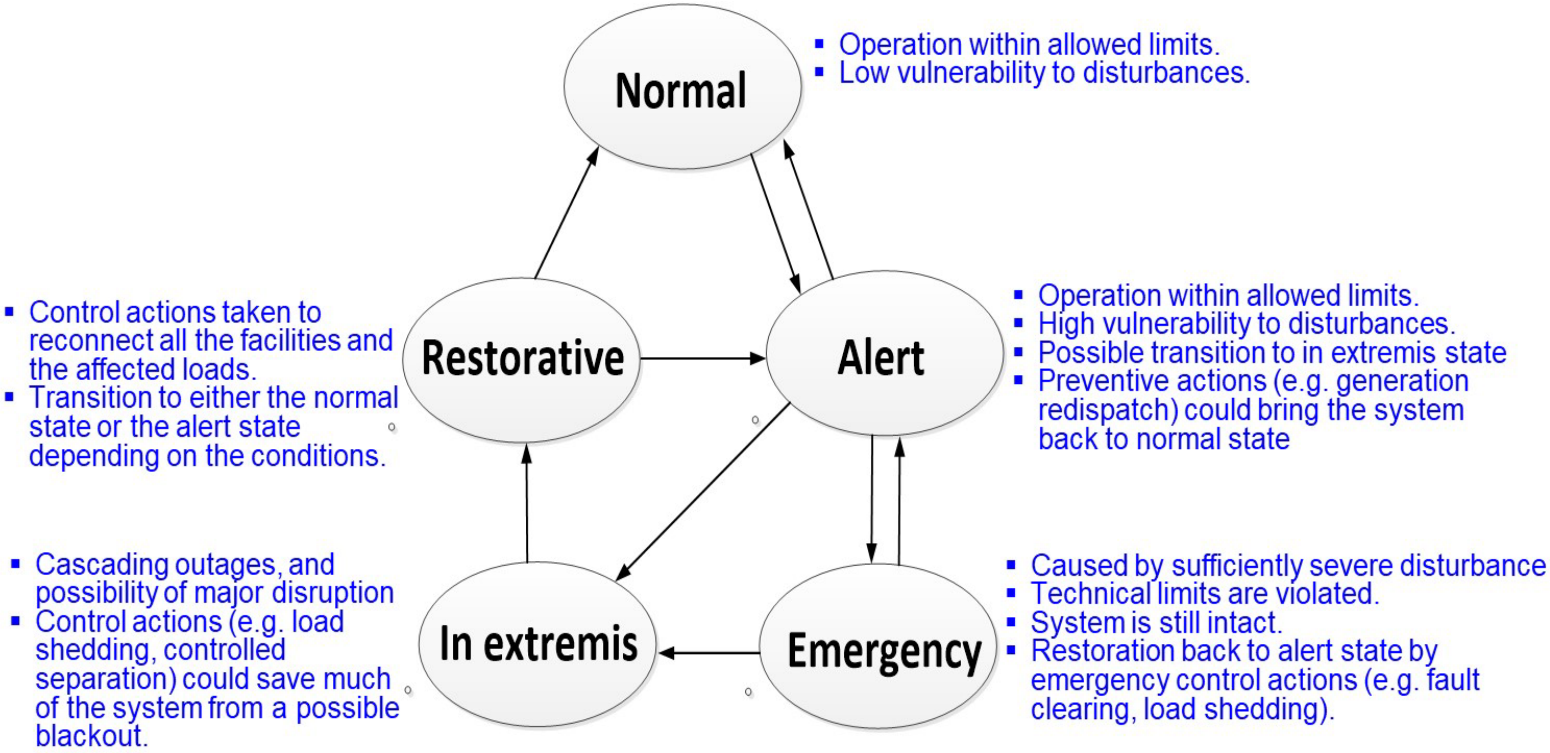
https://badber.github.io/

Power system reliability

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

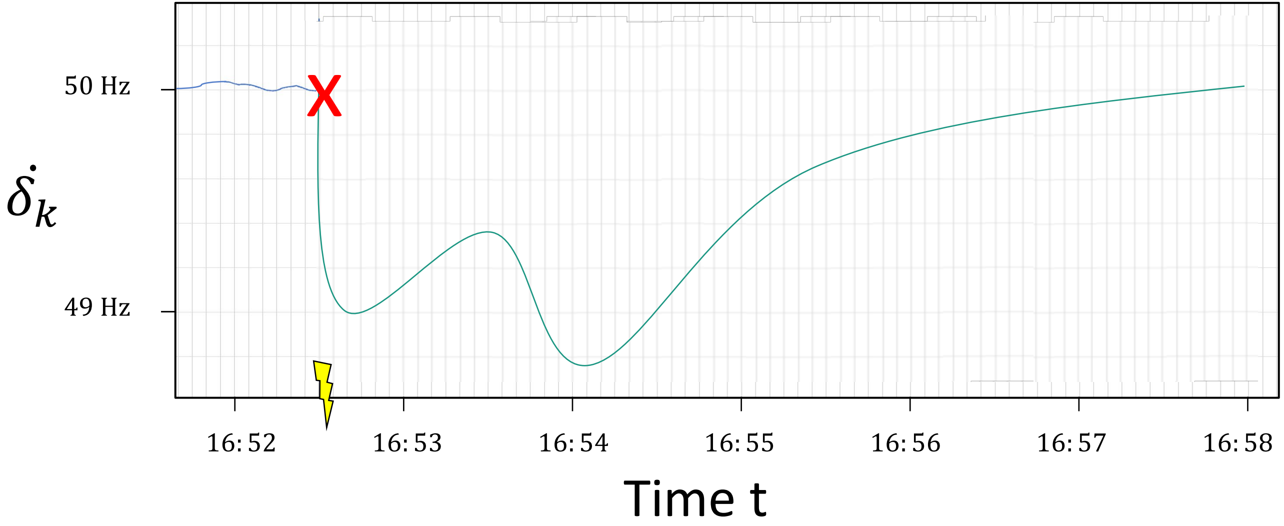
[4] International Electrotechnical Commission, Electropedia: The worlds online electrotechnical vocabulary, http://www.electropedia.org/; 2016 [accessed 16 August 2018].

Operating states of power systems



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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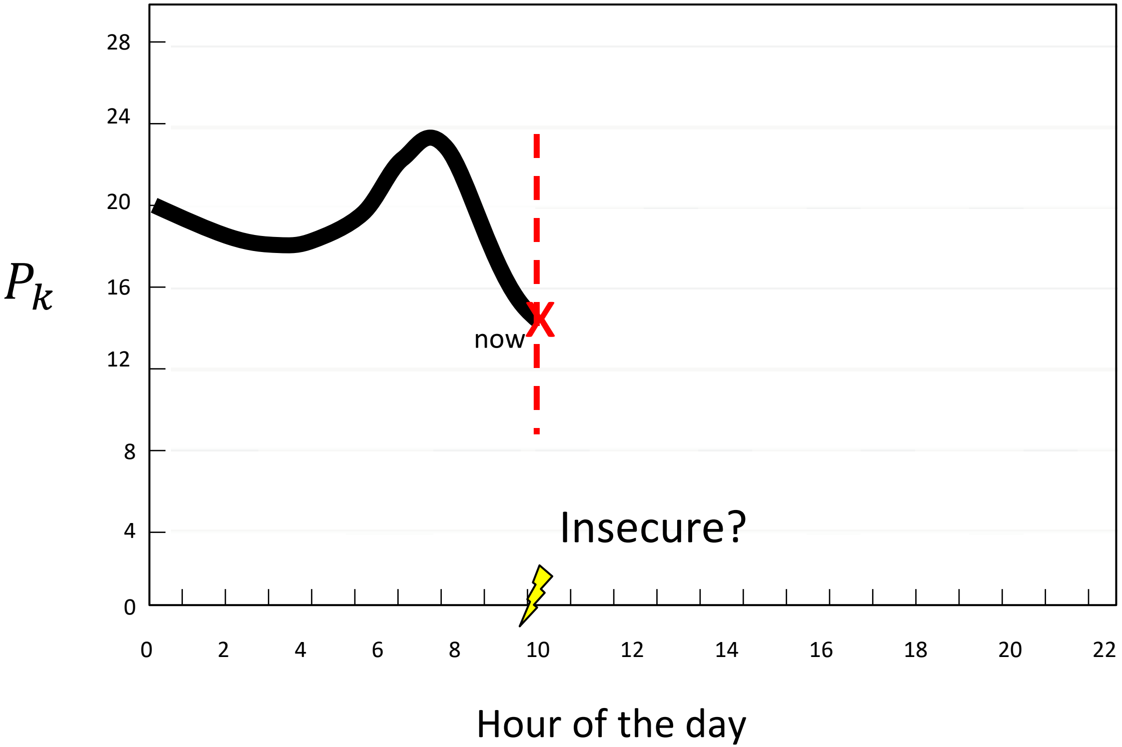
Real-time dynamic security assessment

Objective: predicting security in real-time

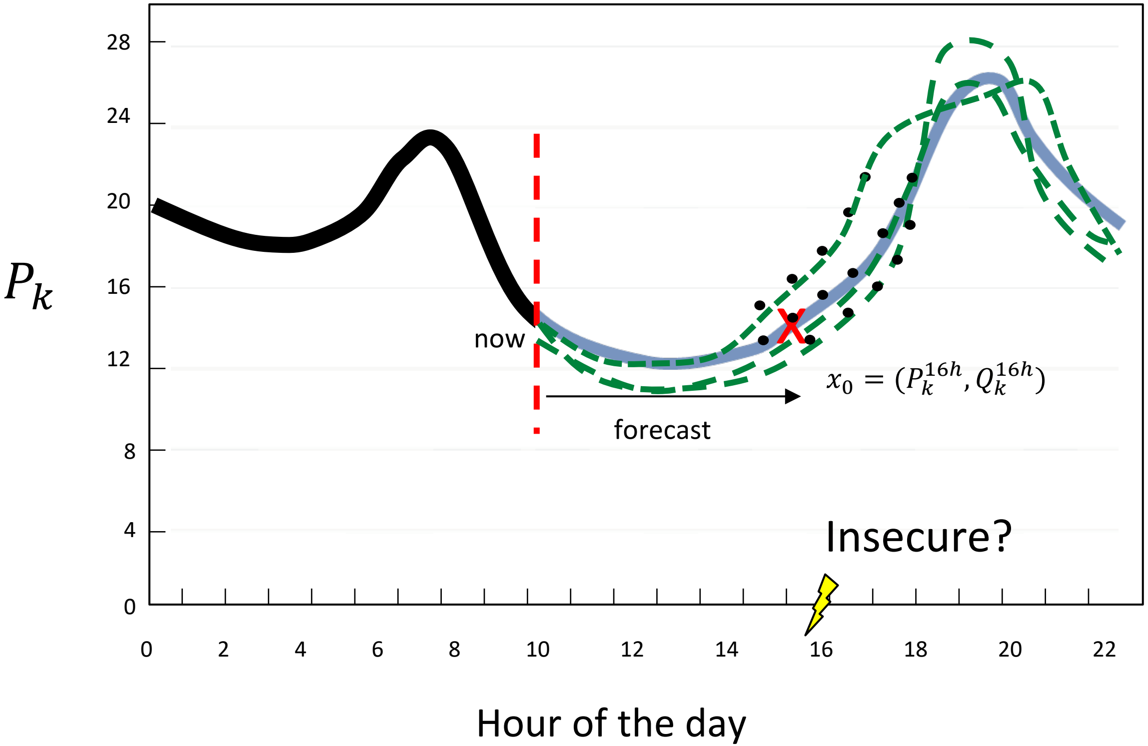
In response, use corrective actions in (near) real-time



