Weakly-Supervised, Strongly Reliable: Machine Learning Challenges for Secure Energy Operations

DACH Energy Informatics 2025, Aachen

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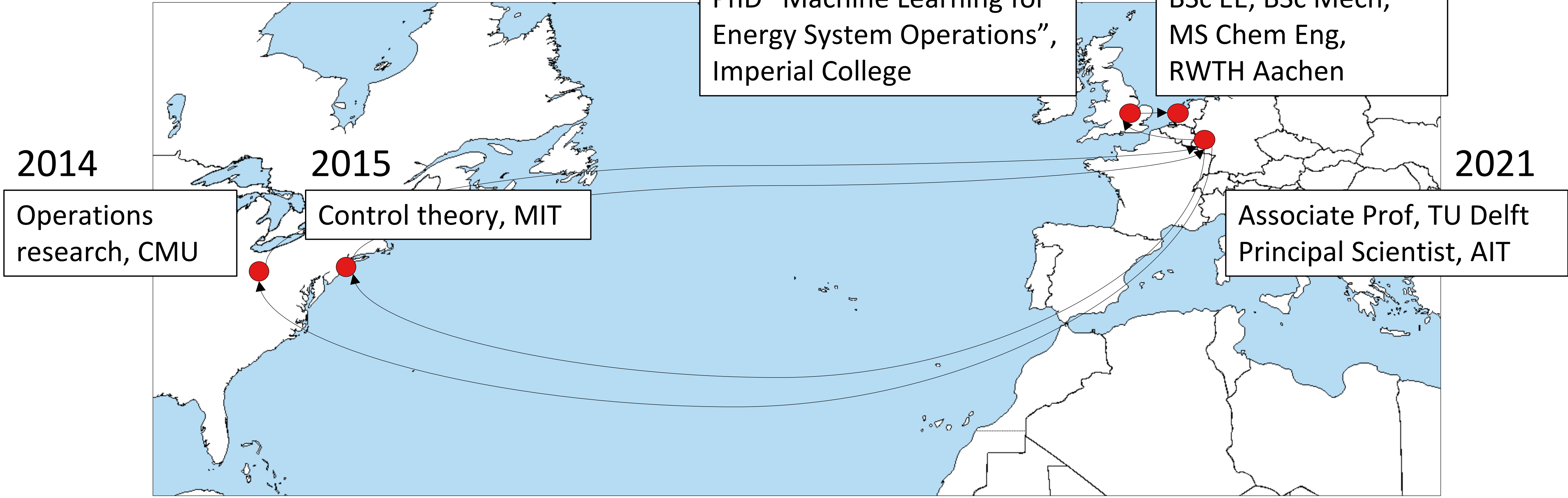
Introduction



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

DAIEnergyLab

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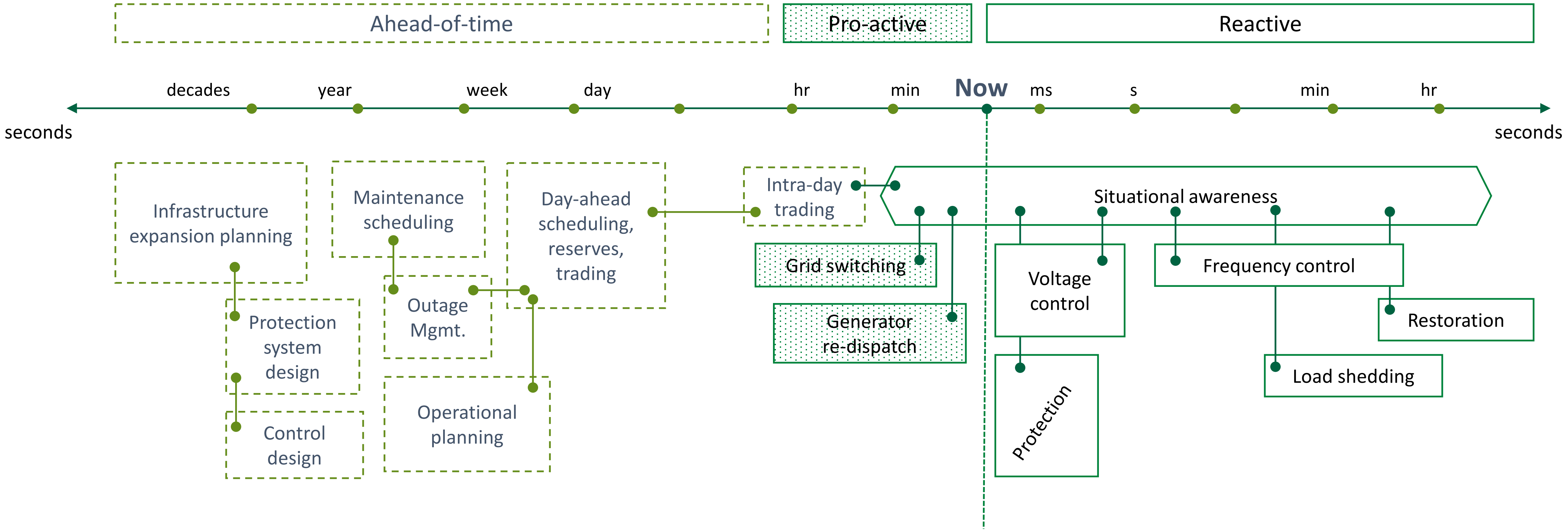
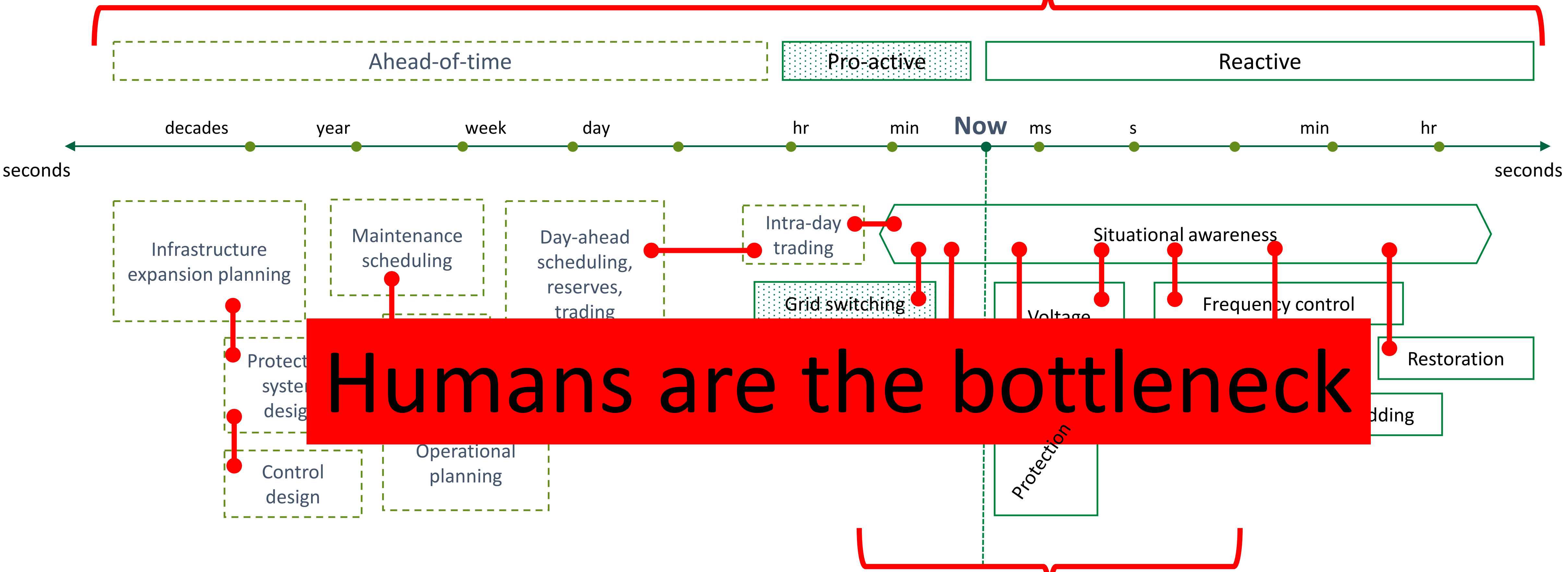
Experts are in charge to manually operate the power system based on **experience** and with **the support of tools**

A complex process



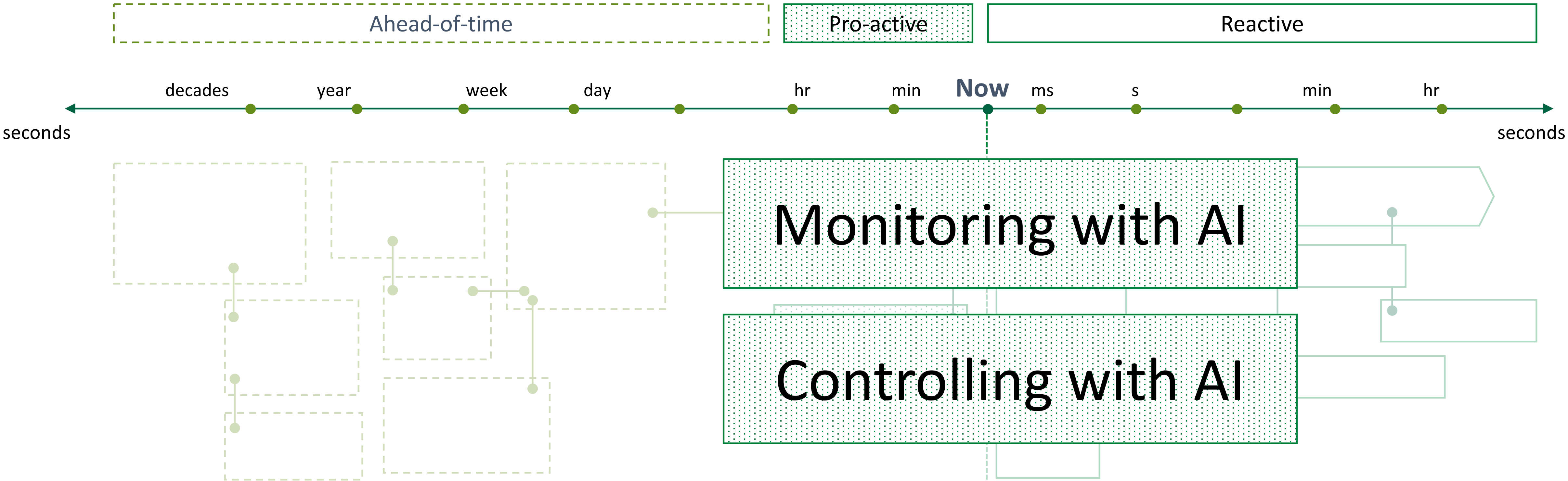
What's the issue?

