All AI models are wrong, but some are useful … for power systems

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Credits & team

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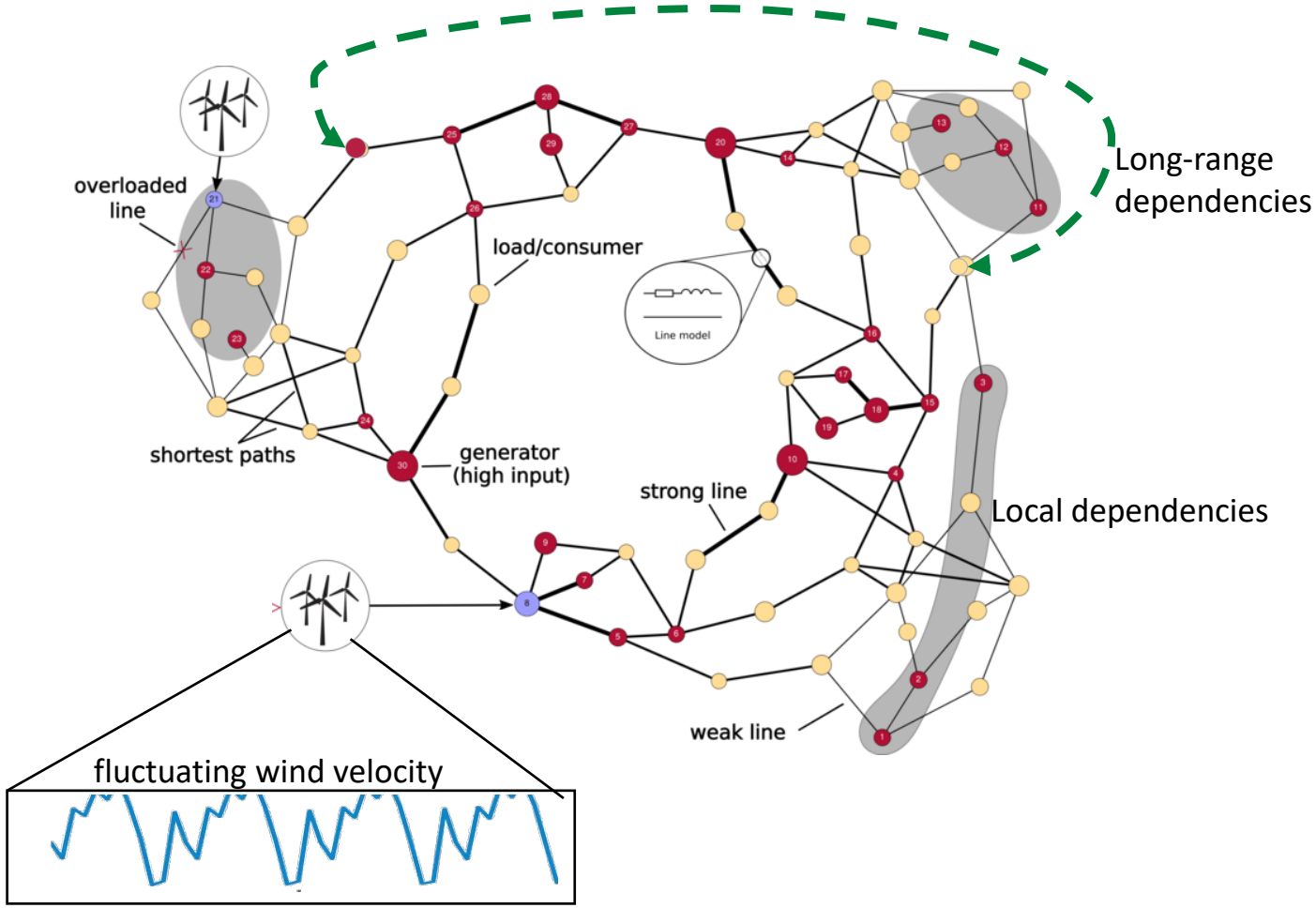
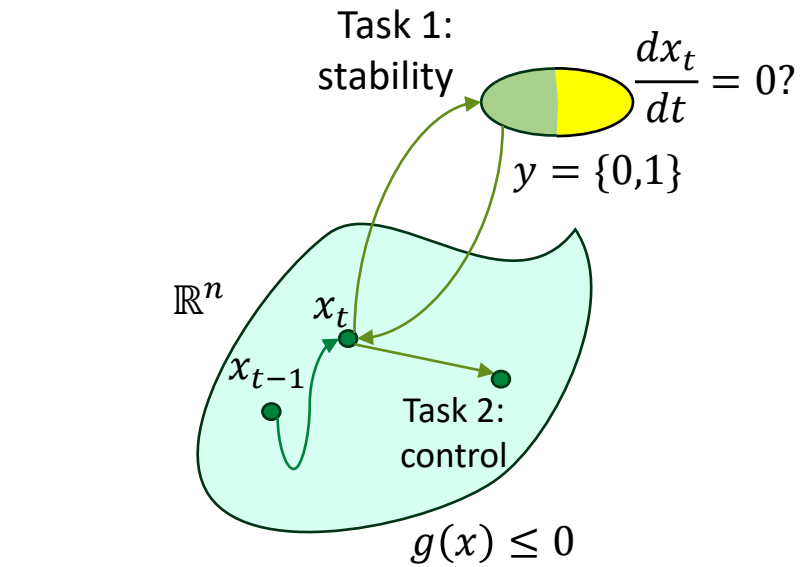
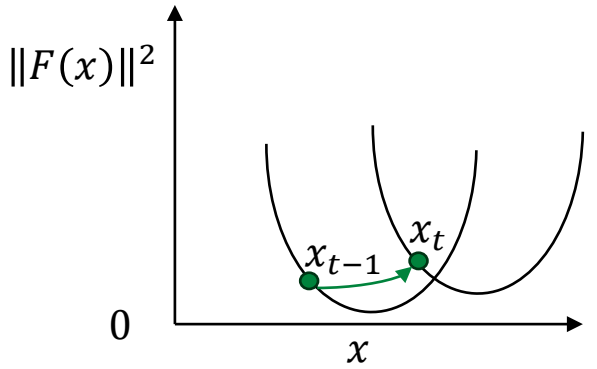
"All models are wrong, but some are useful", George E. P. Box