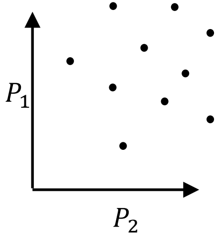
(Preventive) real-time dynamic security assessment

For N-1 security

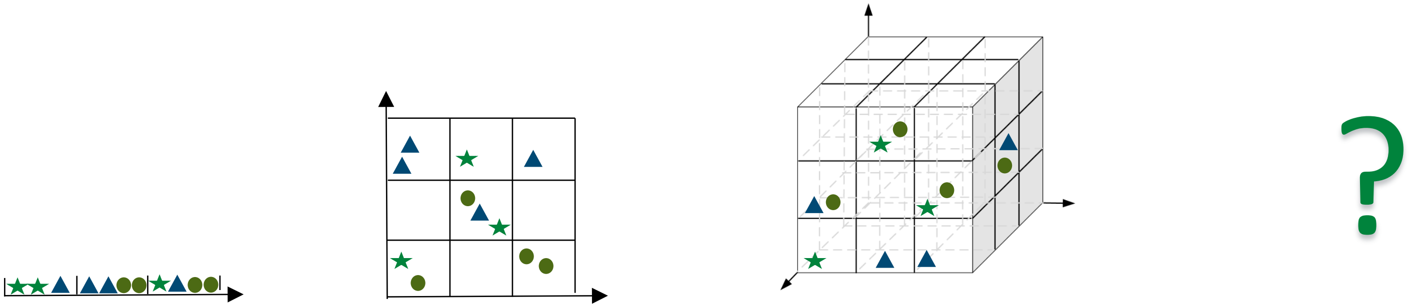
Preventive actions



High-dimensional



Curse of Dimensionality

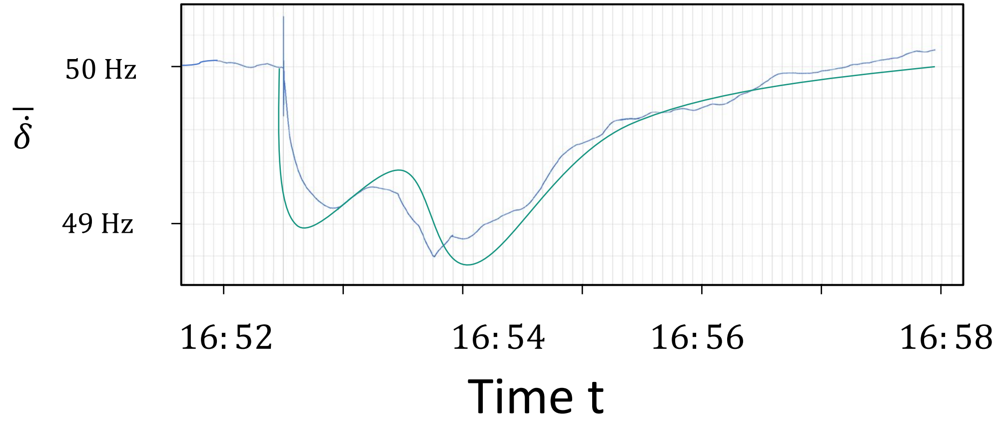


1d: 3 regions   2d: 3^2 regions   3d: 3^3 regions   1000d: hopeless

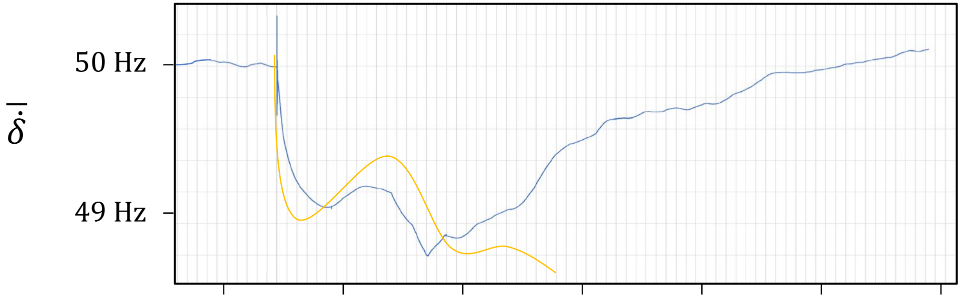
As dimensionality grows: fewer samples per region.

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

Security of power systems

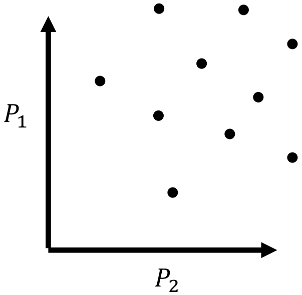


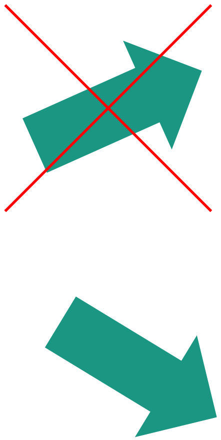
secure $y = 0$



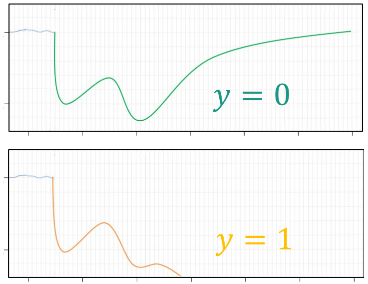
insecure $y = 1$

Machine learning model to predict security

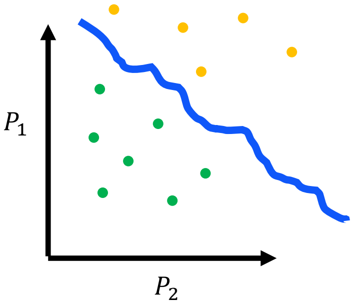




Time-domain simulation



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



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.

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

Notation: Power system s, model m, parameter x

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

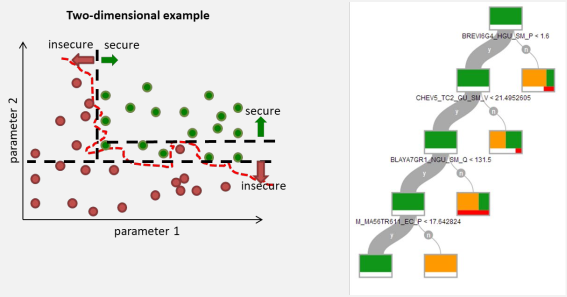
Surrogate approach

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

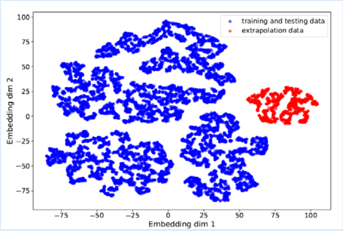
Applications

- 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

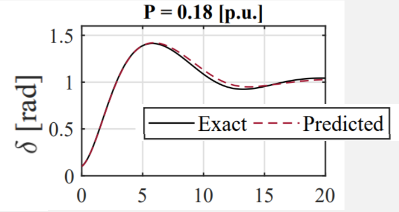
Physics-informed approach

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**

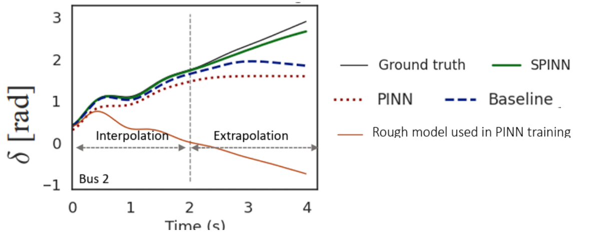
Applications

- 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.

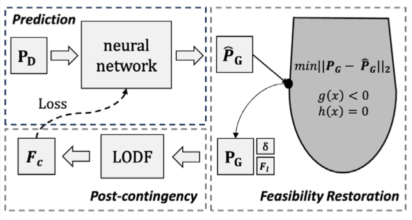
Approach

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

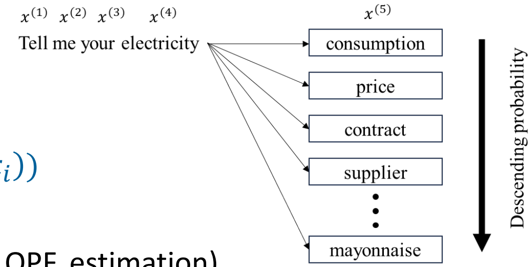
- Inexact supervision $s \neq m$ not so important as success defined by task-loss
- System shift in s or m
- Data coverage. Diverse samples are needed for generalization

[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)

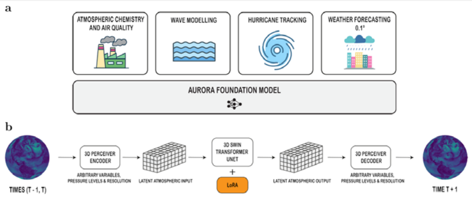
Benefits: Good initialization when little data, good transfer to downstream tasks

Challenges

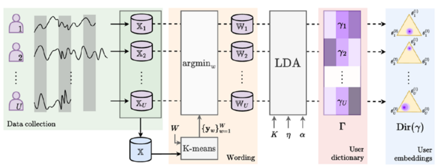
- Design pretext loss and model architectures with broad set of tasks, grid conditions, topologies
- Generate large data sets
- …

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.