Interdependencies challenge manual rules

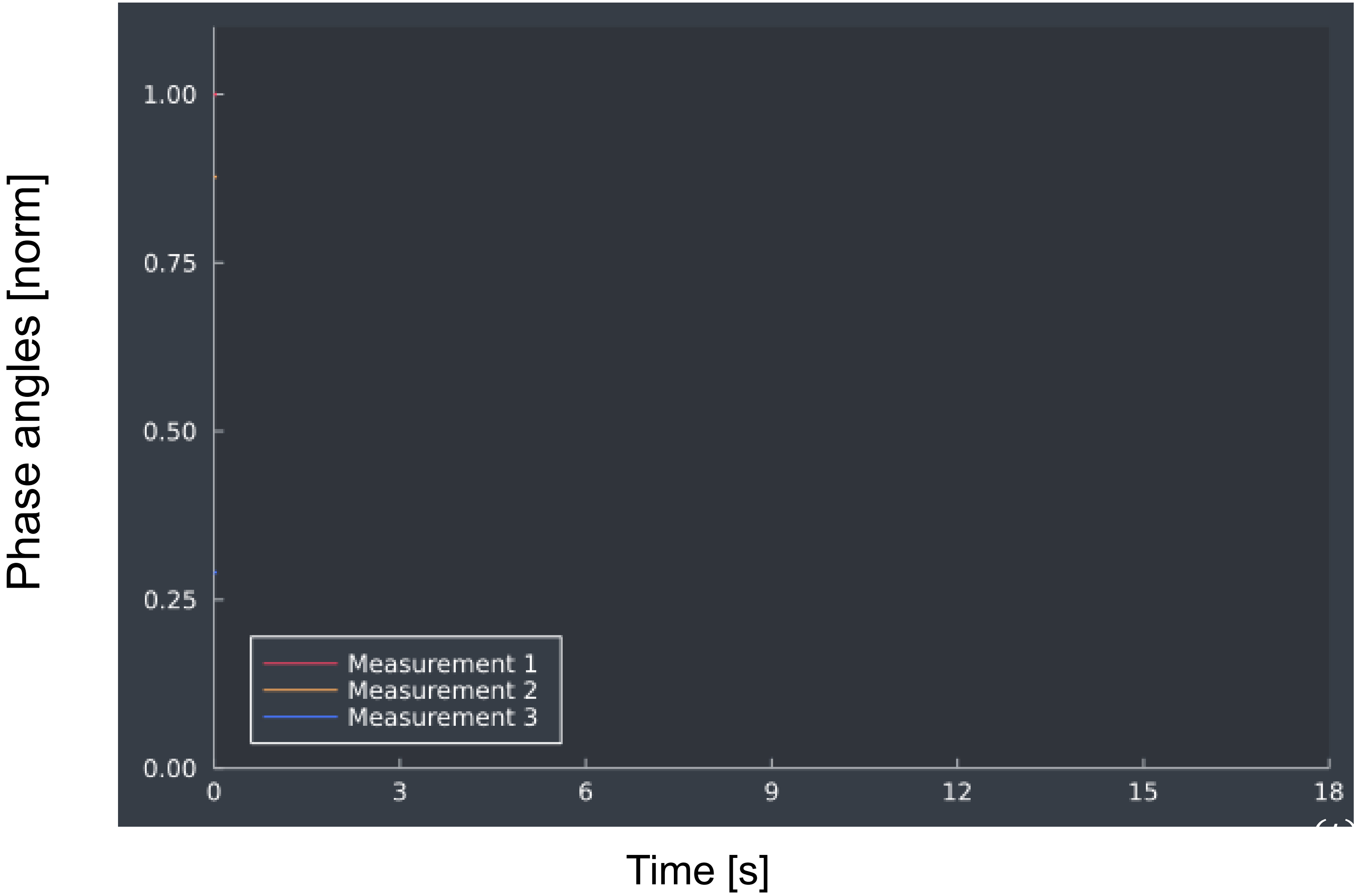


Human decisions are too slow

Automation first realised where urgently needed

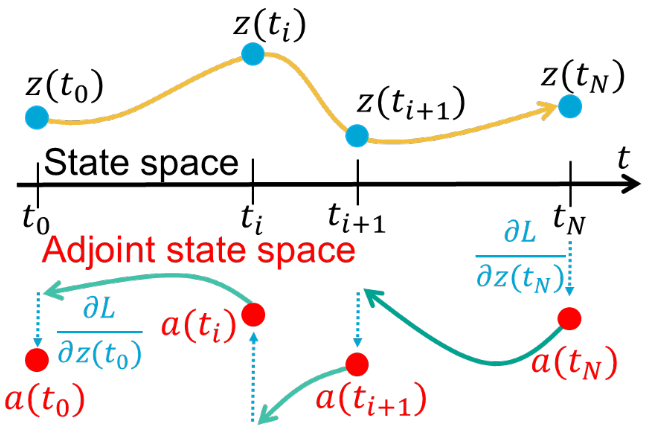


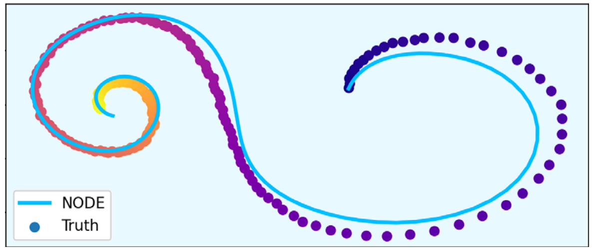
Real-time security assessment of disturbances



Mert Karaçelebi
https://mert-node.vercel.app/

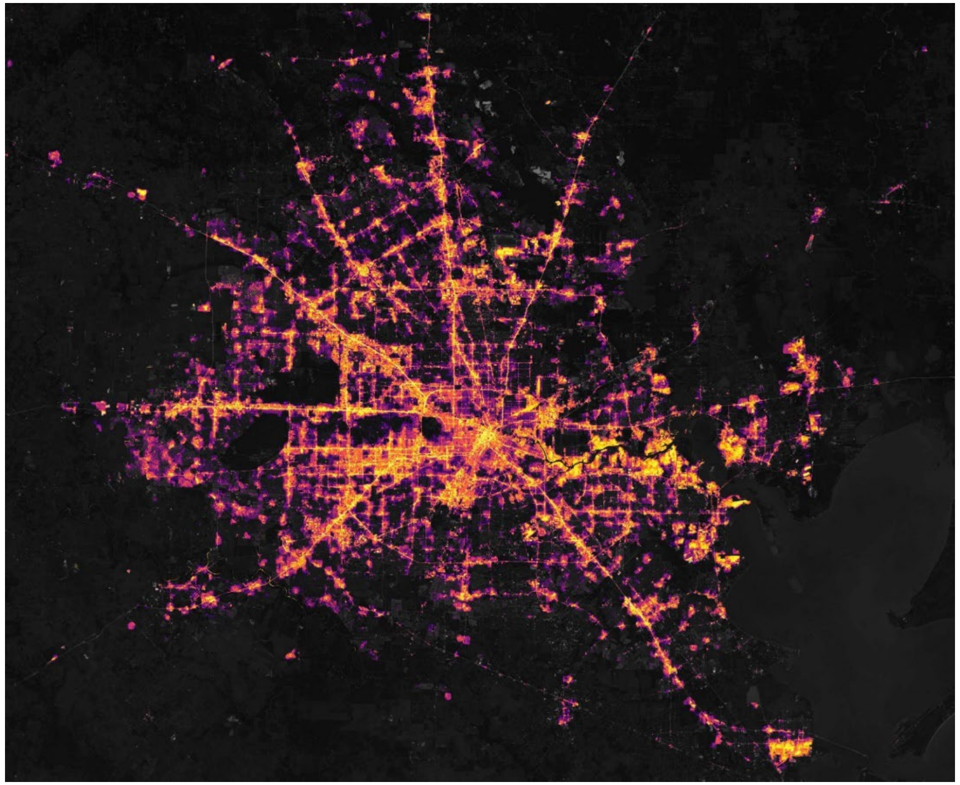
Neural ordinary differential equations





[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, "Power system frequency monitoring and emergency control 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?