Simplifying complex systems like the grid

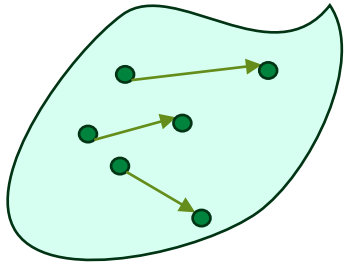






Supervised Learning for Surrogate Models

Notation: Power system s, model m, parameter x



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

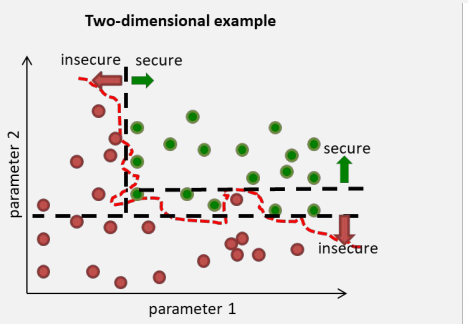
Surrogate approach

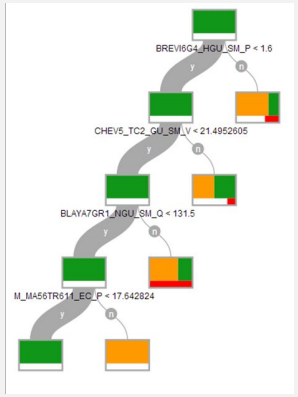
1. Generate a training dataset $\Omega^T = \{(x_i, y_i)\}_{i=1}^N$ where $y_i = m(x_i)$ from the full simulator
2. Train surrogate $f(x) \rightarrow \hat{y}$ with supervised loss $\sum_{i \in \Omega^T} \|y_i - \hat{y}_i\|$
3. Use $f(x_j)$ for new j $\notin \Omega^T$

Benefit: speed at inference

Applications

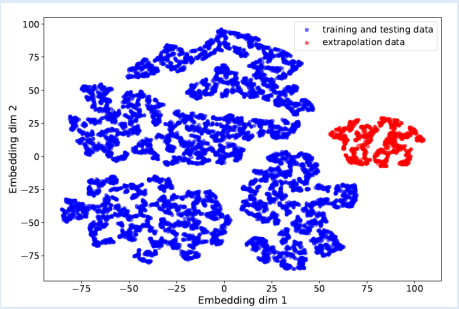
- Real-time dynamic security assessment ([1,2] and many others)





Challenges

- Out of distribution risks: What if s and m changes? e.g., topology changes
- What if the model is uncertain $s \neq m$? e.g., inverter-based controls
- Need large, representative training data



[1] Wehenkel, Louis, and Mania Pavella. "Decision trees and transient stability of electric power systems." *Automatica* 27.1 (1991): 115-134.
[2] 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.
[3] 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 generalisation

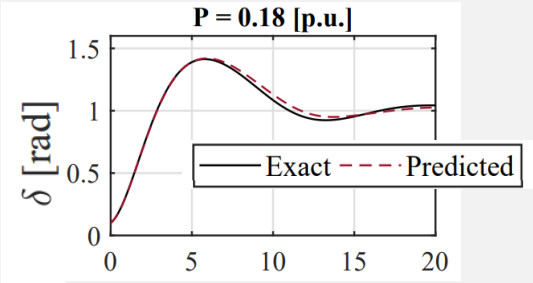
Physics-informed approach

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**

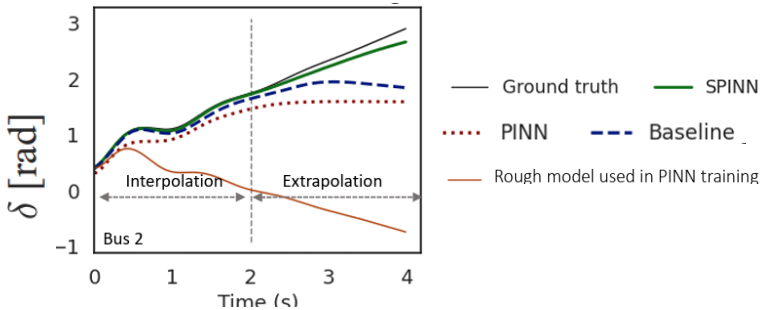
Applications

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



Challenges

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



[4] 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

[5] Stiasny, Jochen, Baosen Zhang, and Spyros Chatzivasileiadis. "PINNSim: A simulator for power system dynamics based on physics-informed neural networks." Electric Power Systems Research 235 (2024): 110796.

[6] 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.

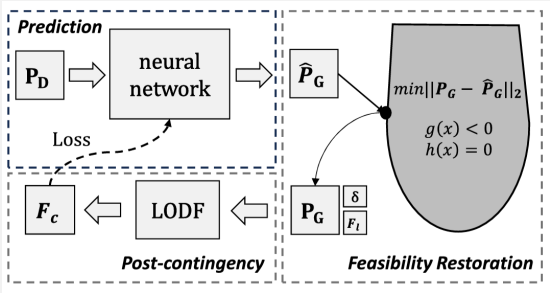
Approach

1. Generate many inputs $\Omega^T = \{(x_i)\}_{i=1}^N$
2. Model task loss $\sum_{i \in \Omega^T} \mathcal{L}(\tilde{m}(f(x_i))$
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[7]
- Replace conventional solvers with NN [8]
- Distribution system state estimation [9]
- N-k security constrained OPF [10]