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Graph Neural Networks

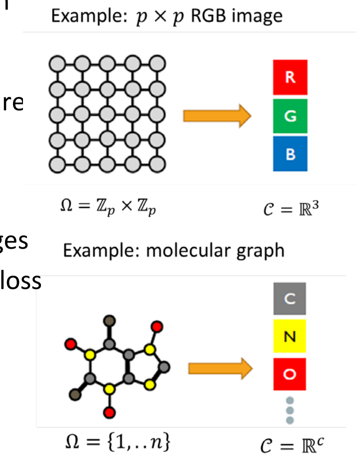
Objective: Improve generalization performance in learning tasks on network-structured systems (like power grids)

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

Approach

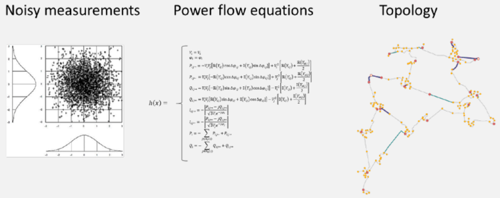
1. Construct graph $G = (V, \mathcal{E})$ with features on nodes and edges
2. Define f_{GNN} and learn with message passing on supervised loss $\sum_{i \in \Omega^T} \|y_i - \hat{y}_i\|$
3. Use $f(x_j)$ for new j $\notin \Omega^T$ or on unseen graphs G'

Benefits: Data efficient, generalisation to changes in topologies



Applications

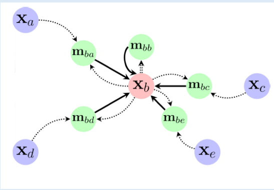
- Graph neural solvers [20] for ACOPF [21]
- Distribution system state estimation [22]



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



[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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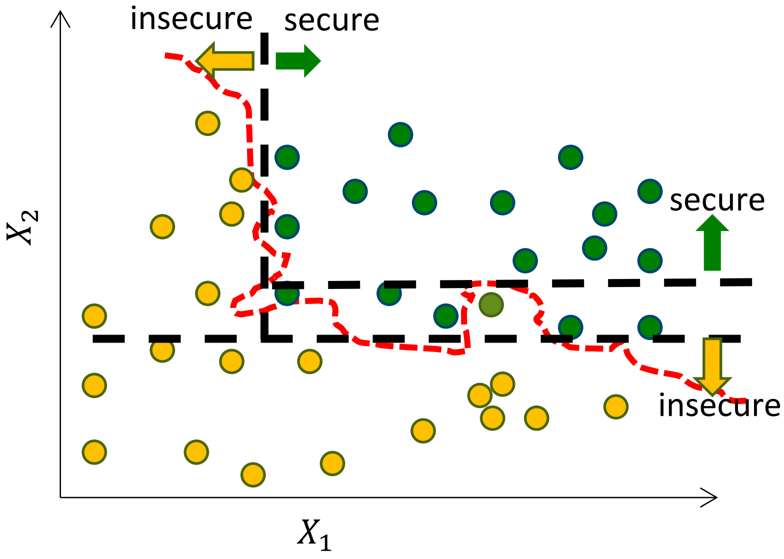
System operation

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

Interpretable models

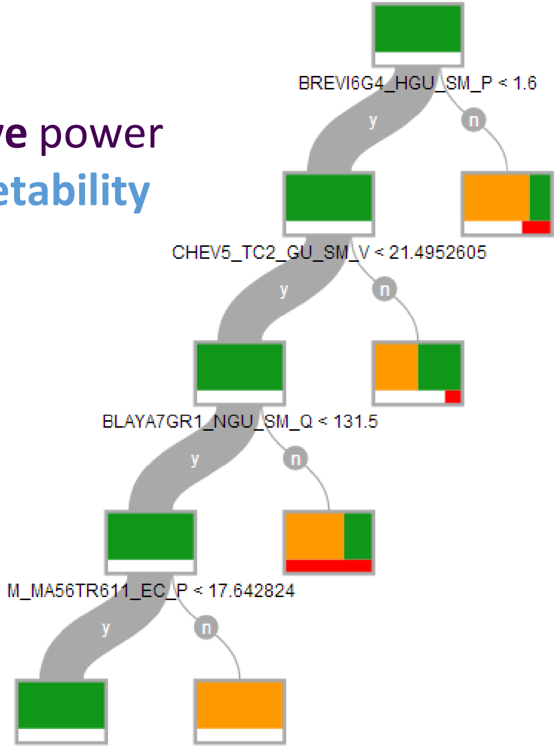
Decision Trees as a model?

Two-dimensional example

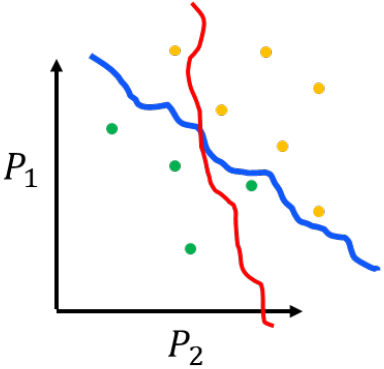


Decision trees:

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

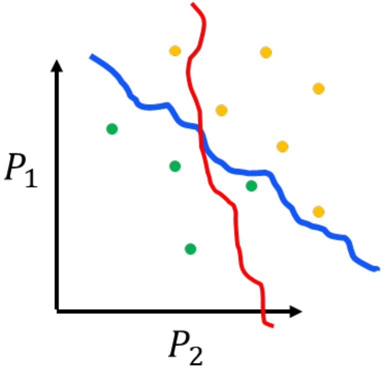


Metrics for classification



Predicted and actual security limits are different!

Metrics for classification

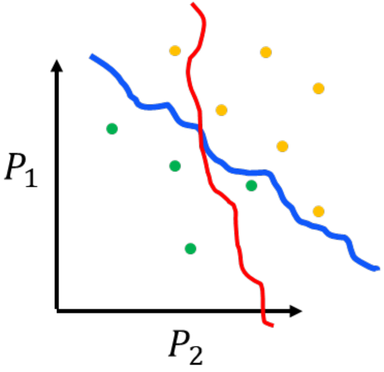


Predicted and actual security limits are different!

		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!

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

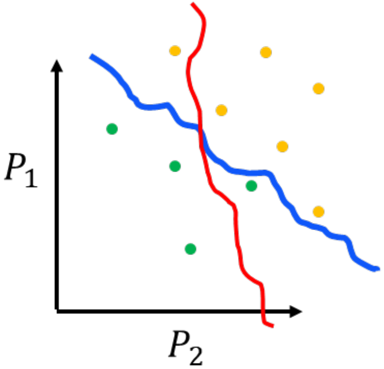
Confusion Matrix

<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!**)

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

<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!**)

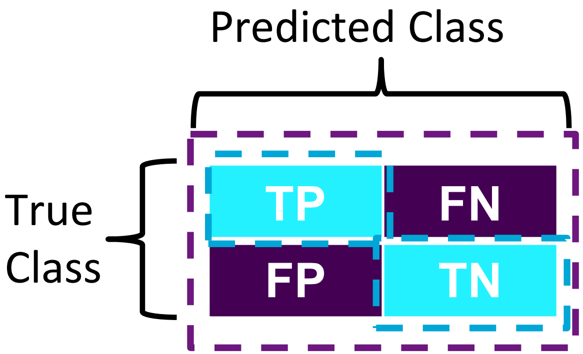
<u>Two types of wrong predictions</u>:

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!

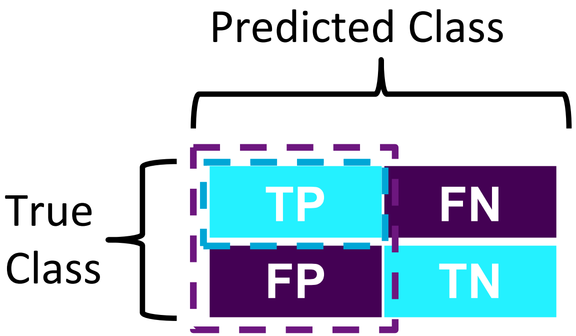
Metrics for classification



Ratio of correct predictions

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

Metrics for classification

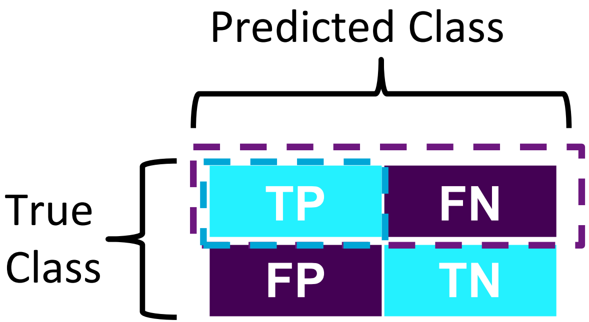


Ratio of correctly found insecure cases to predicted insecure predictions

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

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

Metrics for classification



Ratio of correctly found insecure cases to all insecure cases

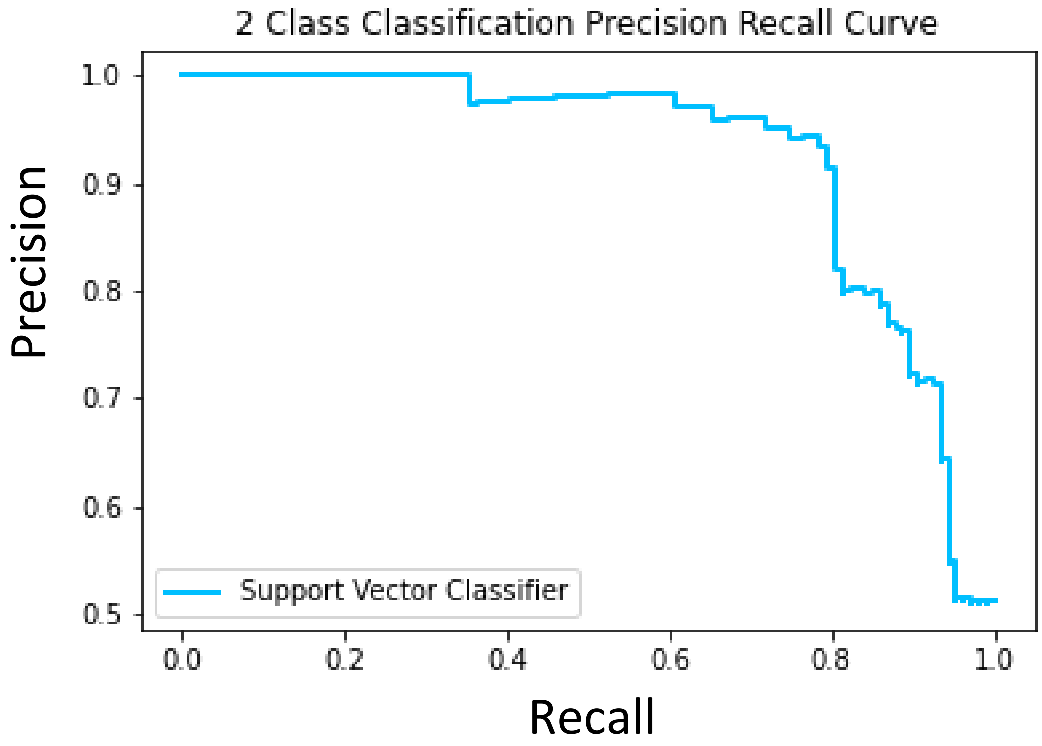
$$\text{Accuracy} = \frac{N_{TP}+N_{TN}}{N_{FP}+N_{TP}+N_{FN}+N_{TN}}$$

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

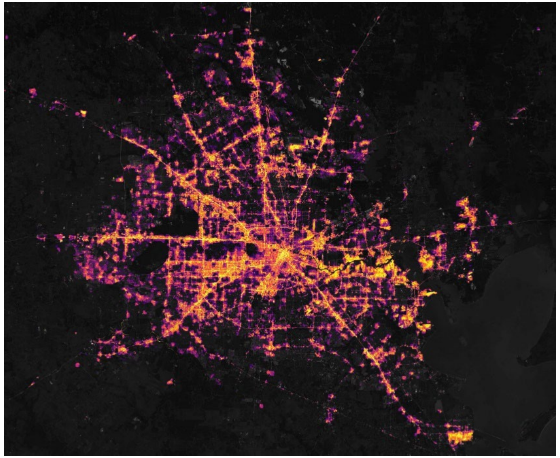
$$\text{Recall} = \frac{N_{TP}}{N_{TP}+N_{FN}}$$

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

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

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

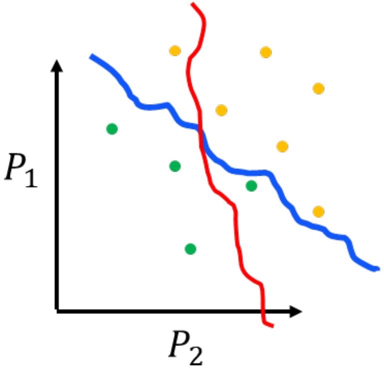
Cost skewness: $C_{FN} \gg C_{FP}$

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: $\pi_+ \ll \pi_-$

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What a classifier can do

Classify points

- is x positive?