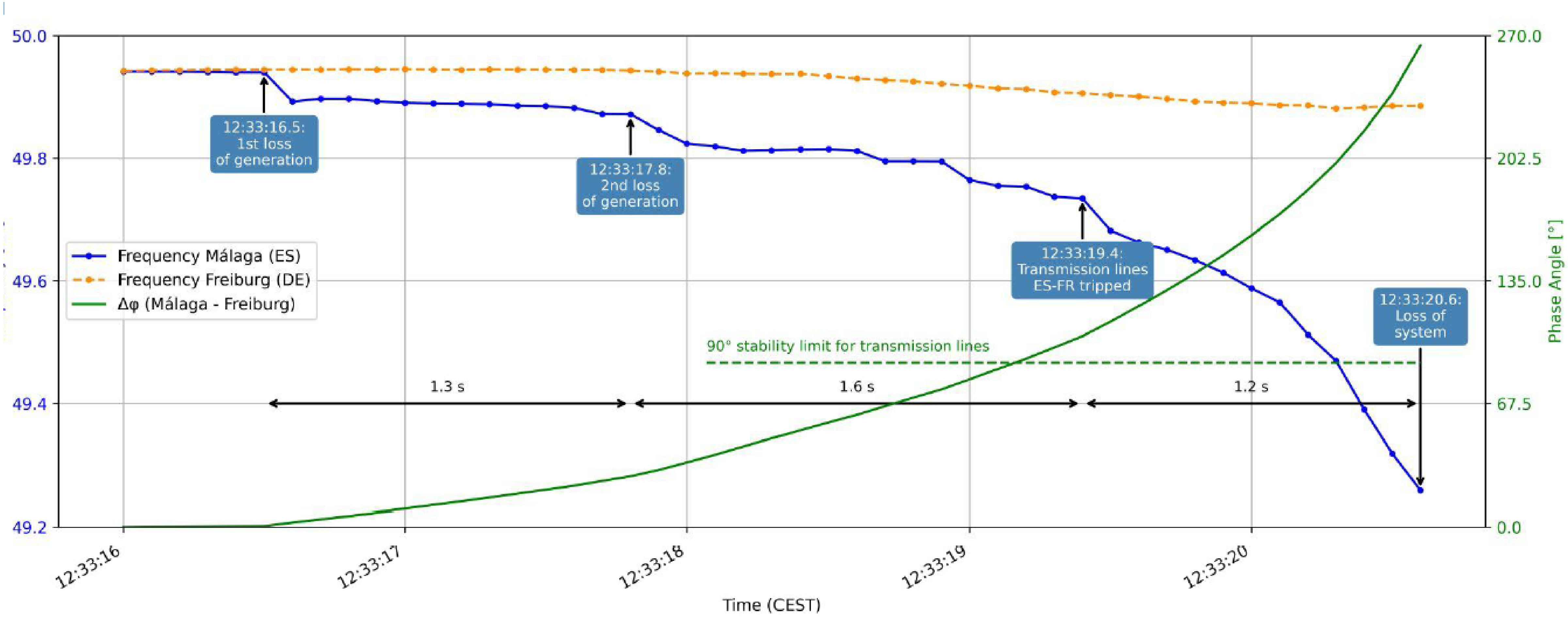
Houston, Texas 07 Feb 2021

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



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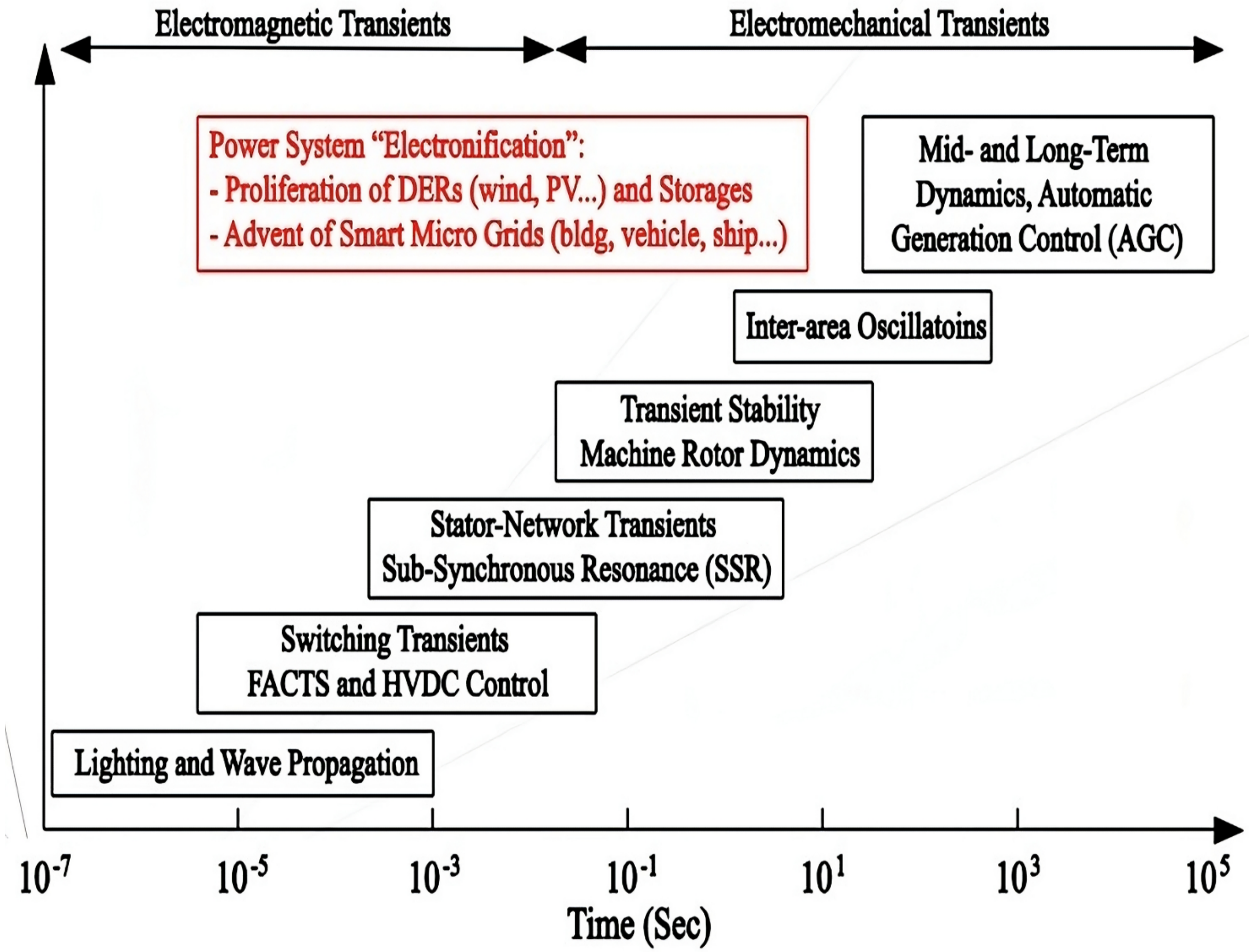
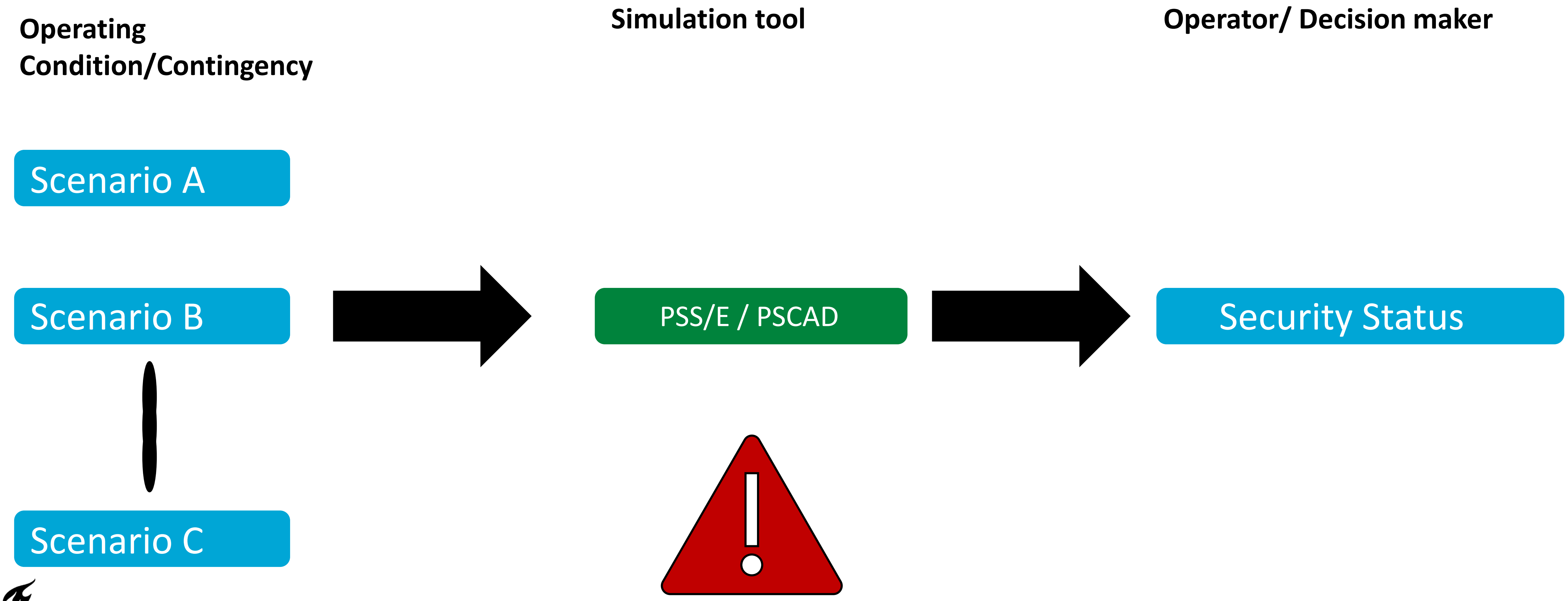
Source

EMT versus RMS simulation

- Electromechanical transient (RMS) simulations are for slower dynamics
- Slower dynamics are dominant in conventional power systems
- EMT simulations are for faster dynamics and switching transients
- Fast dynamics from inverter switching are increasingly dominant in low-inertia systems



Transient Simulation Bottleneck



Speed bottleneck

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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Enter the session ID: 154-454-820

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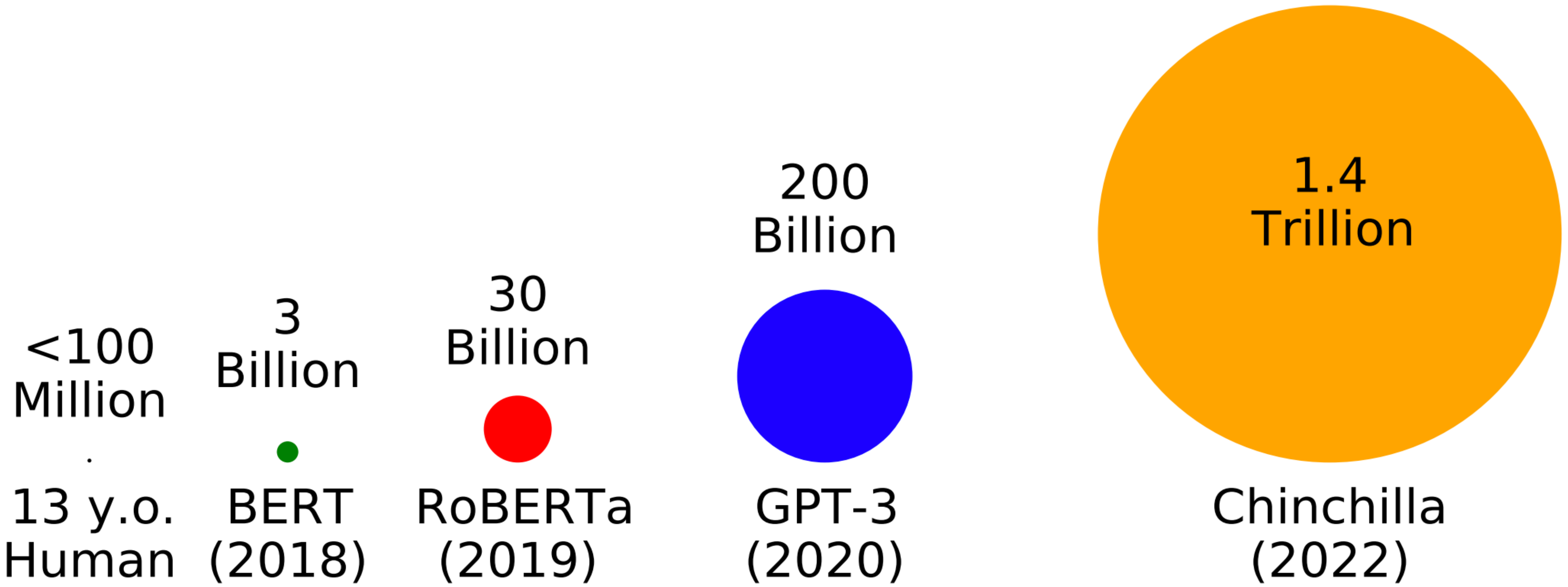
Why not yet a technology breakthrough with AI in power systems?

Why not yet a technology breakthrough with AI in power systems?

RESULTS SLIDE

Is more and more data the answer?



Number of tokens seen during training (babylm.github.io)

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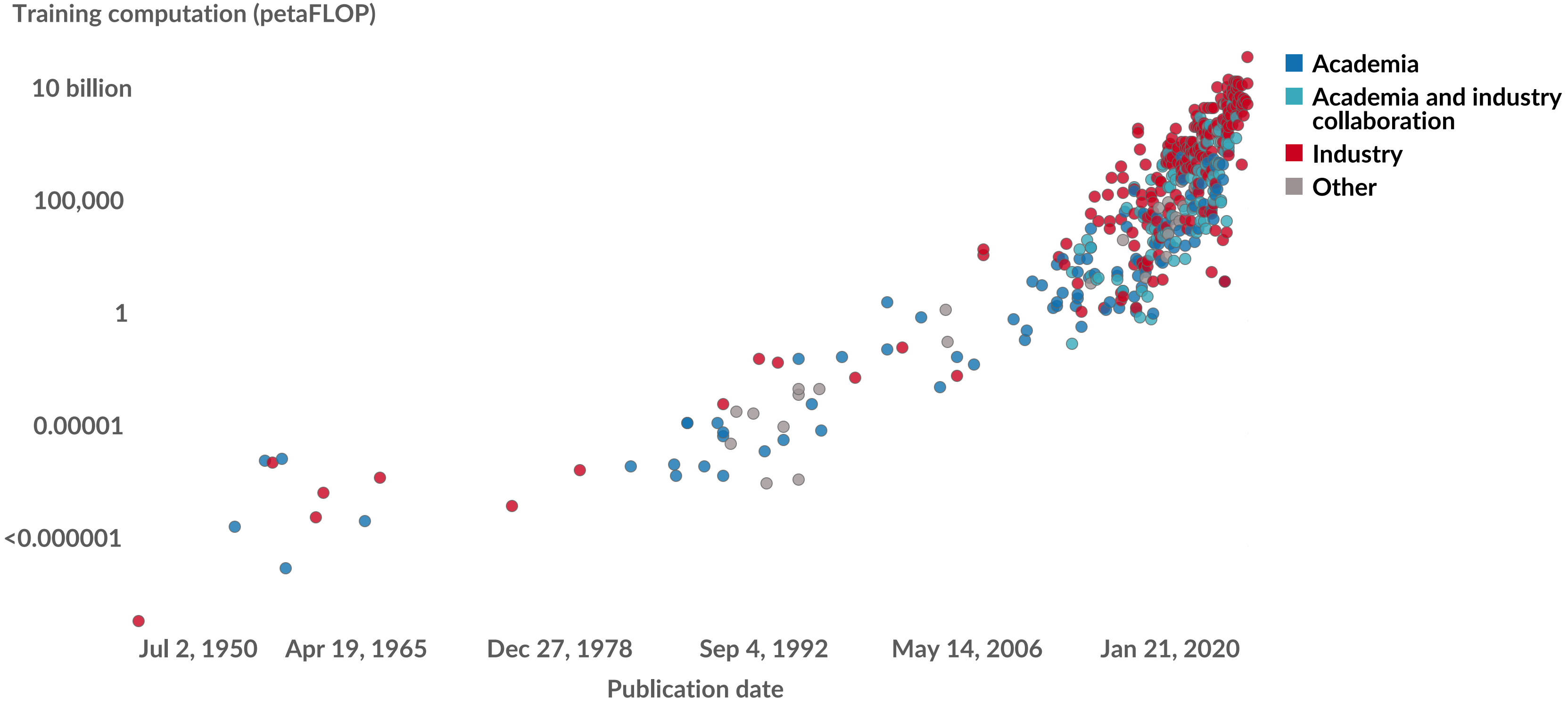
Computation used to train notable AI systems, by affiliation of researchers

Our World in Data

Computation is measured in total petaFLOP, which is 10^{15} floating-point operations[1] estimated from AI literature, albeit with some uncertainty. Estimates are expected to be accurate within a factor of 2, or a factor of 5 for recent undisclosed models like GPT-4.



Data source: Epoch (2024)

Note: The Executive Order on AI refers to a directive issued by President Biden on October 30, 2023, aimed at establishing guidelines and standards for the responsible development and use of artificial intelligence within the United States.