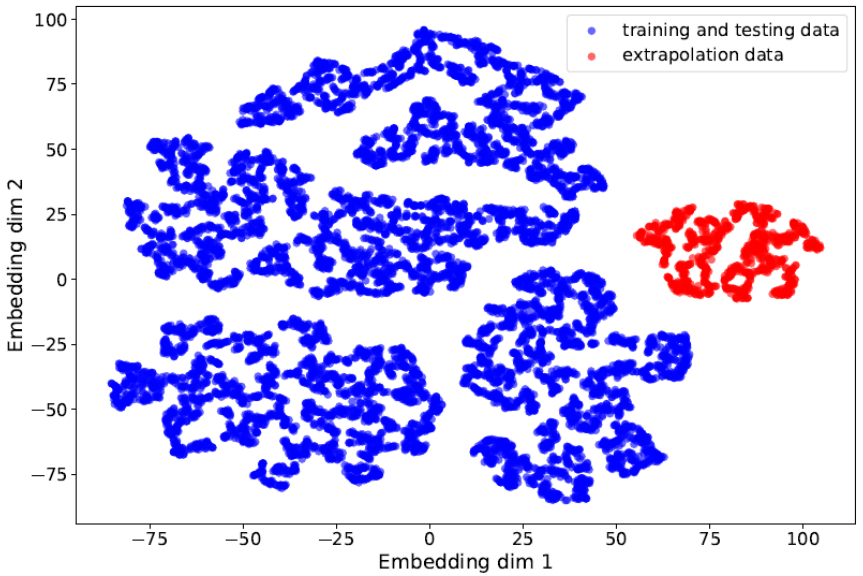
Challenges

- 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 generalisation

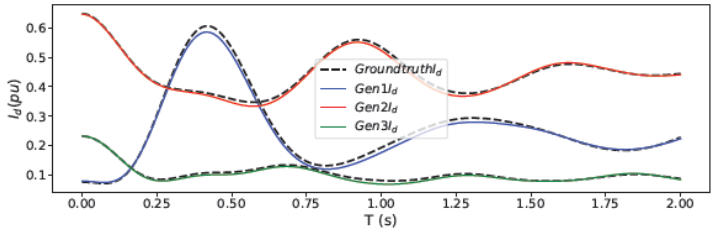
[7] Donti, P., Amos, B., & Kolter, J. Z. (2017). Task-based end-to-end model learning in stochastic optimization. *Advances in neural information processing systems*, *30*.
[8] Donon, B., Liu, Z., Liu, W., Guyon, I., Marot, A., & Schoenauer, M. (2020). Deep statistical solvers. *Advances in Neural Information Processing Systems*, *33*, 7910-7921.
[9] 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.
[10] 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.

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.*

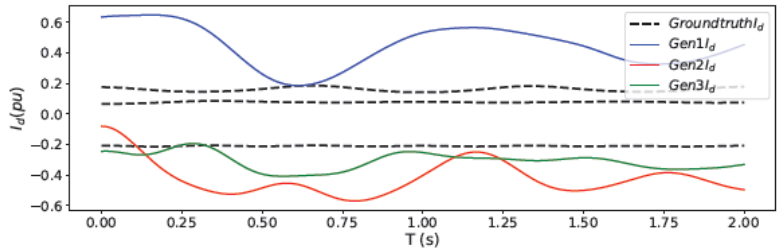


Extrapolation in continuous domain



(a) I_d current trajectory

Extrapolation in nonlinear domain (discrete)

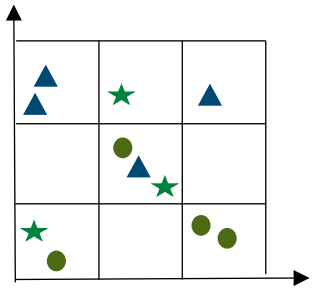


(a) I_d current trajectory

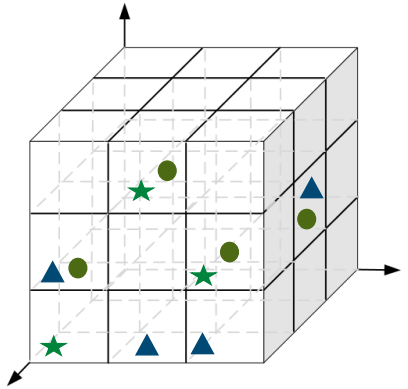
[11] Olayiwola Arowolo, Jochen Stiasny, Jochen Cremer, "Exploring the Extrapolation Performance of Machine Learning Models for Power System Time Domain Simulations", *12th Bulk Power System Dynamics and Control Symposium and Sustainable Energy, Grids and Networks Journal, 2025*