Rank points

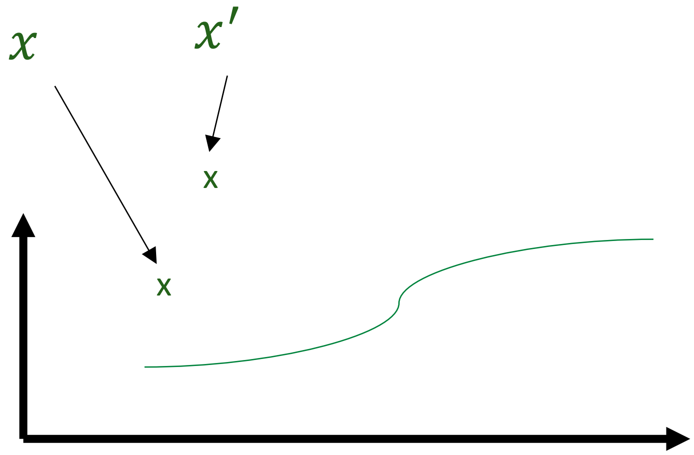
- Is x 'more positive' than x'?

Output a score $s(x)$

- 'How positive' is x?

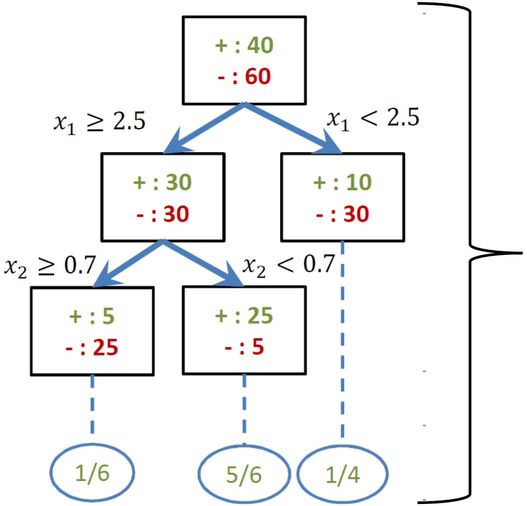
Output a probability estimate $\hat{p}(x)$

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



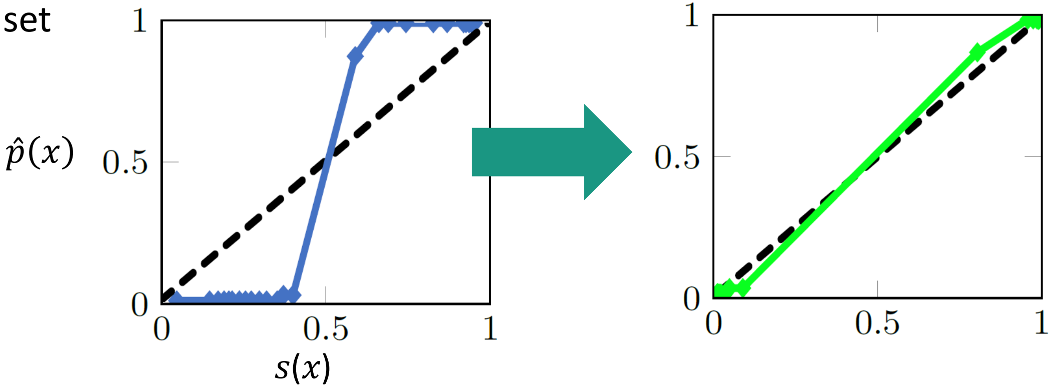
Probability estimation is not easy

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



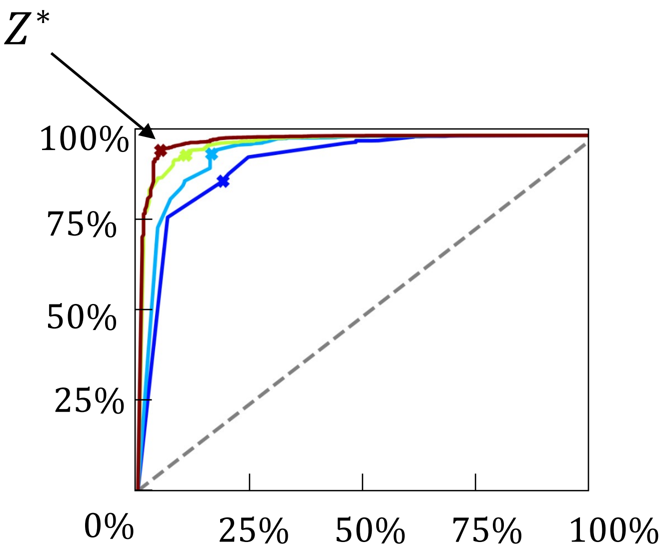
Based on training set

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.

Cost-sensitive learning



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

$$\text{F}PR = \frac{FP}{\pi_+}$$

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

Probability of contingency

'Impact' of contingency

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

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

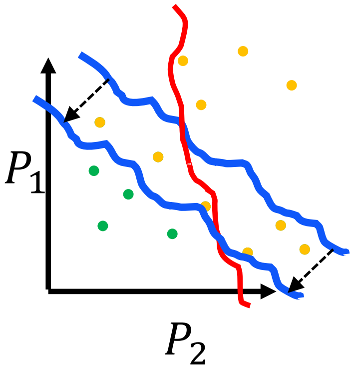
Step 1: Compute risks when predicting x_i as secure $y_i = 1$ and insecure $y_i = 0$

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

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

Step 2: Predict with lowest residual risk

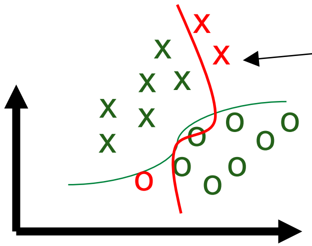
$$R_{\text{secure}} \bigvee R_{\text{insecure}}$$



[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

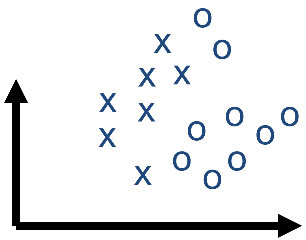
Machine Learning



- Fast
- Sometimes inaccurate

+

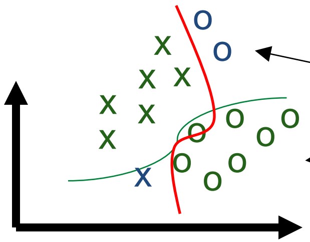
Simulator



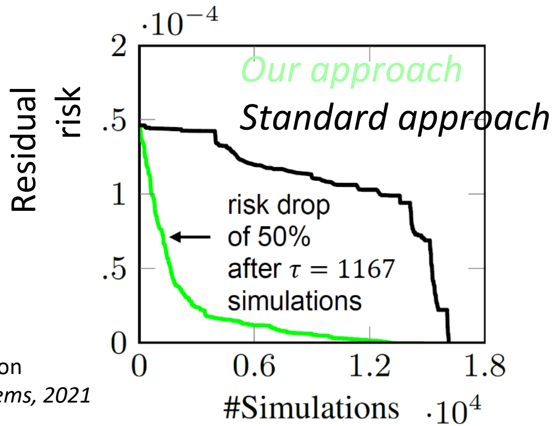
- Slow
- Always accurate

=

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*

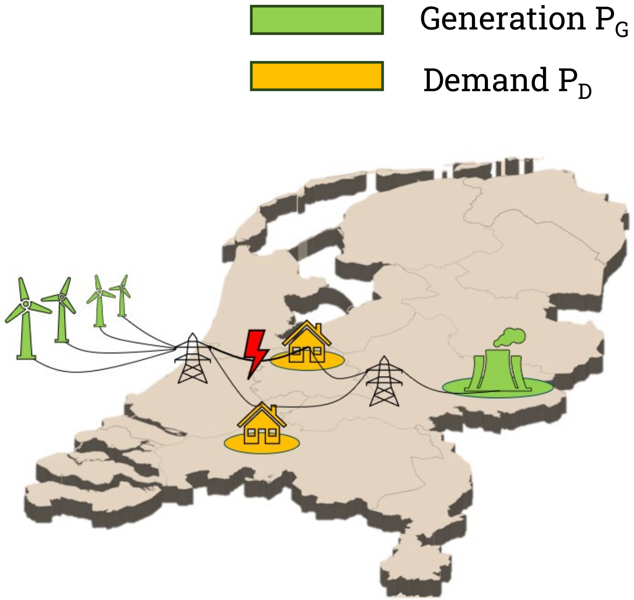
Outline

1. Introduction to reliability management
2. Machine learning approaches
3. Monitoring: Real-time dynamic security
4. Control: Weakly-supervised learning for N-k probabilistic, static security
5. Challenges applying ML to reliability

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



Security constrained optimal power flow (SCOPF)

Objective:	minimize cost	$\min_{n \in \Omega^G} \Sigma\, c_n P_{G_n}$
Constraints:	In = out	$\boldsymbol{B \cdot \delta = P_G - P_D}$
	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

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**)

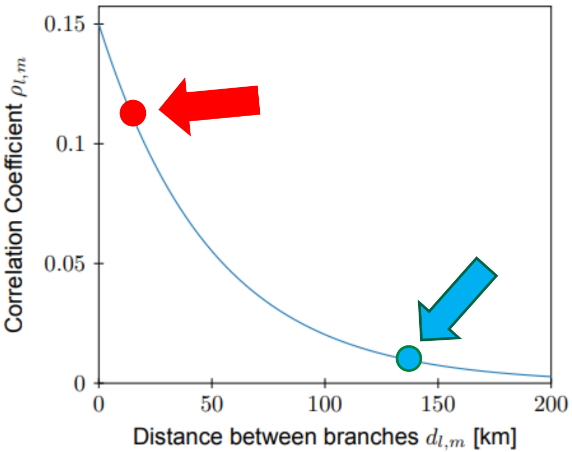
Machine learning approaches often rely on **labeled** training data