1. Floating-point operation: A floating-point operation (FLOP) is a type of computer operation. One FLOP represents a single arithmetic operation involving floating-point numbers, such as addition, subtraction, multiplication, or division.

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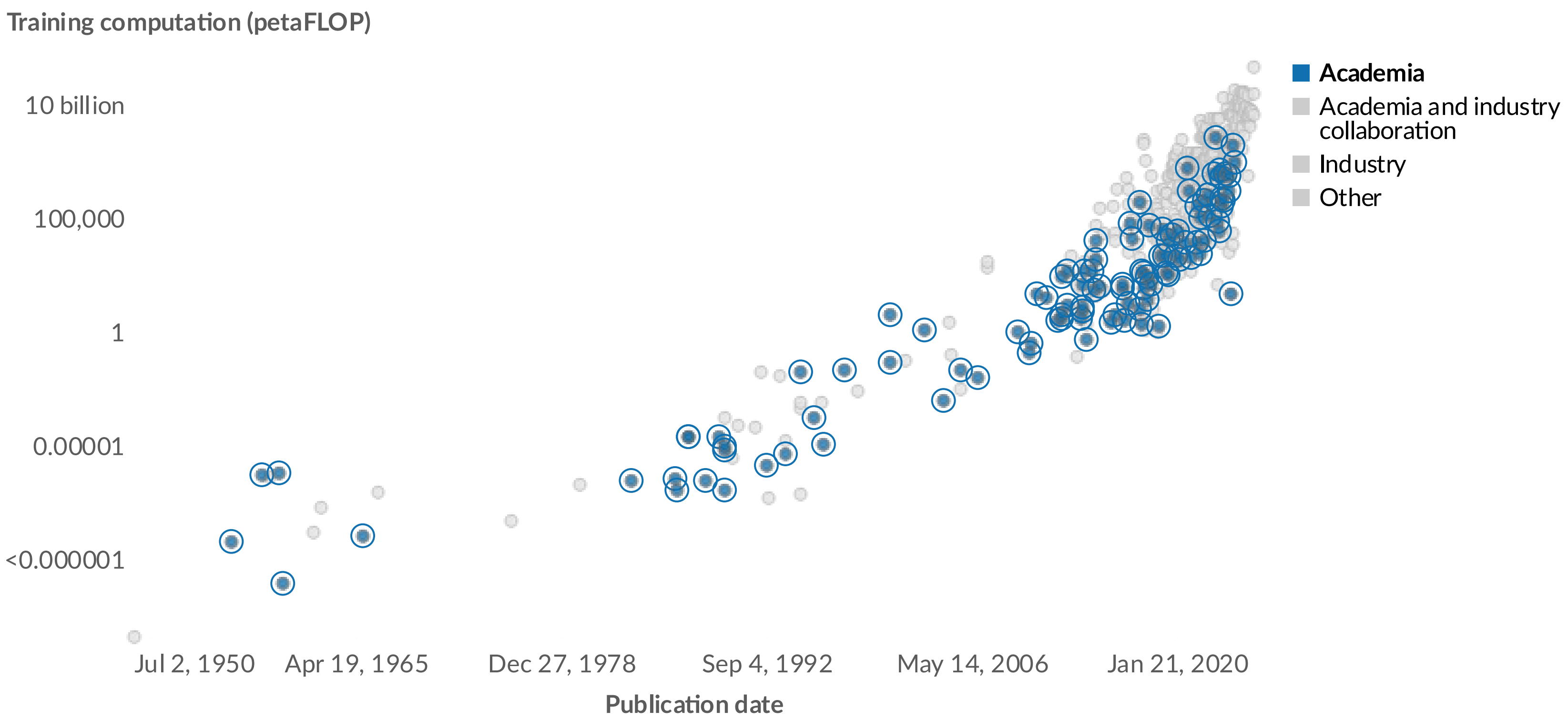

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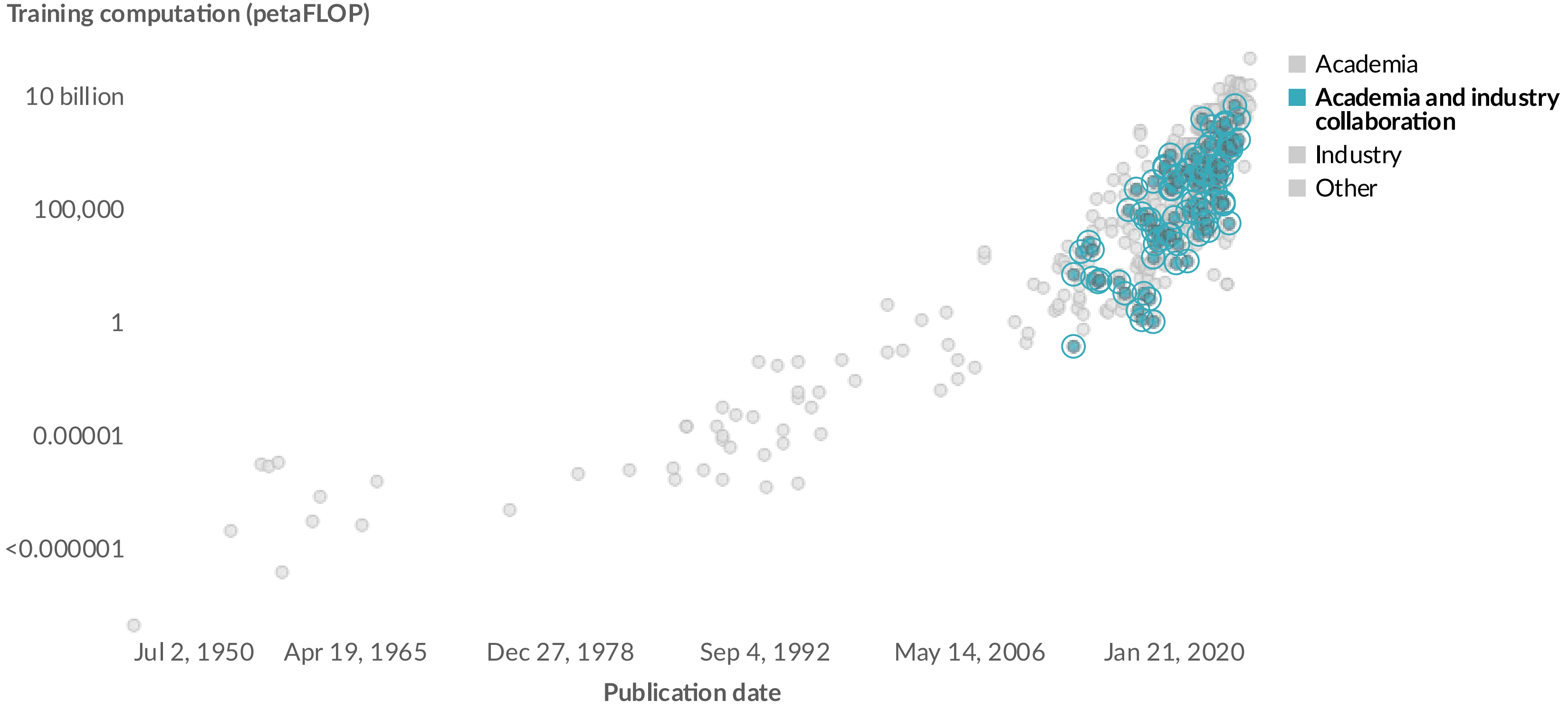

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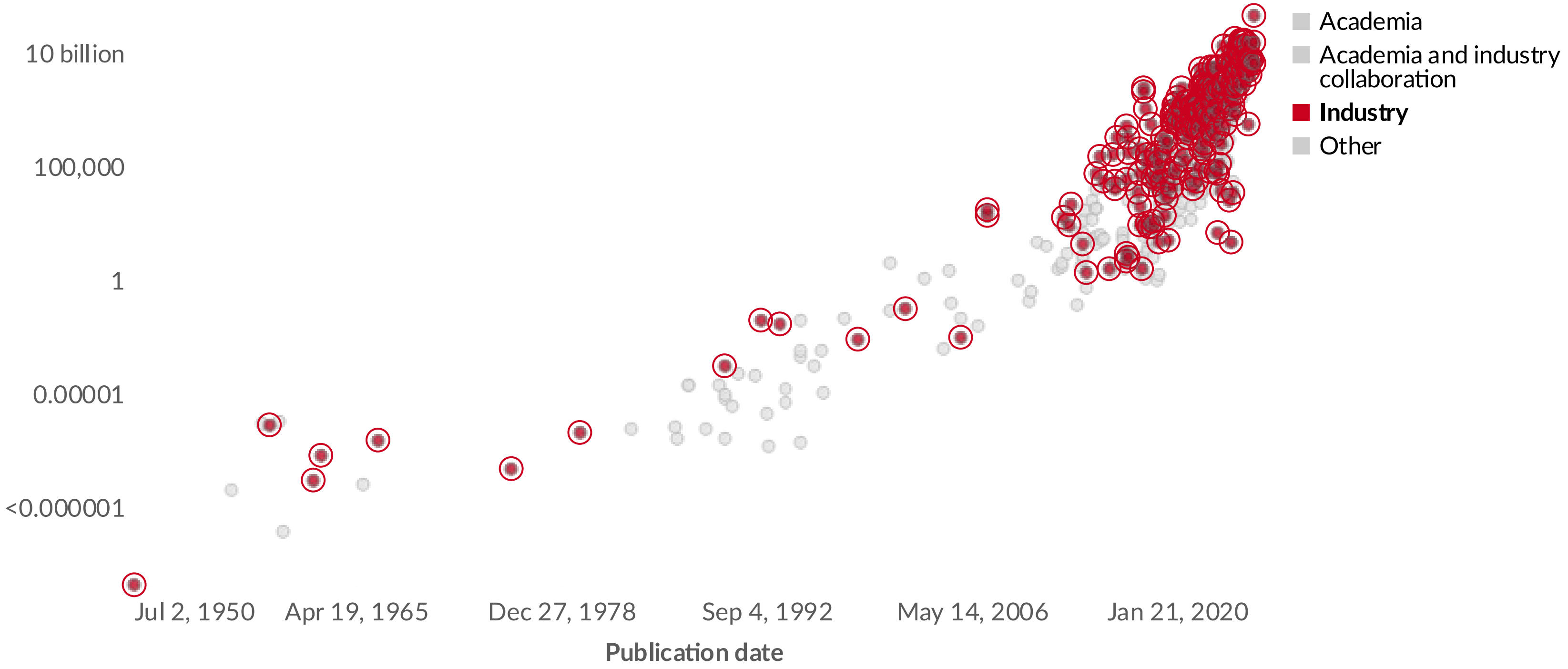