Curse of Dimensionality

1d: 3 regions



2d: 3^2 regions



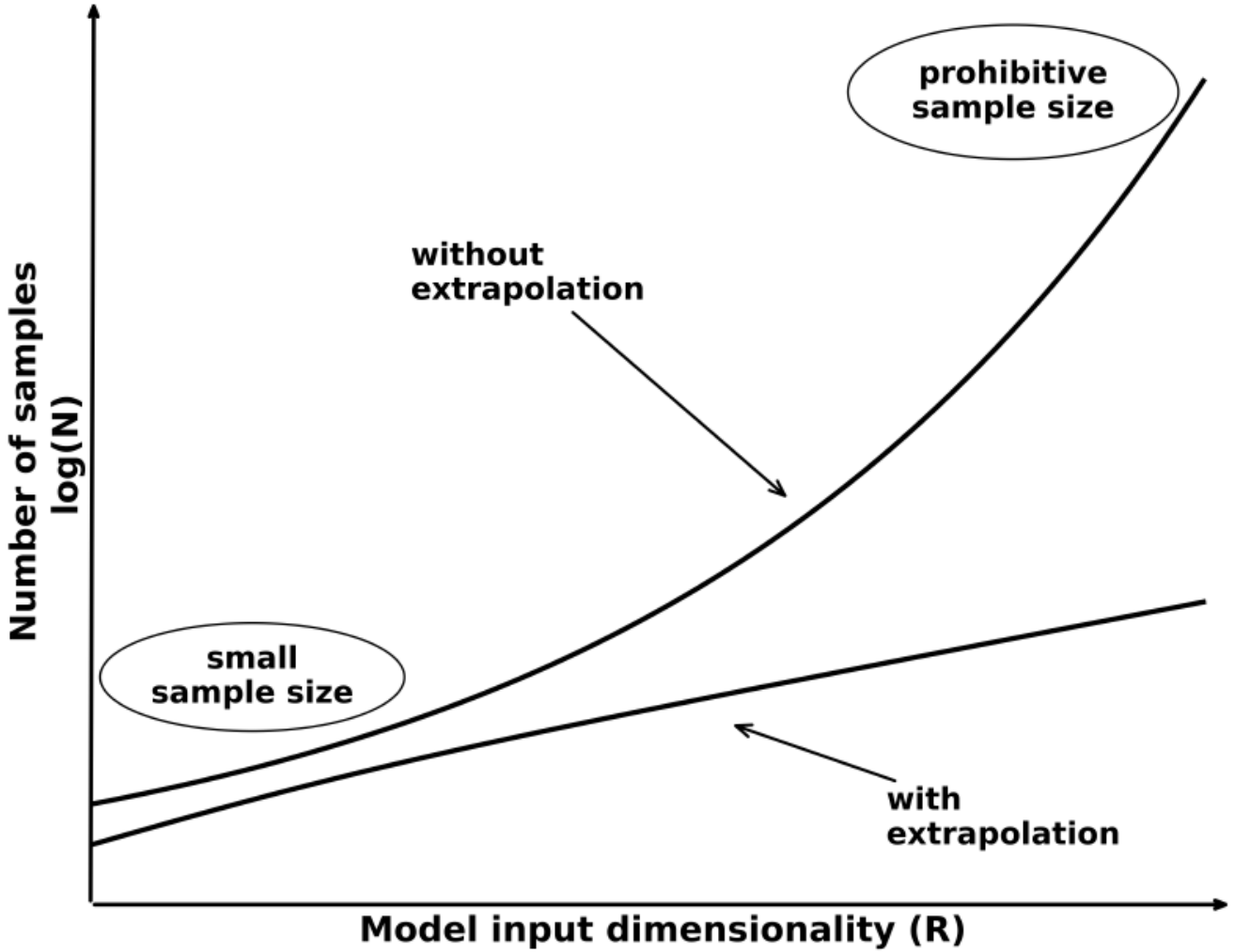
3d: 3^3 regions

1000d: hopeless

As dimensionality grows: fewer samples per region.

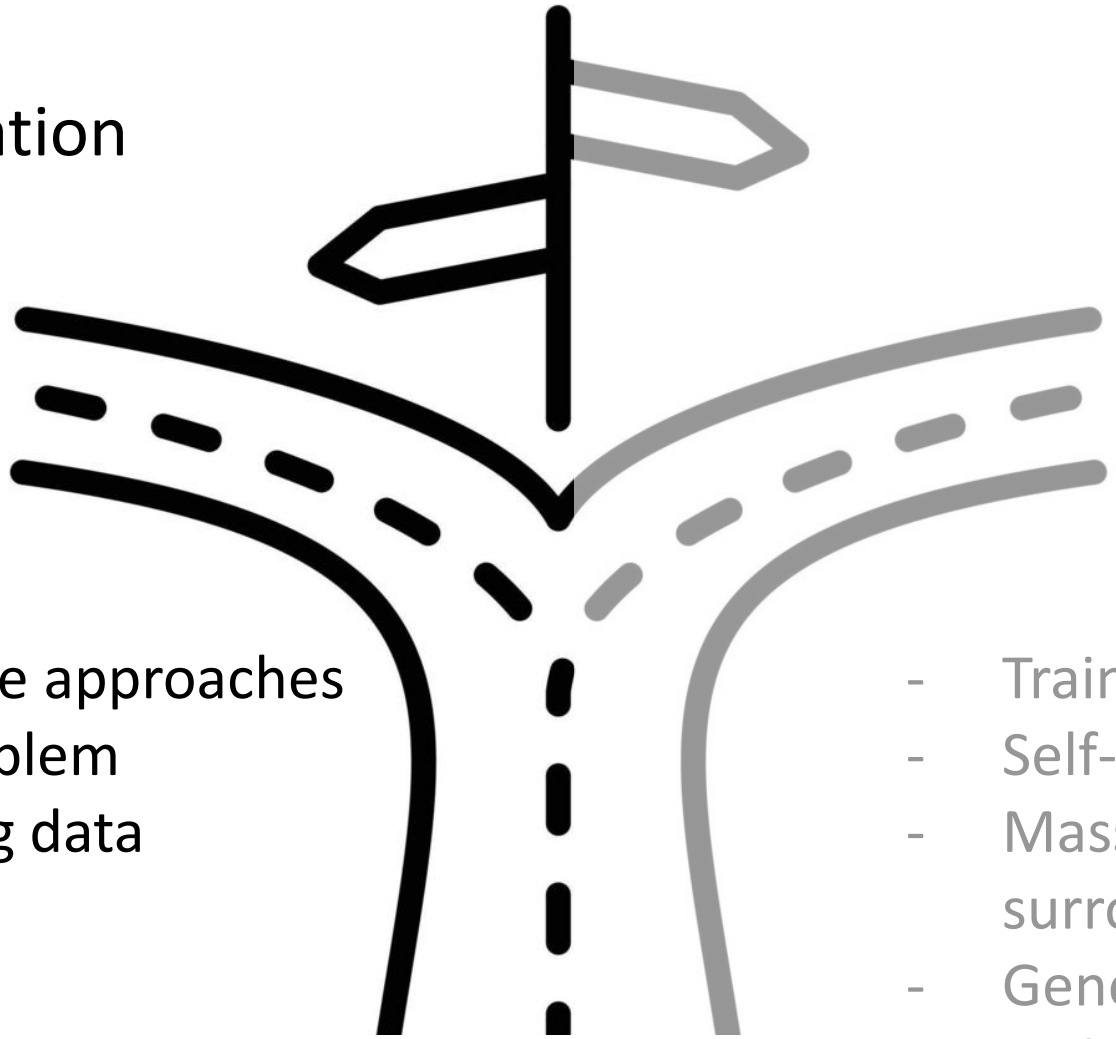
[12] James, Gareth, et al. *An introduction to statistical learning*. Vol. 112. No. 1. New York: springer, 2013.

Priority: think about extrapolation



Power systems ML research at a crossroad

Task specialisation



- Supervised-type approaches
- Exploit the problem
- Limited training data
- Hybrids…

Foundation models

- Trained for broad use
- Self-supervised learning
- Massive amount of ‘cheap’ surrogate data
- Generalisable model architecture…

Security constrained optimal power flow (SCOPF)