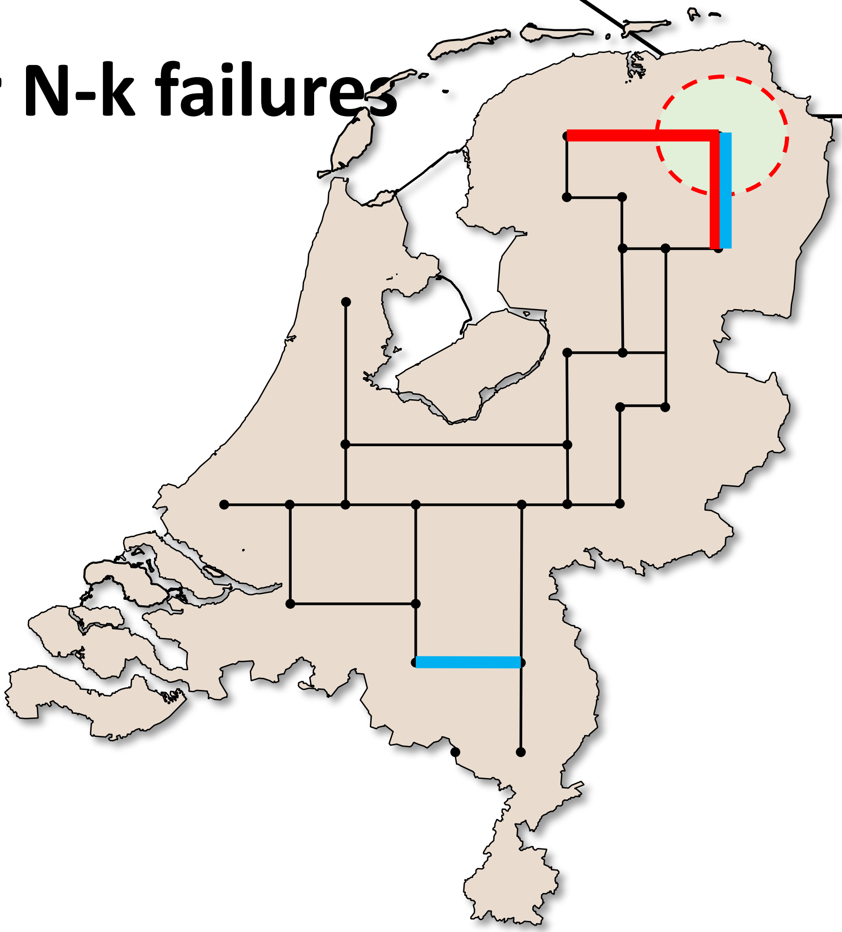
- Intractable for increasing k

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

Probabilistic security for N-k failures

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





Proposed constraint-driven approach

Main advantages

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

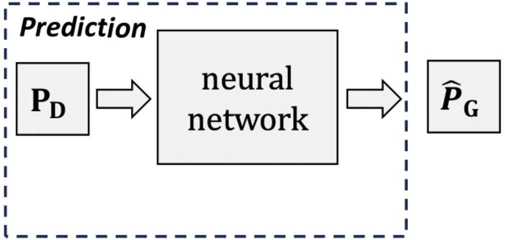
Contributions

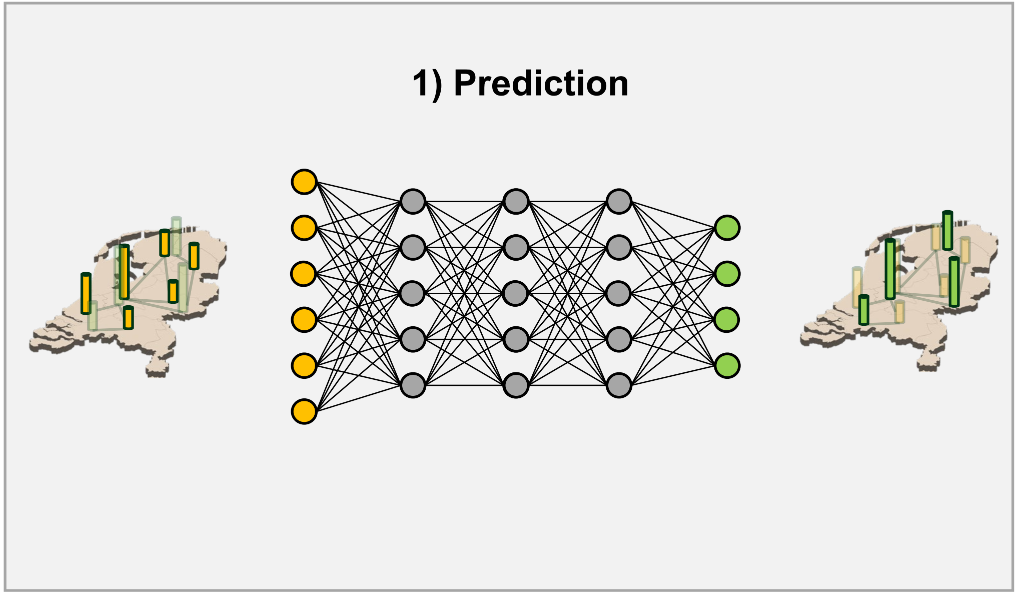
- The deterministic constraint-driven approach to approximate N-k SCOPFs, considering all line contingencies using LODFs.
- The computational graph memory reduction for fast and efficient implementation.
- The probabilistic security assessment to formulate a N-k risk-based security criterion, providing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





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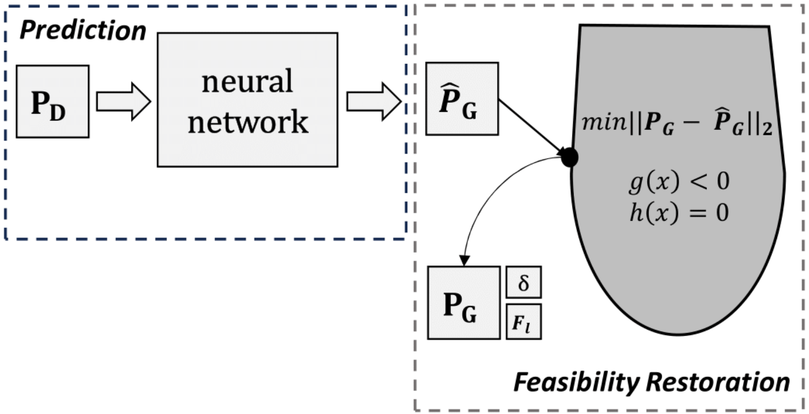


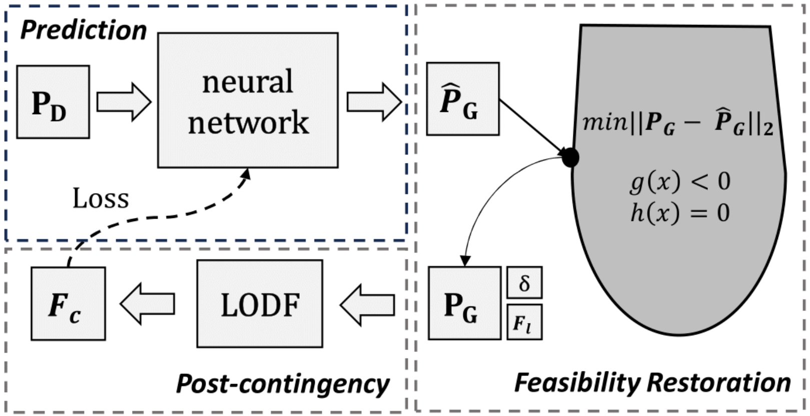
2) Feasibility Restoration

- 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

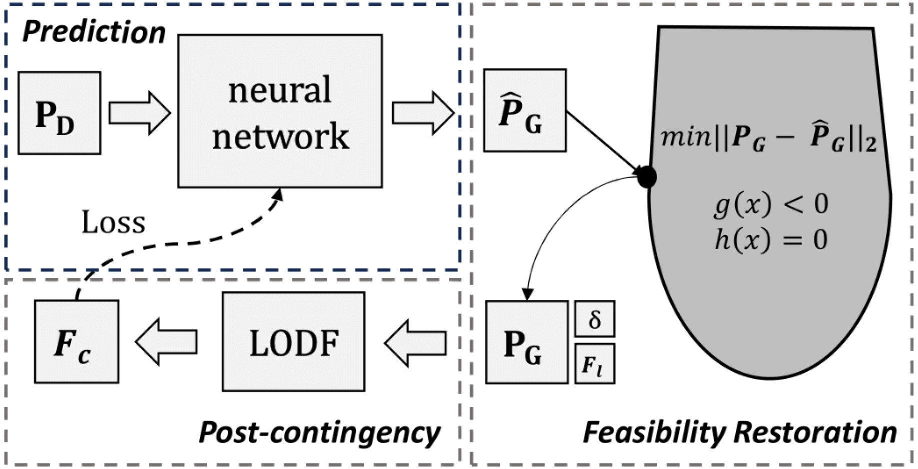
$$\boldsymbol{F^c = F^0 + LODF_{N-k} \times F^0}$$

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

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 $\lambda_c \sum \boldsymbol{P}_{\boldsymbol{G}} \boldsymbol{c}_{\boldsymbol{G}}$

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

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

4) Power imbalance $\lambda_2 \left\| \sum \widehat{\boldsymbol{P}}_{\boldsymbol{G}} - \sum \boldsymbol{P}_{\boldsymbol{D}} \right\|_1$

$$Loss = \lambda_c \sum \boldsymbol{P}_{\boldsymbol{G}} \boldsymbol{c}_{\boldsymbol{G}} + \lambda_0 \left\| ReLU(|\widehat{\boldsymbol{F}}^{\mathbf{0}}| - \boldsymbol{F}^{max}) \right\|_1 + \lambda_1 \| ReLU(|\boldsymbol{F}^{c}| - \boldsymbol{F}^{max}) \|_1 + \lambda_2 \left\| \sum \widehat{\boldsymbol{P}}_{\boldsymbol{G}} - \sum \boldsymbol{P}_{\boldsymbol{D}} \right\|_1$$

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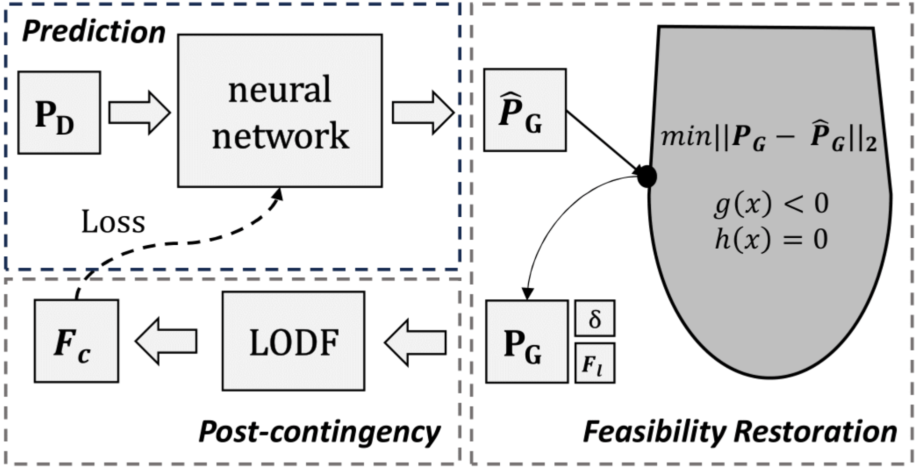
Proposed constraint-driven approach