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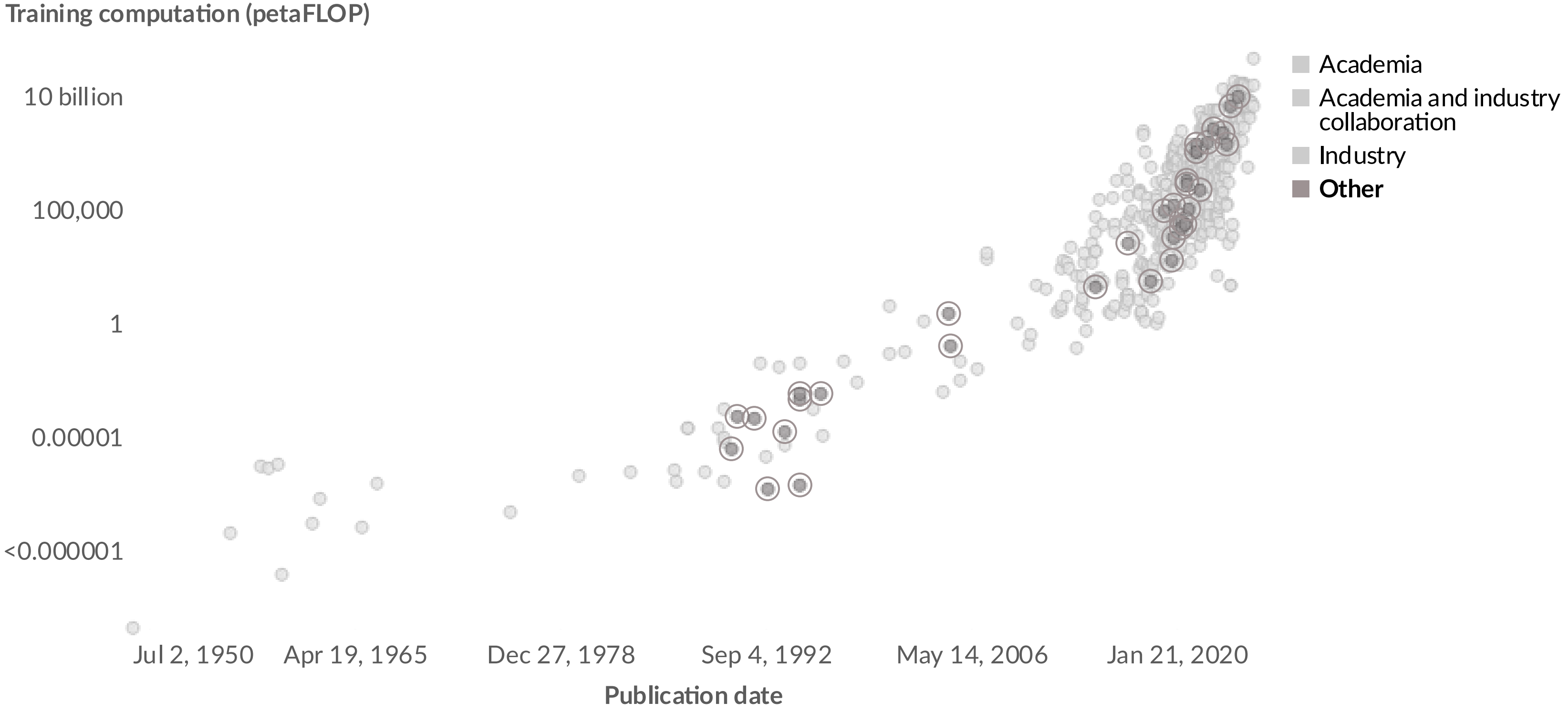

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Supervised Learning for Surrogate Models

Notation: Power system s, model m, parameter x

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

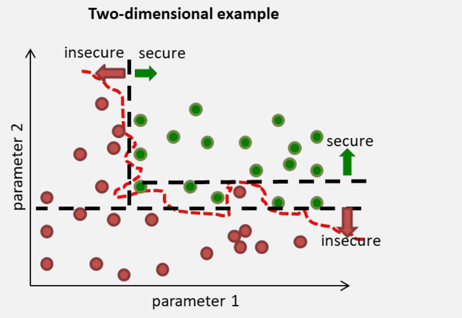
Surrogate approach

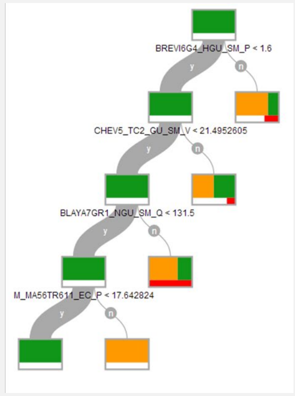
1. Generate a training dataset $\Omega^T = \{(x_i, y_i)\}_{i=1}^N$ where $y_i = m(x_i)$ from the full simulator
2. Train surrogate $f(x) \to \hat{y}$ with supervised loss $\sum_{i\in\Omega^T} ||y_i - \hat{y}_i||$
3. Use $f(x_j)$ for new j $\notin \Omega^T$

Benefit: speed at inference

Applications

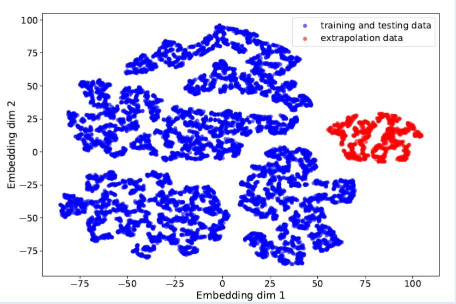
- Real-time dynamic security assessment ([4,5] and many others)



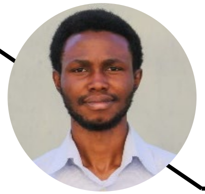


Challenges

- Out of distribution risks: 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



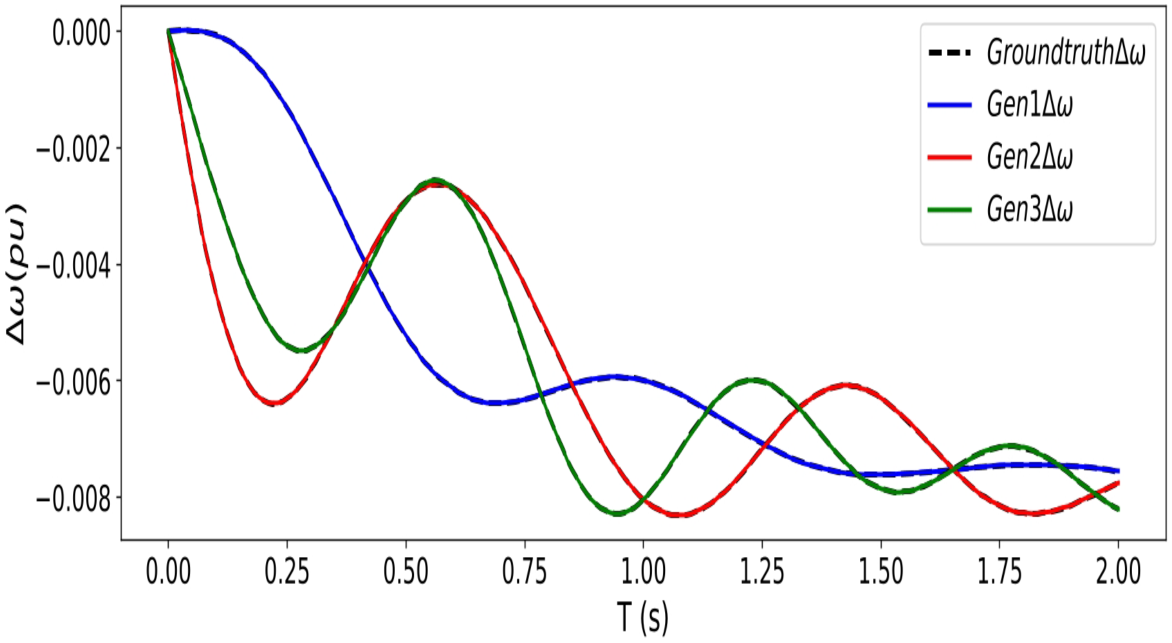
[4] Wehenkel, Louis, and Mania Pavella. "Decision trees and transient stability of electric power systems." *Automatica* 27.1 (1991): 115-134.
[5] Cremer, Jochen L., Ioannis Konstantelos, and Goran Strbac. "From optimization-based machine learning to interpretable security rules for operation." *IEEE Transactions on Power Systems* 34.5 (2019): 3826-3836.
[6] 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*



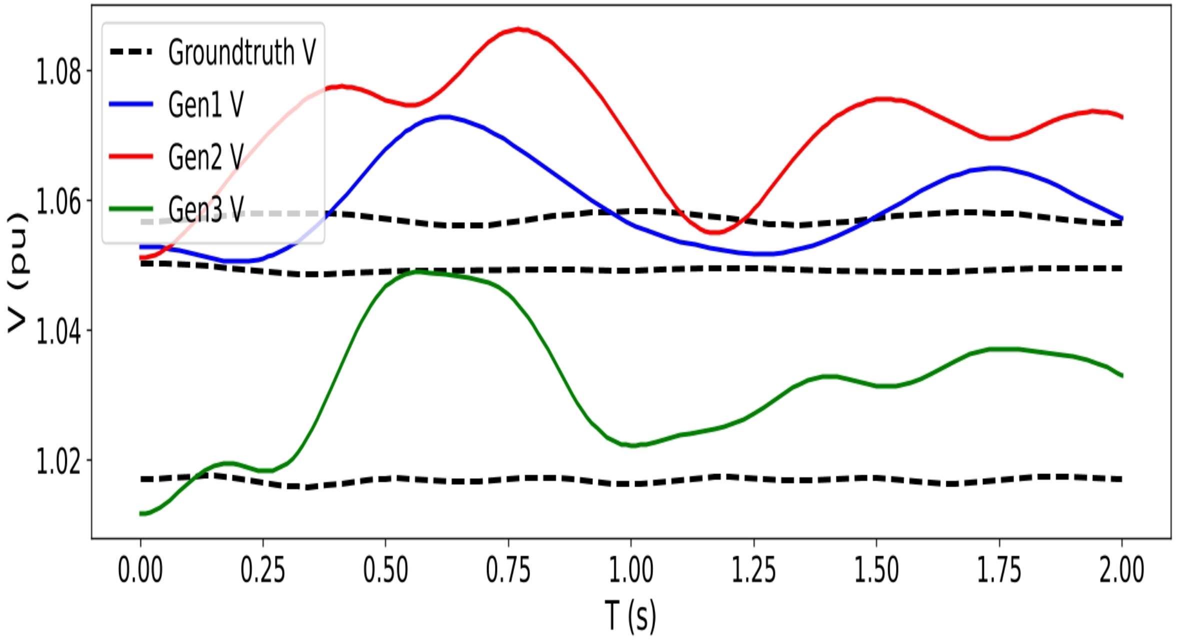
Olayiwola Arowolo

Extrapolation of ML Models in Transient Simulation

Model performs well for continuous disturbances within the training data distribution



Model fails to extrapolate for OOD discrete disturbances.



[6] 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

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 geode learning and improve generalization

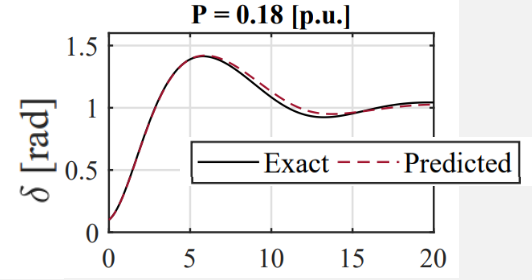
Physics-informed approach

1. Generate offline training dataset $\Omega^T = \{(x_i, y_i)\}_{i=1}^N$ with $y_i = m(x_i)$
2. Train surrogate $f(x) \to \hat{y}$ 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**

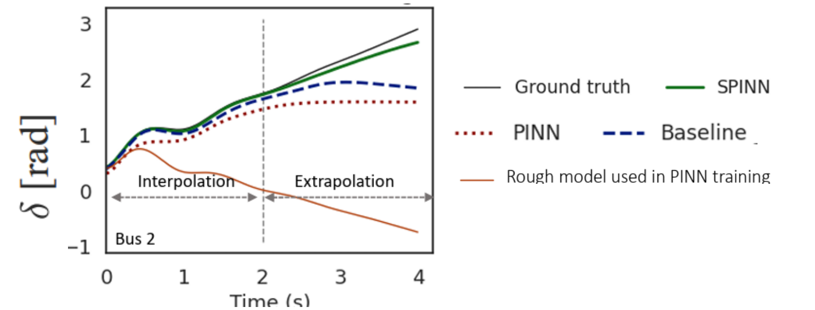
Applications

- 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



[7] 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.
[8] 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.

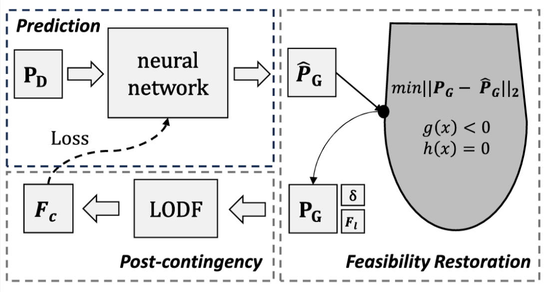
Approach

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[9]
- Replace conventional solvers with NN [10]
- Distribution system state estimation [11]
- N-k security constrained OPF [12]



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

[9] 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*.
[10] 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.
[11] 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.
[12] 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.