Objective:	minimize cost
Constraints:	In = out
	Generator limits
	Line flow limits
Contingency Constraints:	Line flow limits

$$\min_{n \in \Omega^G} \Sigma \, c_n P_{G_n}$$

$$\boldsymbol{B \cdot \delta = P_G - P_D}$$

$$P_{G_n}^{min} < P_{G_n} < P_{G_n}^{max} \; \forall n \in \Omega^G$$

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

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

Combinatorial complexity

Conventional approaches

Outaged line

Line flow changes

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

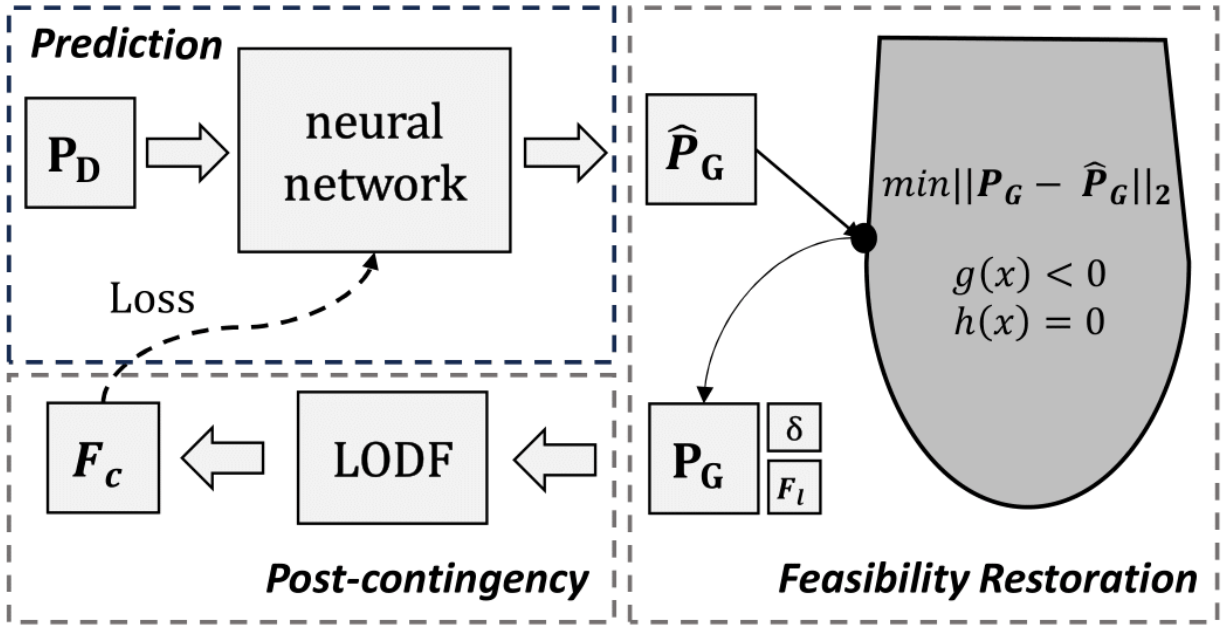
- Benders decomposition
- Column and constraint generation algorithm with robust optimization
- Line outage distribution factors (**LODF**)

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

- Intractable for increasing k

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

Proposed constraint-driven approach



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

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

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

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

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

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

[14] J. L. Cremer, "Polynomial Line Outage Distribution Factors for Estimating Expected Congestion and Security," *in IEEE Transactions on Power Systems,* vol. 40, no. 3, pp. 2532-2544, May 2025

Performance

Two baselines

- Contingency screening (CS) baseline: the N-k SCOPF optimization with iterative CS. At each iteration, the 20 most critical contingency cases are added to the SCOPF. We repeat the CS for 3 iterations.
- Heuristic (H) baseline: a set of critical contingency set is created offline on a separate dataset. The N-k SCOPF optimization is solved considering only this set of critical contingencies.

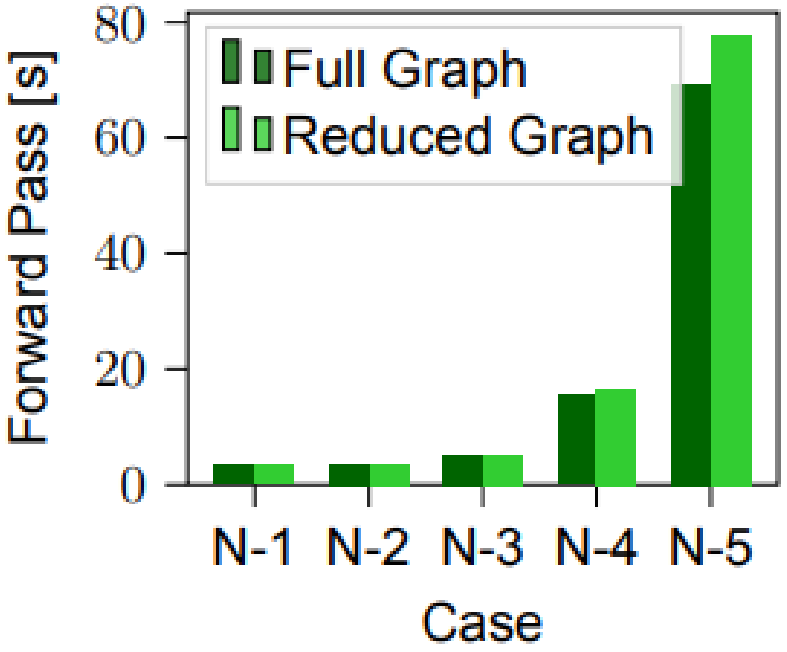
		39-bus		118-bus	
		Cost [%]	Speedup	Cost [%]	Speedup
CS	N-1	+1.44	12×	+2.51	158×
	N-2	+1.17	49×	−6.13	173×
	N-3	+0.51	41×	−5.29	27×
H	N-1	+1.45	15×	+2.88	76×
	N-2	+1.22	21×	−6.41	165×
	N-3	+0.10	21×	−4.92	15×

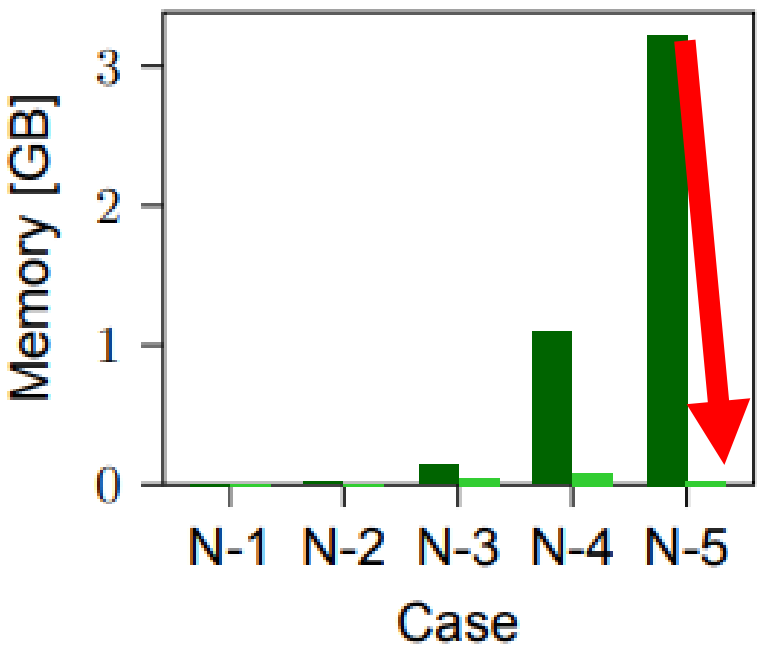
Post-contingency

System	Model	#violations [%]		
		N-1	N-2	N-3
39-bus	Proposed approach	0.31	1.33	2.16
	CS	0.06	0.74	3.30
118-bus	Proposed approach	1.08	1.70	2.64
	CS	0.91	1.03	5.88