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

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

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

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

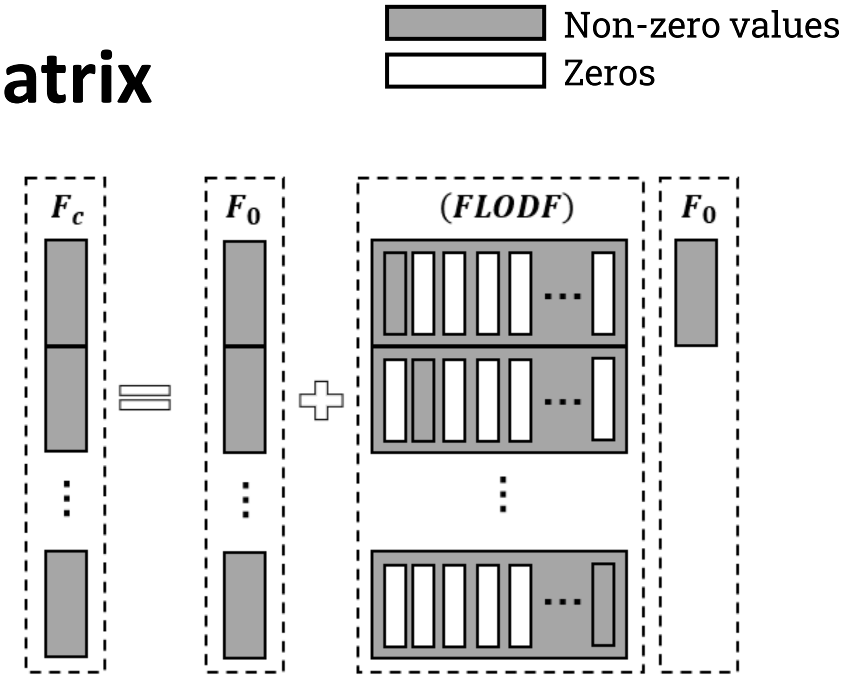
$$Loss = \lambda_c \sum \boldsymbol{P_G c_G} + \lambda_0 \left\| ReLU(|\hat{\boldsymbol{F}}^{\boldsymbol{0}}| - \boldsymbol{F^{max}}) \right\|_1 + \lambda_1 \| \boldsymbol{\pi_{N-k}} \cdot ReLU(|\boldsymbol{F^c}| - \boldsymbol{F^{max}}) \|_1 + \lambda_2 \left\| \sum \hat{\boldsymbol{P}}_{\boldsymbol{G}}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

$\boldsymbol{\pi_{N-k}}$ = 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

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



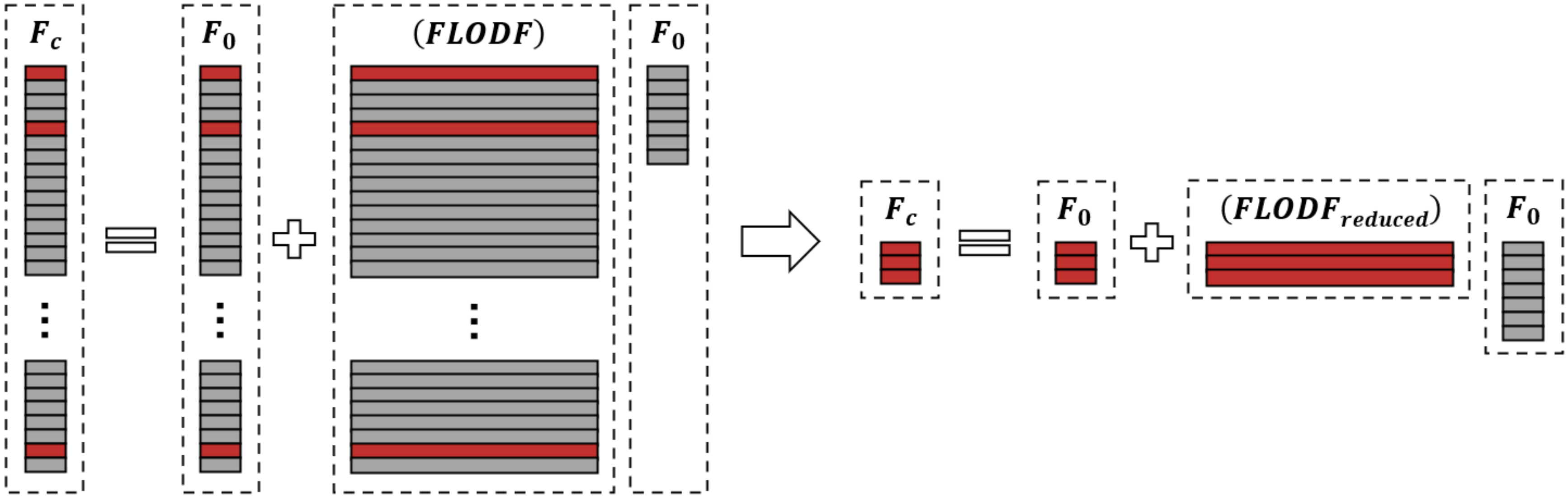
FLODF = ‘Full LODF’

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



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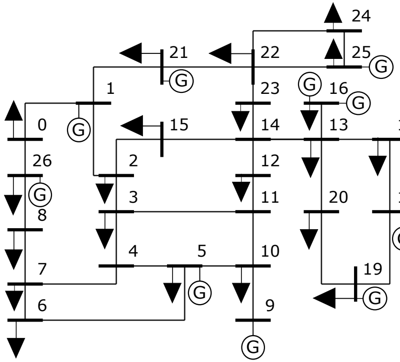
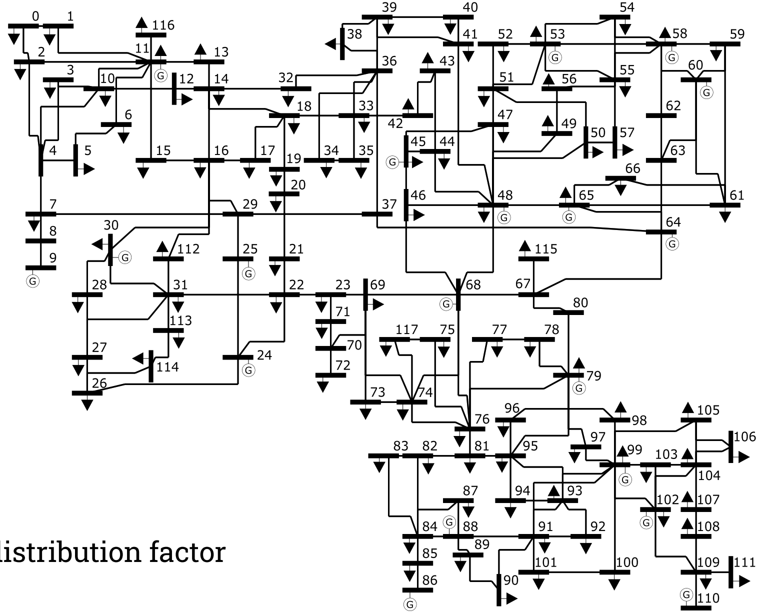
Case studies

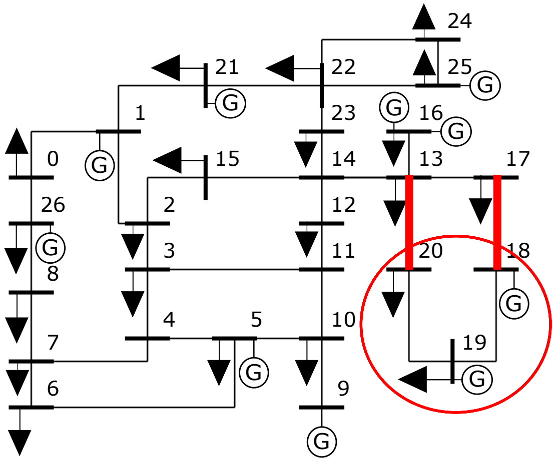
- IEEE 39-bus and 118-bus test systems
- k = {1,2,3}
- Baseline: iterative contingency screening with LODFs
- Code: https://github.com/TU-Delft-AI-Energy-Lab/Constraint-Driven-SCOPF