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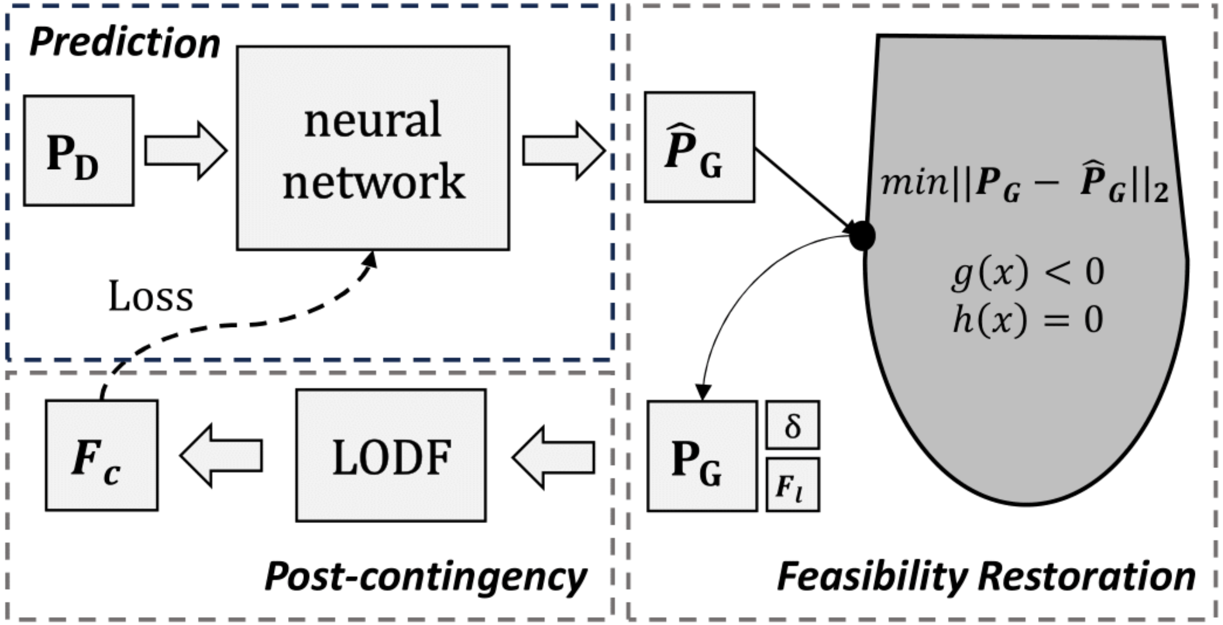
Learn Surrogate for N-k Security Constrained OPF

Learning challenge: Computing labels is already computationally intense
Weakly-Supervised Learning benefit: No (accurate) labels needed



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	$\lambda_2 \left\| \sum \boldsymbol{\hat{P}_G} - \sum \boldsymbol{P_D} \right\|_1$

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

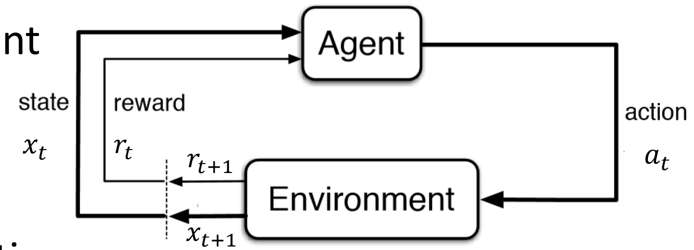
[12] Giraud, Bastien N., Ali Rajaei, and Jochen L. Cremer. "Constraint-driven deep learning for nk security constrained optimal power flow." *Electric Power Systems Research* 235 (2024): 110692.

Reinforcement Learning

Notation: Environment S, action a, state x

Objective: $\pi(a|x)$ to maximise $J(\pi) = \mathbb{E}_{\pi}[\sum_{t=0}^{T} \gamma^t r(x_t, a_t)]$

Idea: Learn by interacting with the environment
No supervision, no explicit y_i labels



Approach

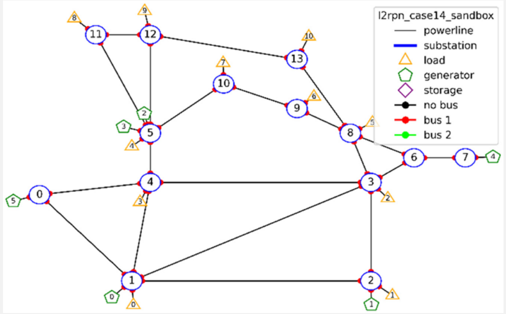
1. Interact with environment S
2. Collect many state-action-reward transitions

$$\Omega^T = \{(x_t, a_t, r_t, x_t')\}$$

3. Use π online for new states t $\notin \Omega^T$

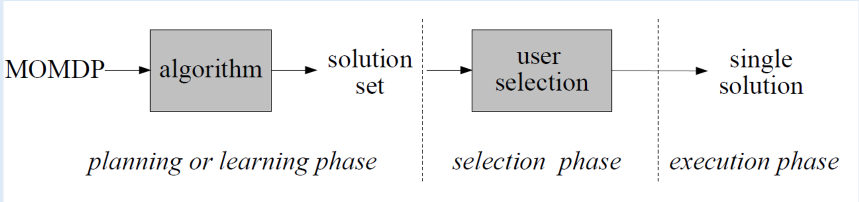
Applications

- Control PV inverters [13]
- Demand response [14]
- Topological reconfiguration[15]



Challenges

- Changes in the environment S
- High-dimensional state & action spaces (often heuristics are applied)
- Are the actions physically feasible?
- Safety & risks: How to explore safely?
- How about Model Predictive Control and Multi-Stage Optimization?



[13] Vergara, P. P., Salazar, M., Giraldo, J. S., & Palensky, P. (2022). Optimal dispatch of PV inverters in unbalanced distribution systems using reinforcement learning. *International Journal of Electrical Power & Energy Systems*, *136*, 107628.
[14] Čović, N., Cremer, J. L., & Pandžić, H. (2024). Learning a reward function for user-preferred appliance scheduling. *Electric power systems research*, *235*, 110667.
[15] Marot, A., Donnot, B., Romero, C., Donon, B., Lerousseau, M., Veyrin-Forrer, L., & Guyon, I. (2020). Learning to run a power network challenge for training topology controllers. *Electric Power Systems Research*, *189*, 106635.

Graph Neural Networks

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

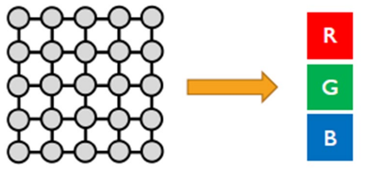
Idea: embedding graph topology directly into the model architecture as bias

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'

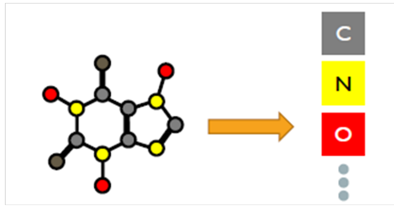
Benefits: Data efficient, generalisation to changes in topologies

Example: $p \times p$ RGB image



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

Example: molecular graph

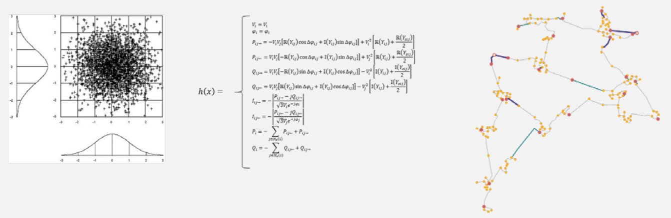


$\Omega = \{1, .. n\}$ $\mathcal{C} = \mathbb{R}^c$

Applications

- Graph neural solvers [16] for ACOPF [17]
- Distribution system state estimation [11]

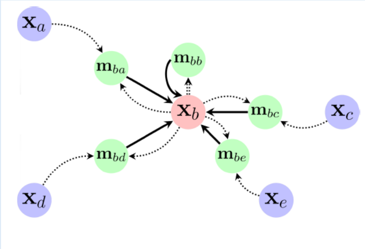
Noisy measurements Power flow equations Topology



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



[16] 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.
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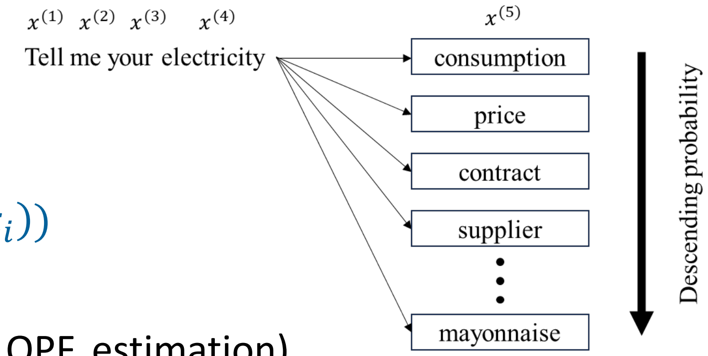
[11] Habib, B., Isufi, E., van Breda, W., Jongepier, A., & Cremer, J. L. (2023). Deep statistical solver for distribution system state estimation. *IEEE Transactions on Power Systems*, *39*(2), 4039-4050

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)

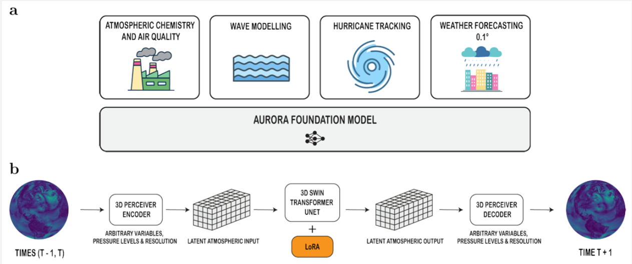
Benefits: Good initialization when little data, good transfer to downstream tasks

Challenges

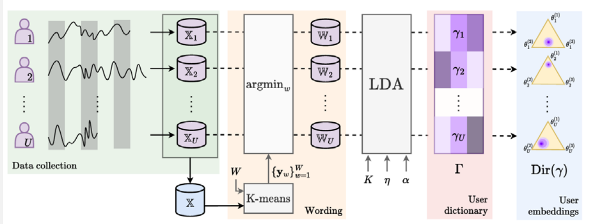
- Design pretext loss and model architectures with broad set of tasks, grid conditions, topologies
- Generate large data sets
- …

Applications

- Natural Language Processing
- Weather foundational models
- Earth system foundational models [18]



Load forecasting of users [19]



Grid foundation models (GFM) [20]

[18] 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*.
[19] Bölat, Kutay, and Simon Tindemans. "GUIDE-VAE: Advancing Data Generation with User Information and Pattern Dictionaries." *arXiv preprint arXiv:2411.03936* (2024).
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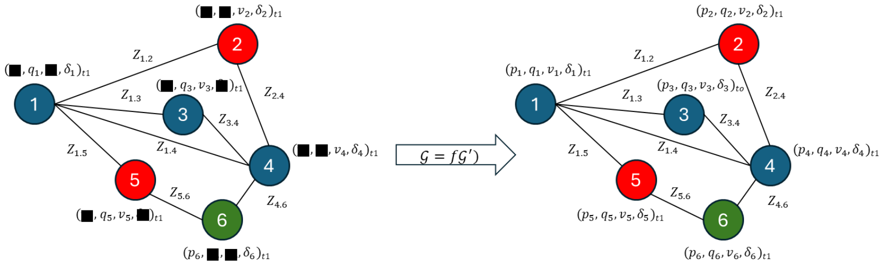
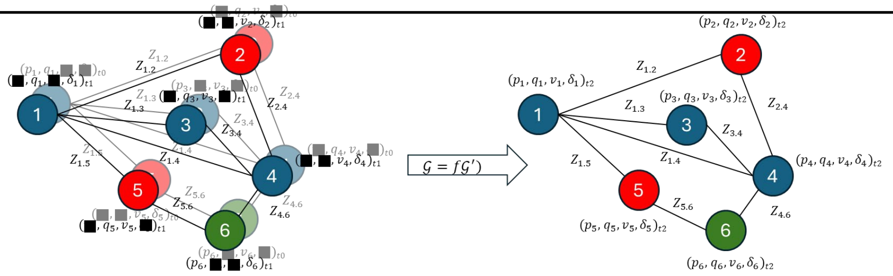
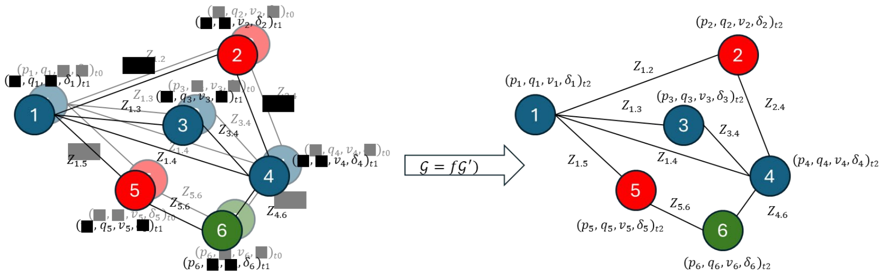
Grid foundation models

#	Pre-training		Enabled 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,*

How to formulate a Power Flow for learning?