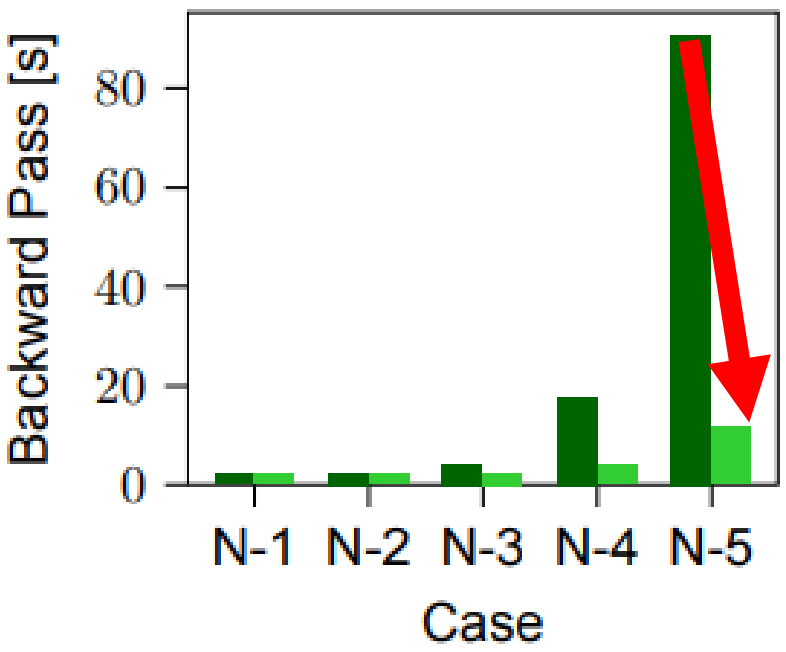
[13] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for n-k security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Reducing computational graph





Reduction in memory



Reduction in computation time

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

Power systems ML research at a crossroad

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- Limited training data
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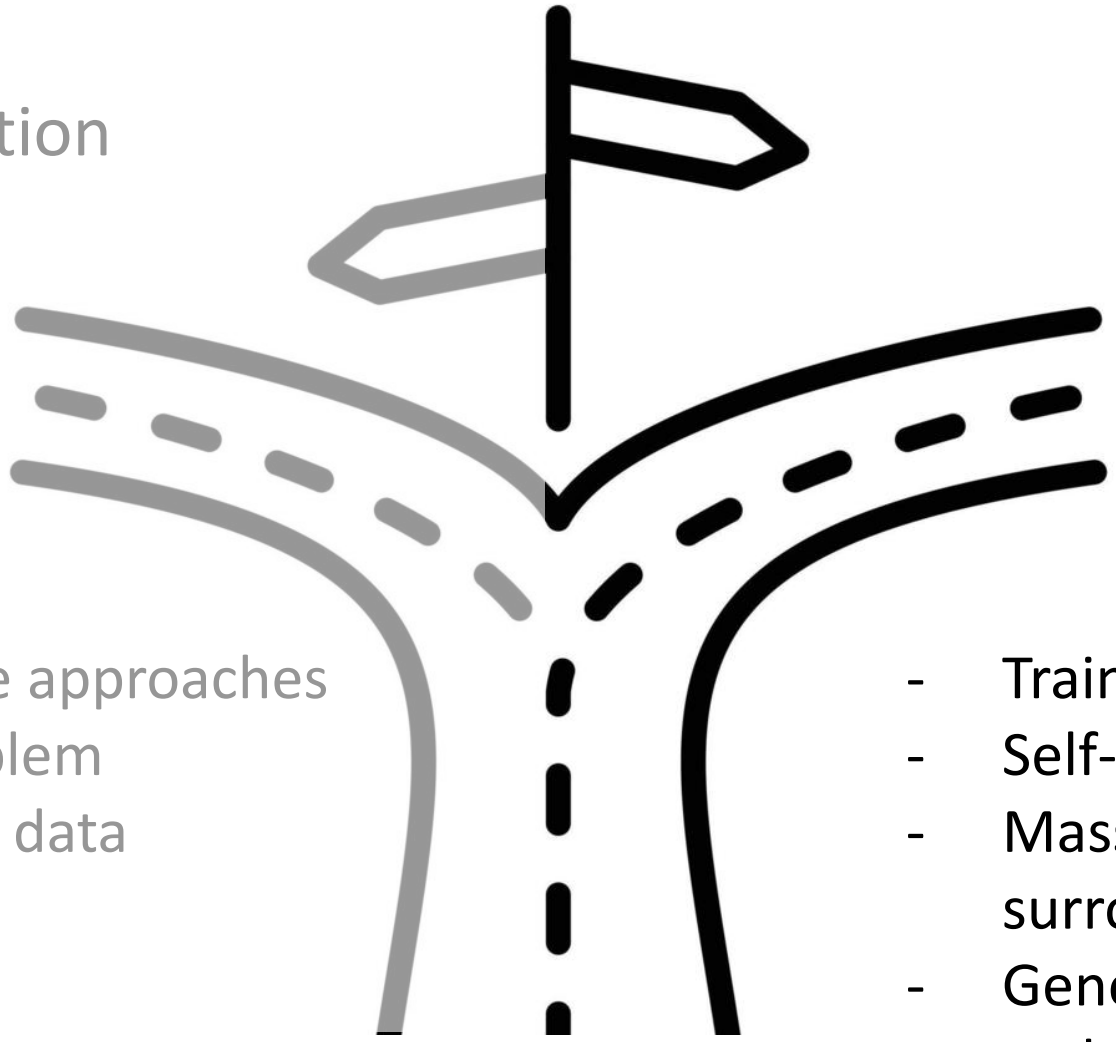