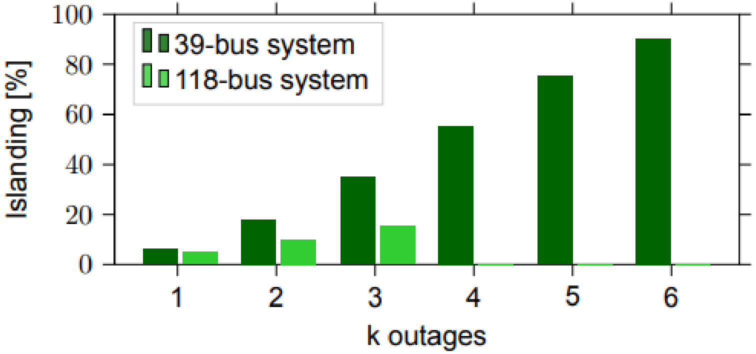




LODF = line outage distribution factor

Islanding

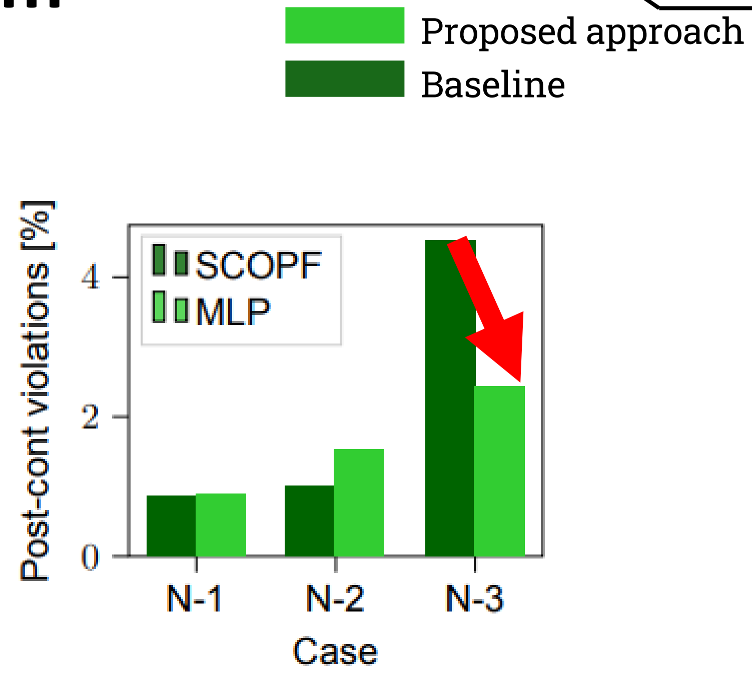




Removing islanding cases

Performance 118-bus system

- 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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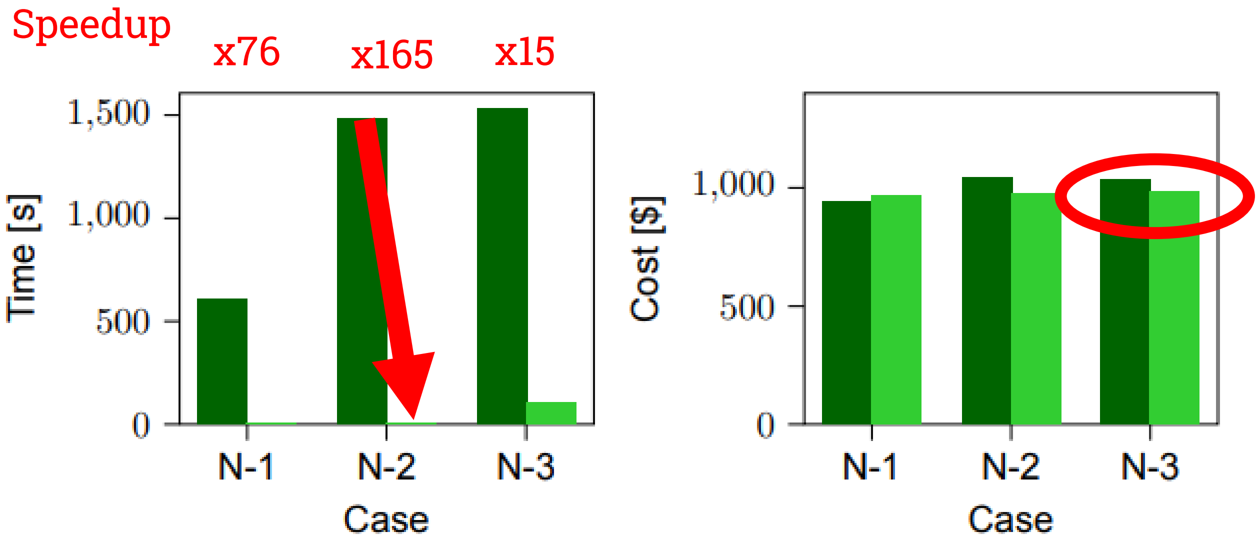
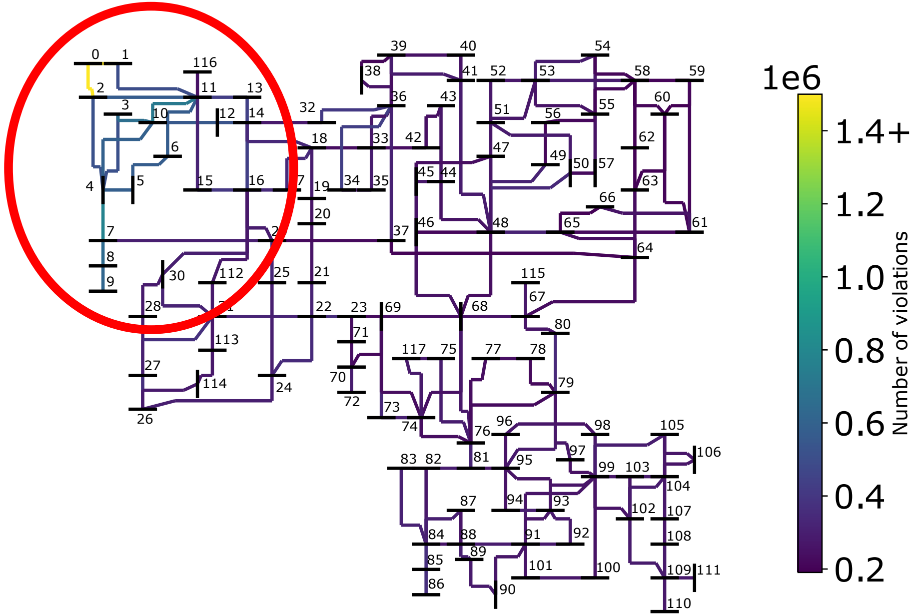
Performance 118-bus system

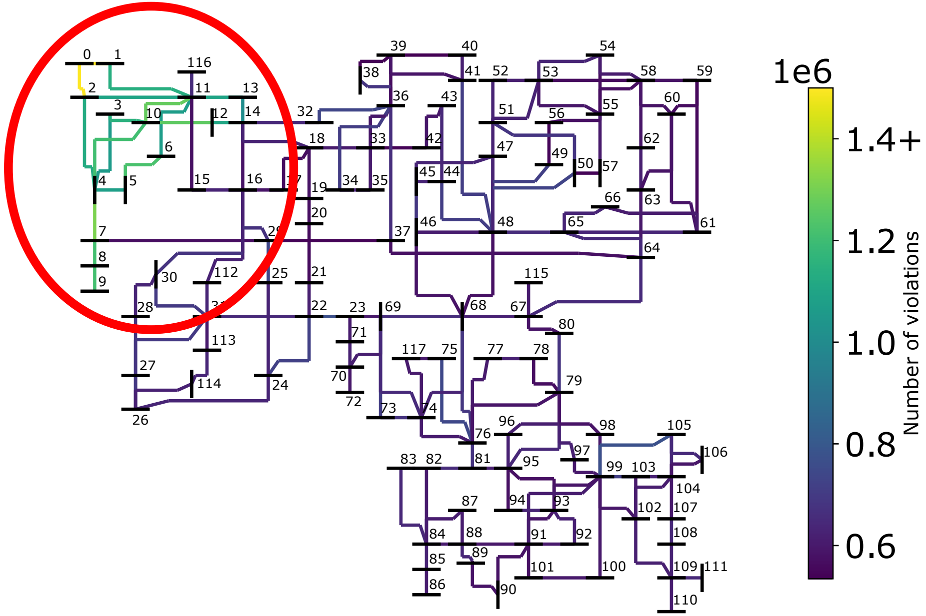


[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

N-3 proposed approach



N-3 baseline



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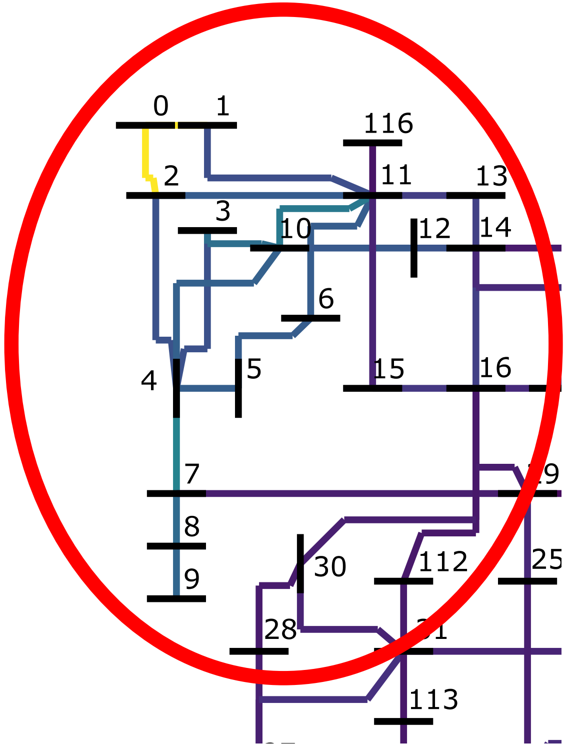
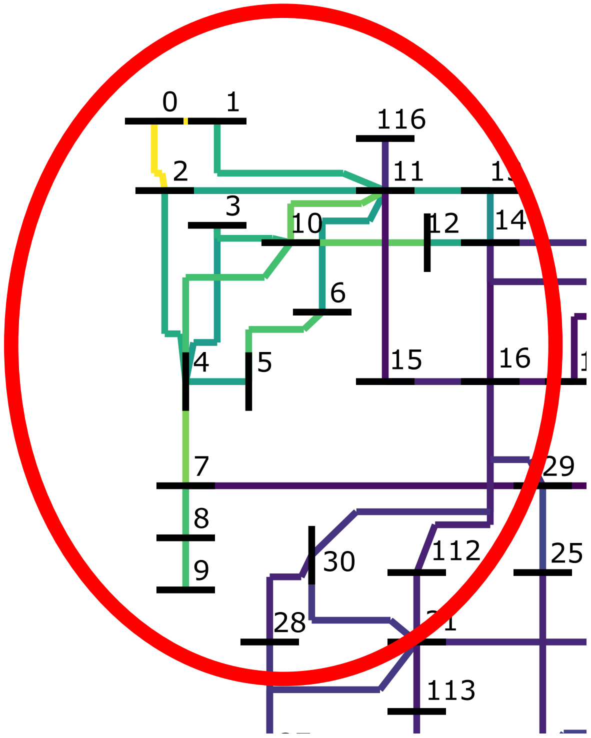
N-3 proposed approach





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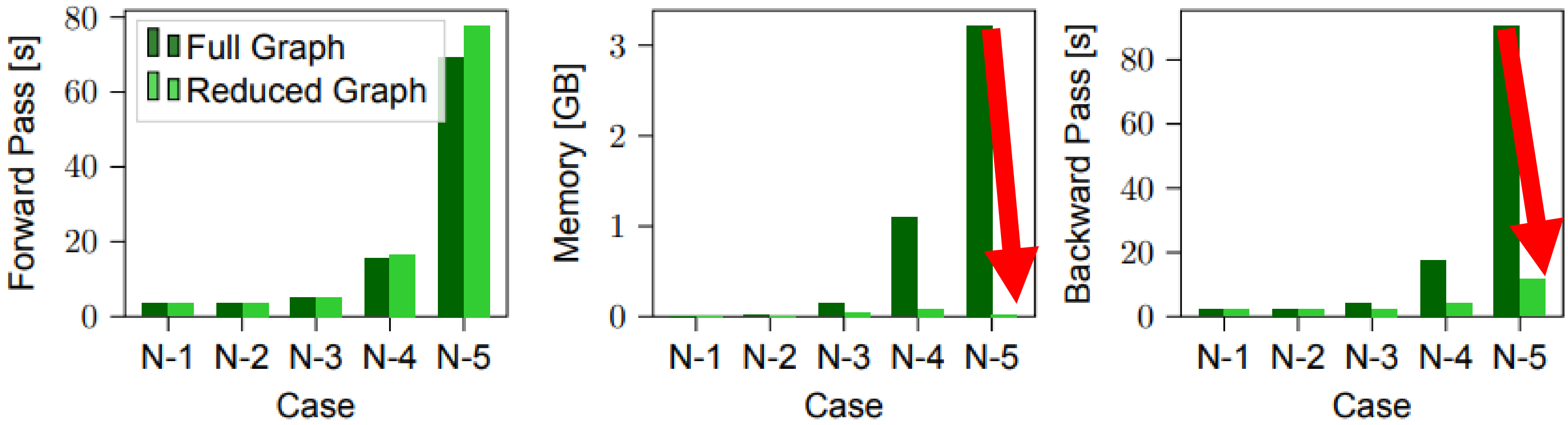
Reducing computational graph