Jochen Stiasny

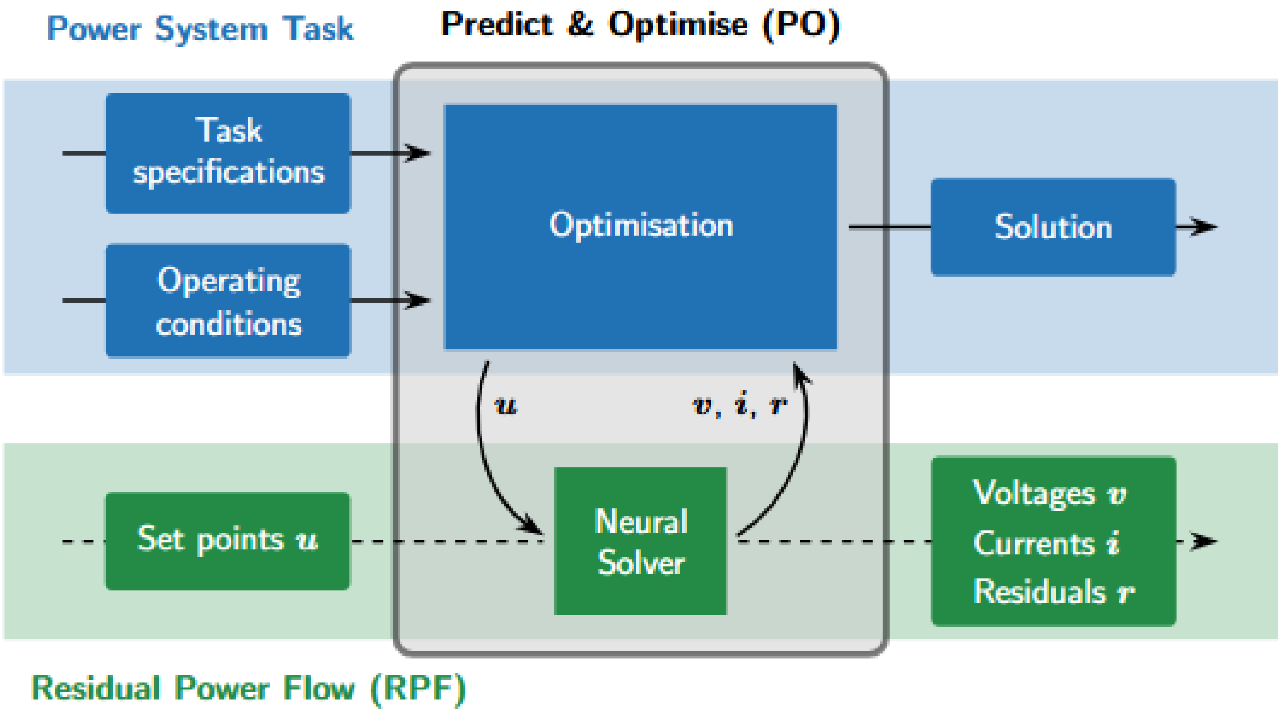
Residual power flow (RPF)

- RPF quantifies infeasibility
- Simpler formulation for neural solvers

Predict-and-Optimise (PO)

- Flexible handling of constraints and objectives
- While minimising infeasibility

→ Preprint soon available



Opportunities for Transient Simulation with Foundation Model

Accelerating transient simulation with GridFM can unlock new use cases with more comprehensive scenario assessments

Potential use cases:

- Planning and commissioning HVDC/FACT devices
  - Investigating interaction phenomena between HVDC and the rest of the grid
  - Testing controllers and software updates
  - Verification with onsite measures
- Investigating inter-area oscillations
  - Getting common in weak grids
  - Root cause of some of these events still unknown
  - Sub-synchronous oscillations from controller interactions need EMT simulations

Non-conventional use cases:

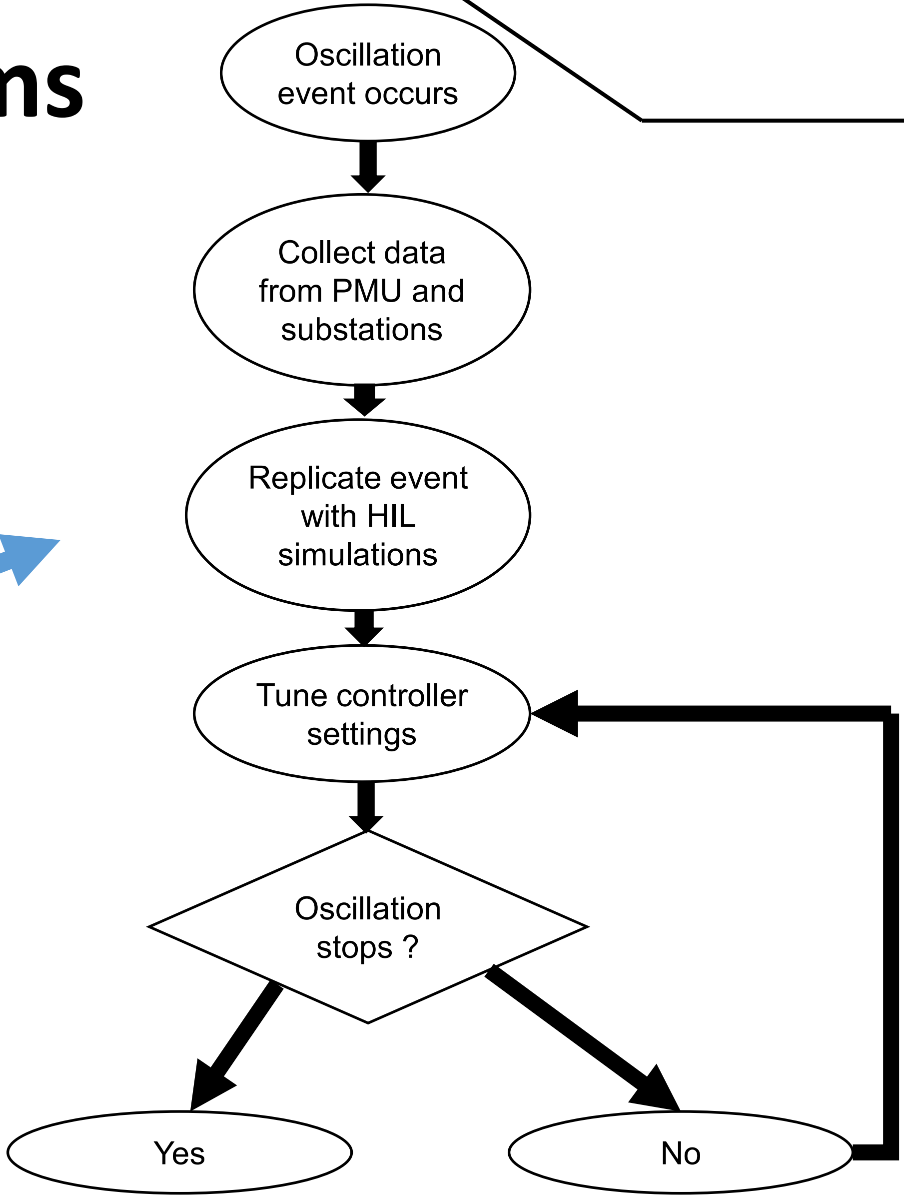
- How to expand the system that maximises transient stability for k-faults?
- How to operate the system secure against transients?

[12] 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*
[2] Mert Karaçelebi, Jochen L. Cremer, "Power system frequency monitoring and emergency control with neural ordinary differential equations", *12th Bulk Power System Dynamics and Control Symposium and Sustainable Energy, Grids and Networks Journal, 2025*

Integration of offshore wind farms

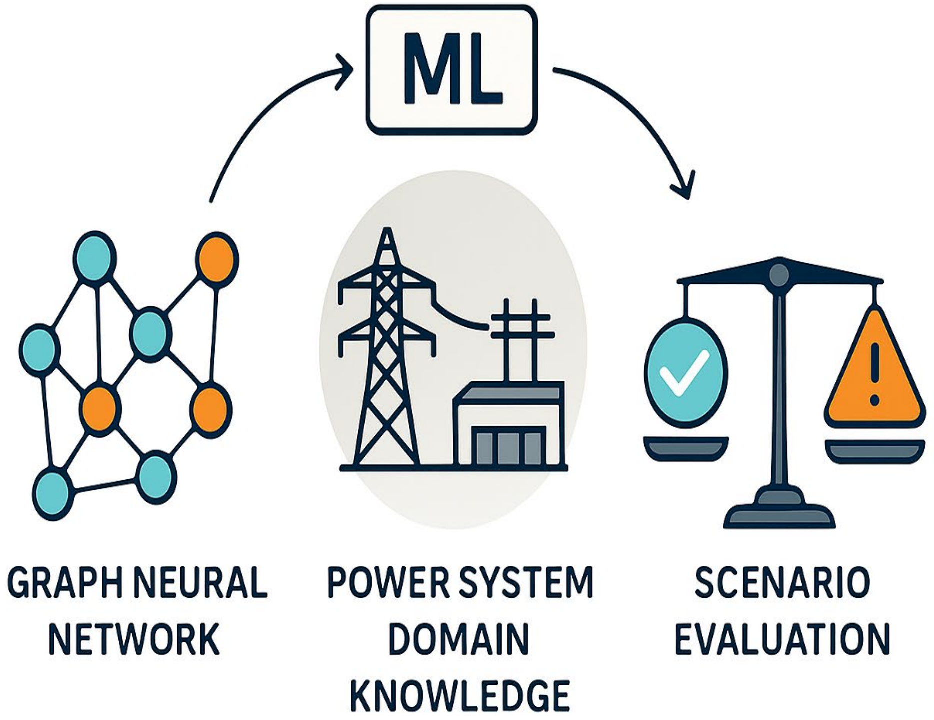
- Require detailed models of turbines and controllers
- Assessment of background harmonic amplification
- Locating sources of sub-synchronous oscillations

The existing setting is time-consuming



Approaching a Foundation Model for Transient Simulation

- Potential for graph-based modelling of power system transients
- Graphs can easily handle discrete changes to system topology
- EMT and RMS simulations may be unified by simulating a system of DAEs.
- The best way to formulate an appropriate graph is an open question