Foundation models

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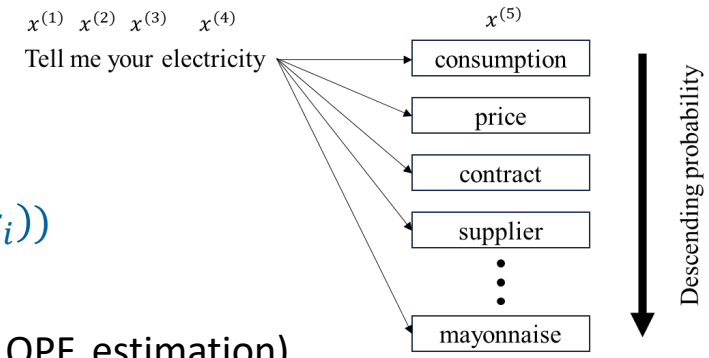
- Massive amount of ‘cheap’ surrogate data
- Generalisable model architecture…

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)

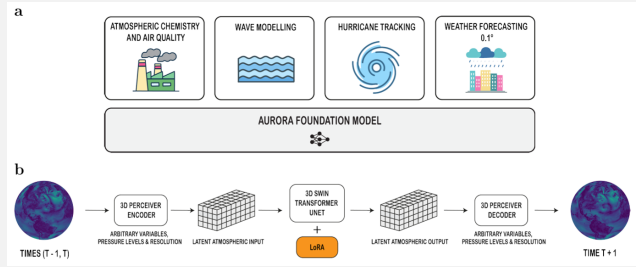
Benefits: Good initialisation when little data, good transfer to downstream tasks

Challenges

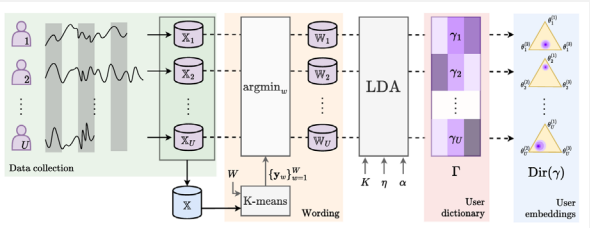
- Design pretext loss and model architectures with broad set of tasks, grid conditions, topologies
- Generate large data sets
- …

Applications

- Natural Language Processing
- Weather foundational models
- Earth system foundational models [13]



Load forecasting of users [14]



Grid foundation models (GFM) [15]

[15] 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*.
[16] Bölat, K., & Tindemans, S. (2024). GUIDE-VAE: Advancing data generation with user information and pattern dictionaries. arXiv preprint arXiv:2411.03936.
[17] 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.

We got a long way in other domains like images…

Prompt: “Take the picture and turn into a summer vibe with great swimming pool and a slide”, ChatGPT5.2, 11-02-2026

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

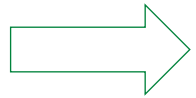
Those are the network parameters to be learned

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

Filter 1 Matrix

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

Filter 2 Matrix

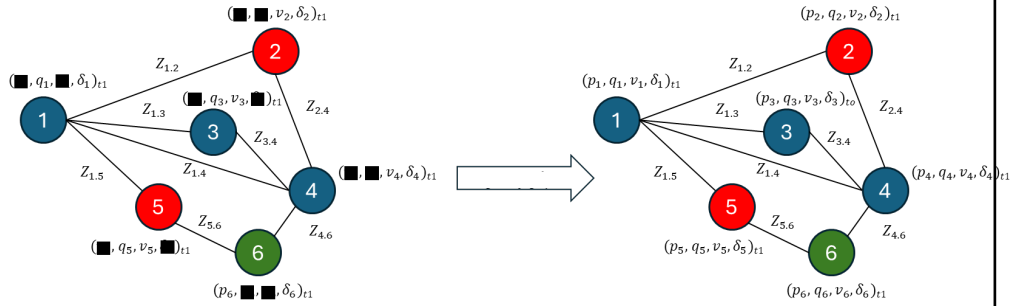
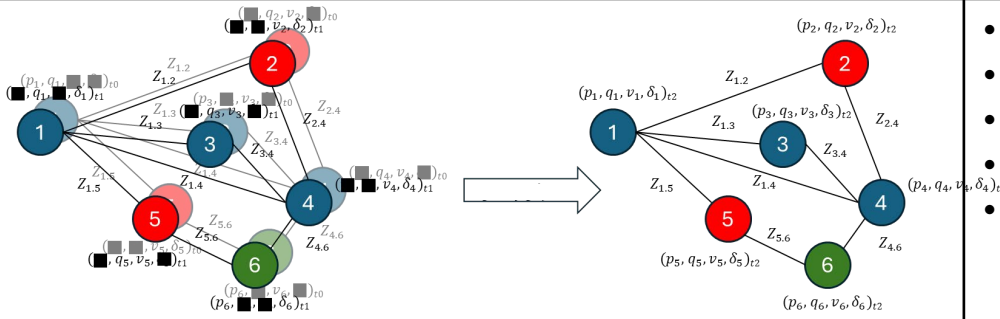
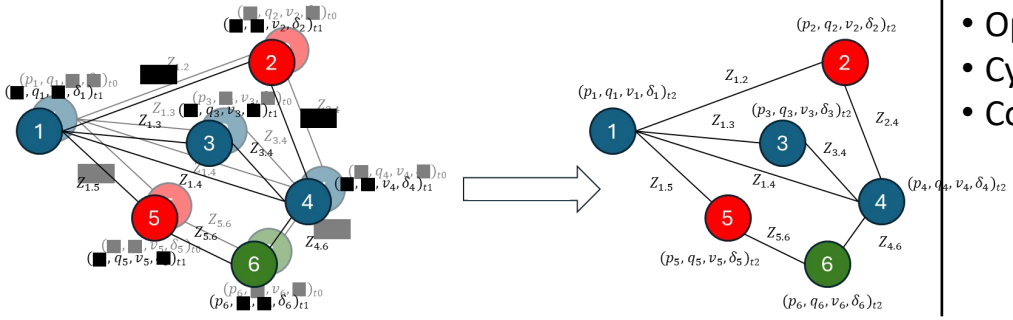


3	-1	-3	-1
-2	1	-1	-3
-2	-4	0	1
-1	0	-2	-1

Each filter detects a small pattern (3 x 3)

[18] LeCun et al. (1990) Handwritten digit recognition with a back-propagation network. In Advances in neural information processing systems.