Reduction in memory

Reduction in computation time

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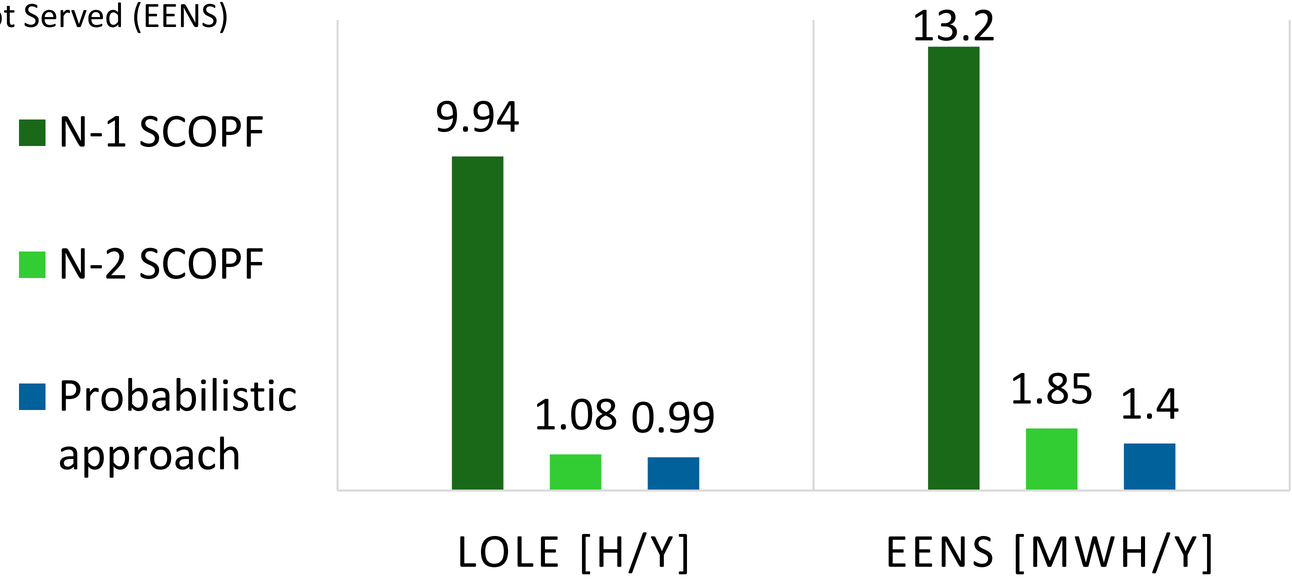
[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

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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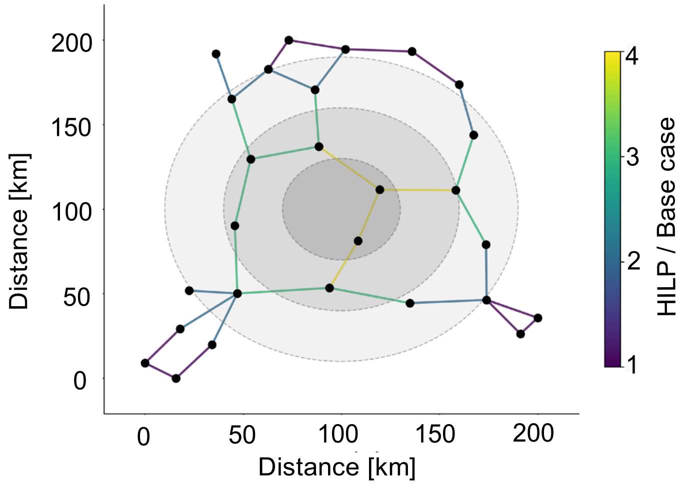
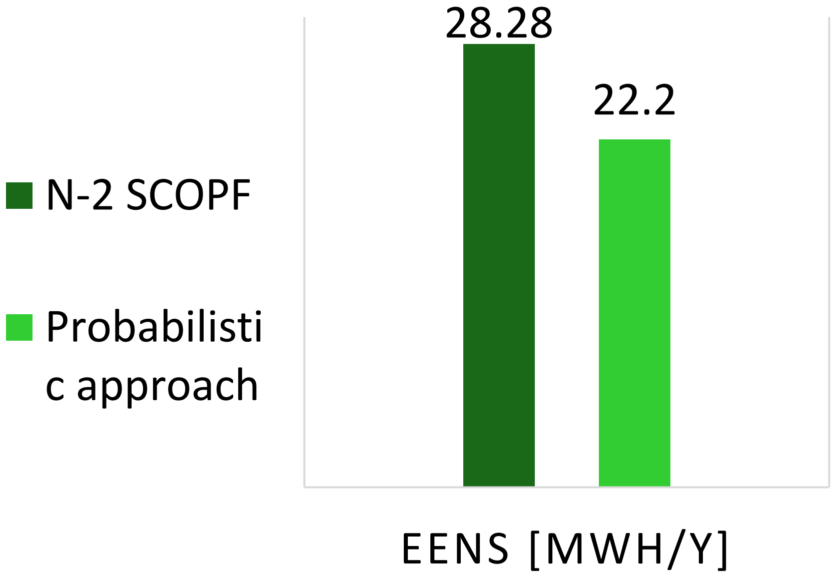
Extreme event

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

Potential for increased resiliency





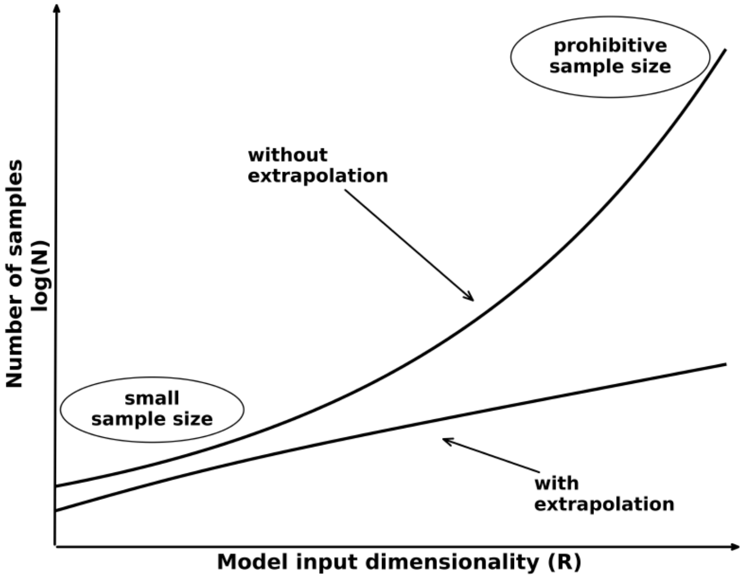
[16] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

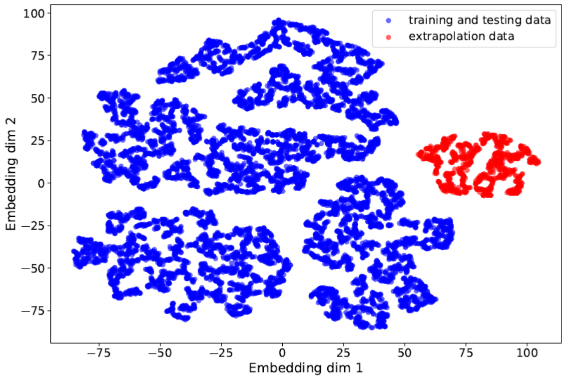
Outline

1. Introduction to reliability management
2. Machine learning approaches
3. Monitoring: Real-time dynamic security
4. Control: Weakly-supervised learning for N-k probabilistic, static security
5. Challenges applying ML to reliability

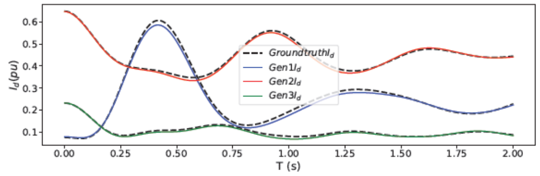
Generalisation to changes in s or m

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



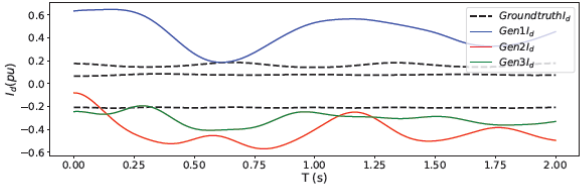


Extrapolation in continuous domain



(a) I_d current trajectory

Extrapolation in nonlinear domain (discrete)

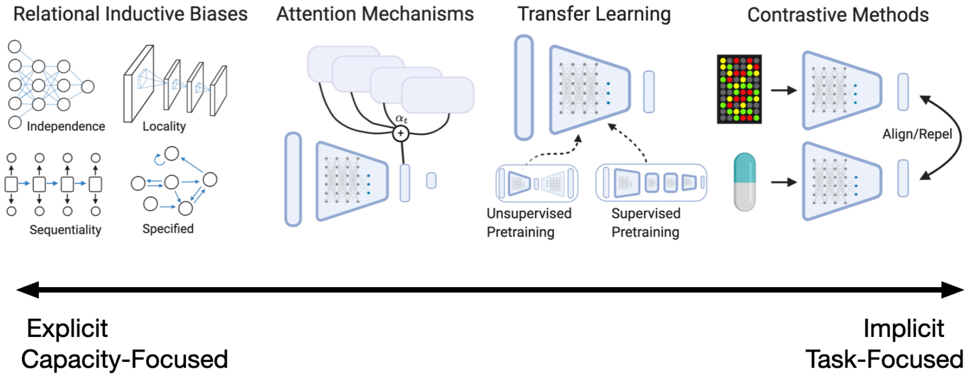


(a) I_d current trajectory

[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*

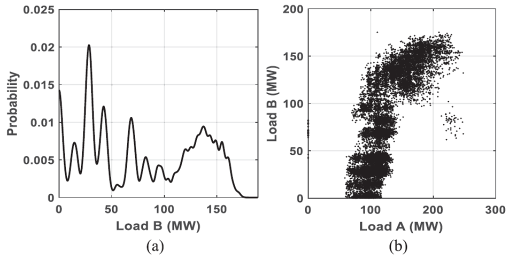
Challenge: Data-efficiency

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

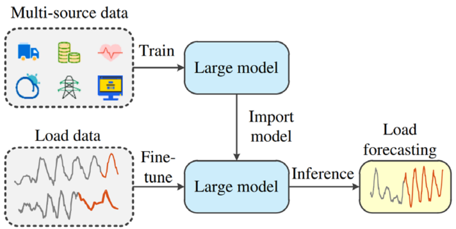


Sampling synthetic data & use real-data

Snapshot sampling



Time-series foundational models



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[27] Al-Amin Bugaje, Jochen L. Cremer, Goran Strbac, “Split-based Sequential Sampling for Realtime Security Assessment”, *International Journal of Electrical Power & Energy Systems, 2022*
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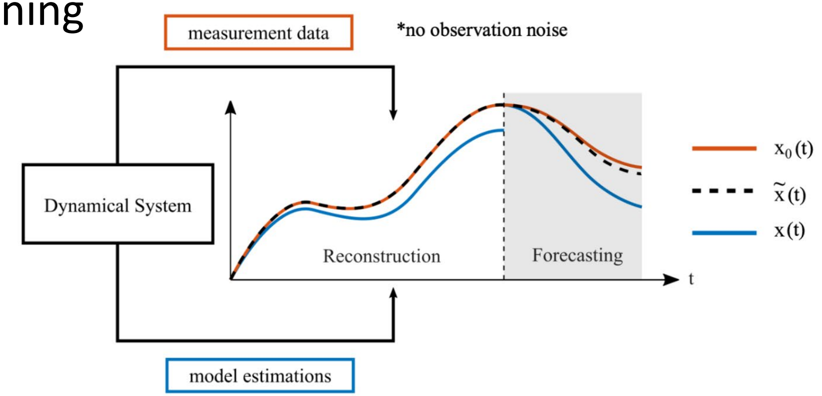
Model inaccuracy $s \neq m$ (data quality issues)

"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



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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

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Goran Strbac

Bastien Giraud

Ali Rajaei

TU Delft

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

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- 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.
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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

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