Self-supervision

#	Pre-training	Related Applications
1	**Bus value Reconstruction** 	• Load flow • State estimation • (N-k) Contingency Analysis with k>1 • Expansion scenarios • (Optimal Power Flow)
2	**+ Temporal Reconstruction** 	• Load forecasting • Renewable energy forecasting • Look-ahead power flow • Look-ahead state transition • (Transient stability analysis)
3	**++ Edge Reconstruction** 	• Optimal expansion planning • Cybersecurity • Control operations

** IBM, Research Foundation Model Workshop Argonne, February 2025,*

Power Flow is at the heart of many power system tasks
How should we formulate a foundational PF?

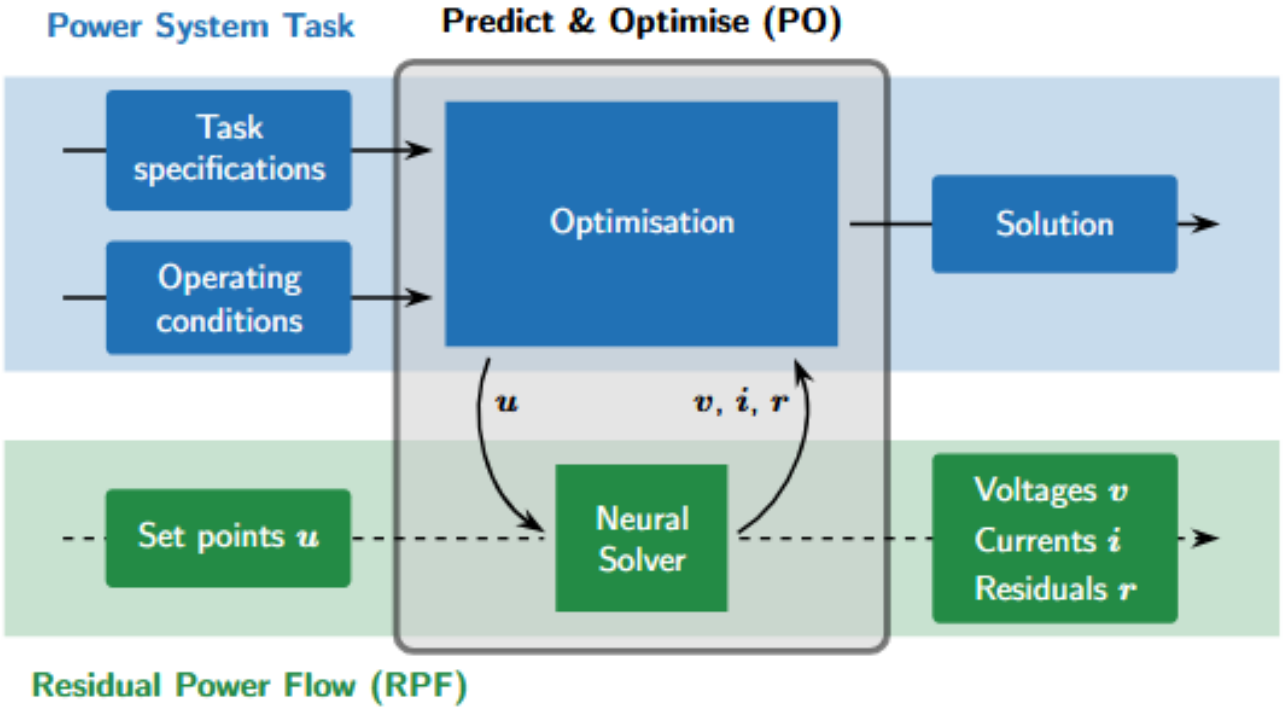
Jochen Stiasny

Residual power flow (RPF)

- RPF quantifies infeasibility
- Simpler formulation for neural solvers

Predict-and-Optimise (PO)

- Flexible handling of constraints and objectives
- While minimising infeasibility



[24] 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.
[25] Stiasny, Jochen, and Jochen Cremer. "Residual Power Flow for Neural Solvers." arXiv preprint arXiv:2601.09533 (2026).

Conclusions

- All models are approximations: usefulness depends on structure and aligning with task
- Purely supervised surrogates struggle with system shift and dimensionality
- Injecting structure (physics, constraints, topology) improves generalisation
- Constraint-driven learning may enable scalable security-constrained optimization
- Foundation-style approaches are promising, however, power systems require domain bias
  - -> The “Power System Neural Network” still needs to be invented…
  - -> Power flow may be the right abstraction for building grid foundation models

Thank you

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Graph Neural Networks as architecture?

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

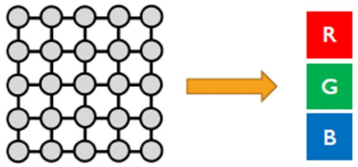
Idea: embedding graph topology directly into the model architecture as bias

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'

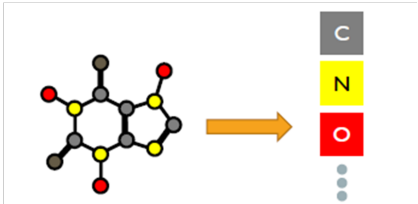
Benefits: Data efficient, generalisation to changes in topologies

Example: $p \times p$ RGB image



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

Example: molecular graph

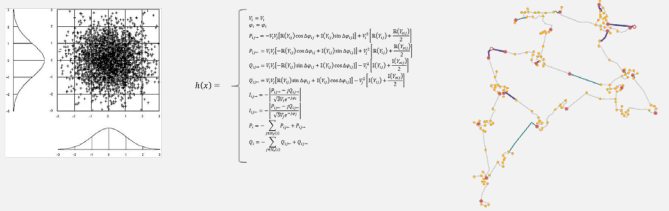


$\Omega = \{1, .. n\}$ $\quad \mathcal{C} = \mathbb{R}^c$

Applications

- Graph neural solvers [19] for ACOPF [20,21], powerflow [22]
- Distribution system state estimation [23]

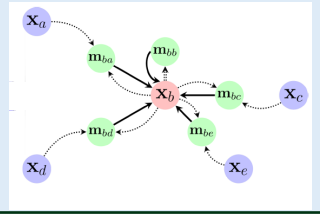
Noisy measurements | Power flow equations | Topology



Challenges

- Model uncertainty $s \neq m$
- 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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