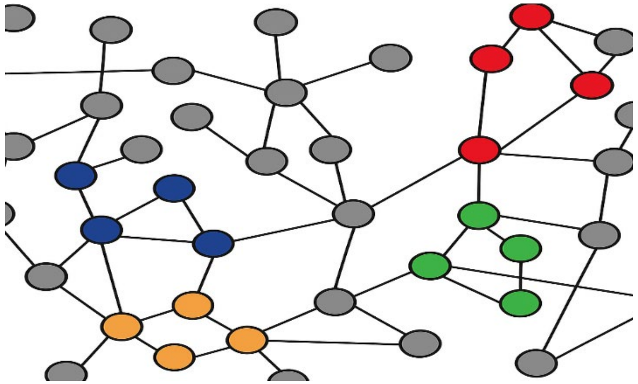


TU Delft

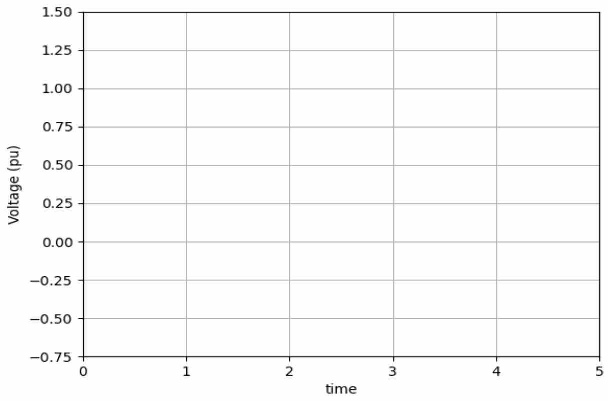
Challenges

- Large-scale simulation training dataset
  - Data variety (synthetic and Real)
  - Data validity
  - Data privacy
- Modelling challenges
  - Architectural definition
  - Computational cost of pretraining
  - Consistency with physical laws
- Application / Validation
  - Experimental or Physical validation

Graph input



Simulation output



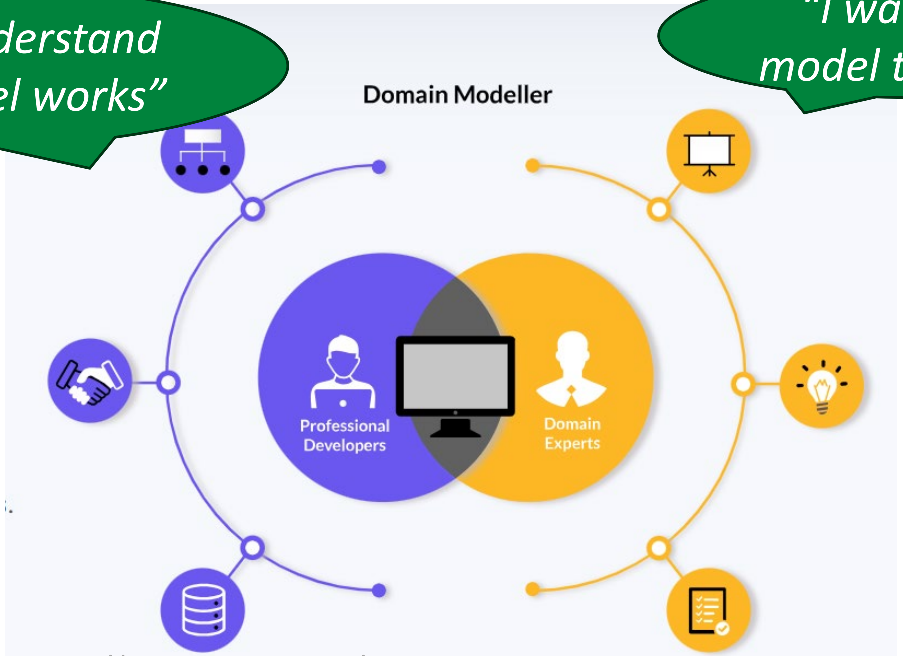
[21] Al-Amin Bugaje, Jochen L. Cremer, Goran Strbac ”Generating Quality Datasets for Real-Time Security Assessment: Balancing Historically Relevant and Rare Feasible Operating Condition” *International Journal of Electrical Power & Energy Systems, 2023*
[22] F. Bellizio, J. L. Cremer, G. Strbac*, "Machine-learned security assessment for changing system topologies." International Journal of Electrical Power & Energy Systems 134. 2022: 107380.*

Explainable & Interpretable AI

Objective: provide **human-understandable reasoning** behind AI decisions.

“I want to understand how the model works”

“I want the model to work”



https://www.devum.com/devum-domain-modeller

Applications

- Interpretable structures (e.g. decision trees) for security assessments [5]
- Post-hoc explanations to complex models for transient stability based, e.g. SHAP values [23]

Challenges

- Some trained models may not be able to state performance guarantees
- Is this action physical compliant?

[5] 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, no. 5 (2019): 3826-3836.
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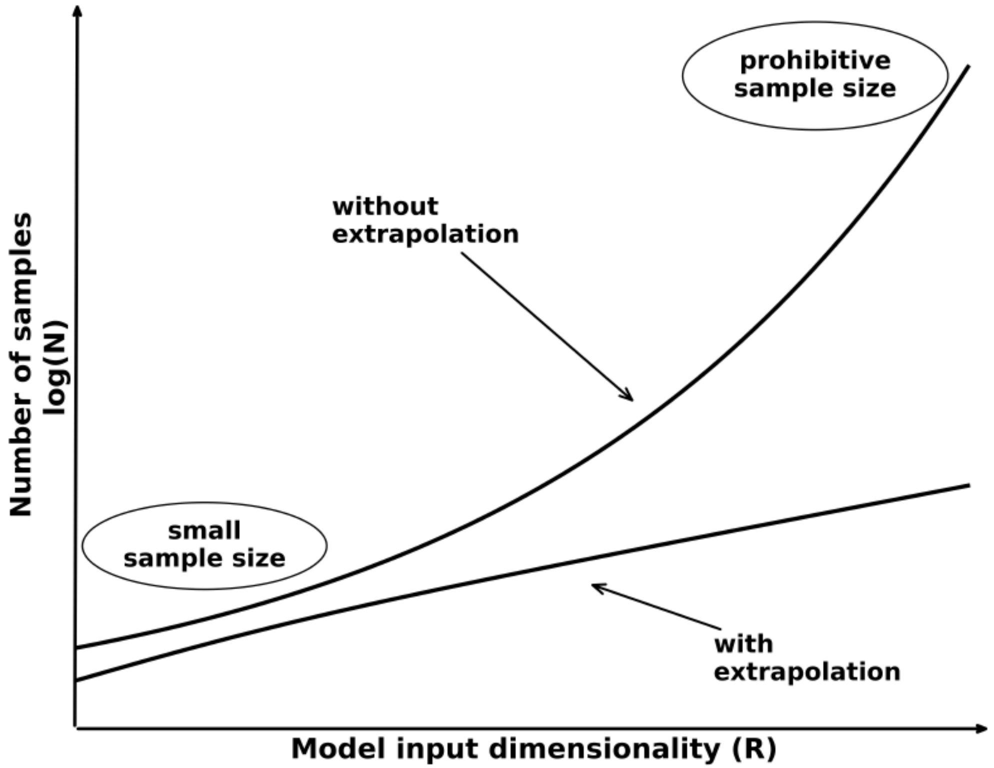
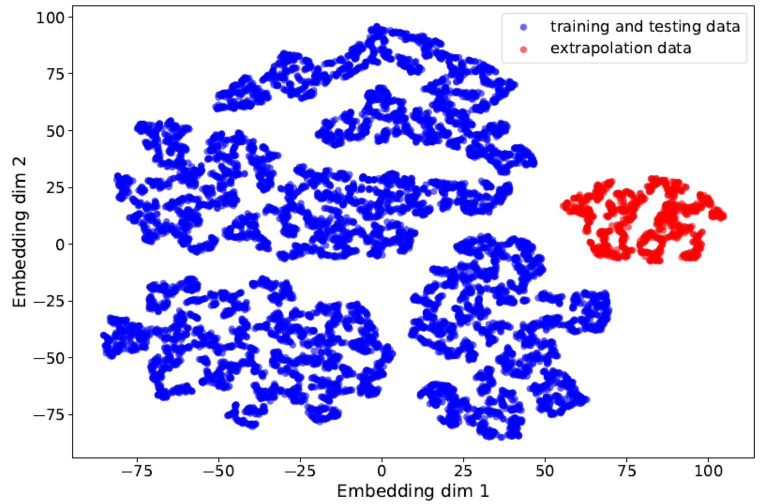
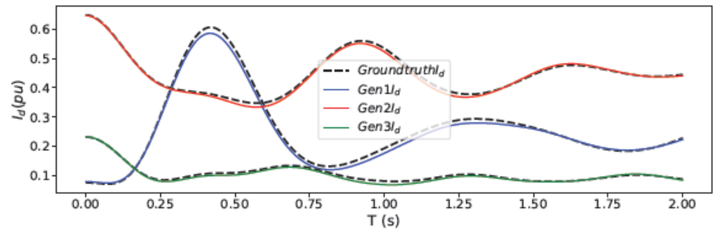
Generalisation to changes in s or m

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



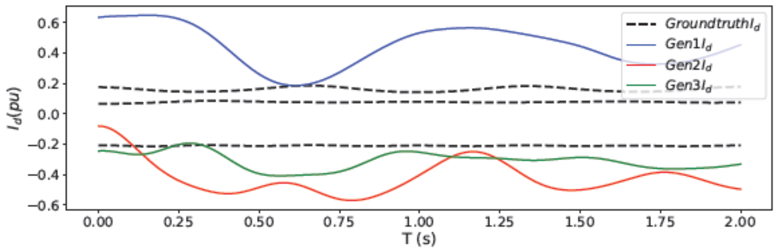


Extrapolation in continuous domain



(a) I_d current trajectory

Extrapolation in nonlinear domain (discrete)

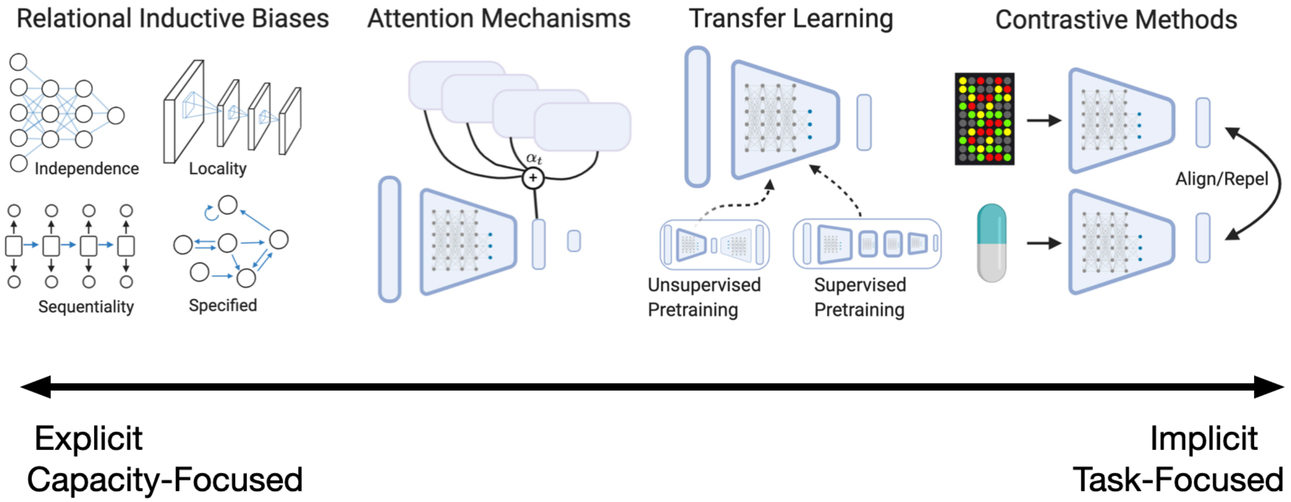


(a) I_d current trajectory

[6] 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*

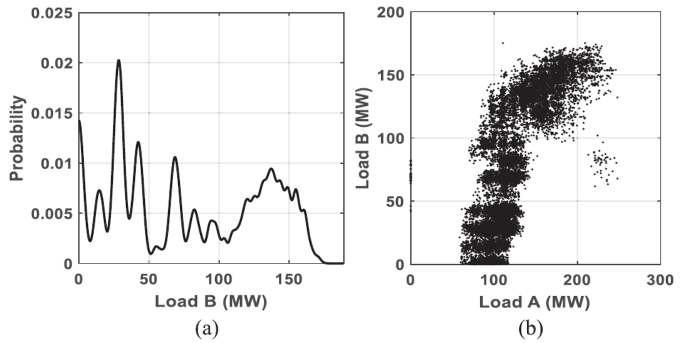
Challenge: Data-efficiency

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

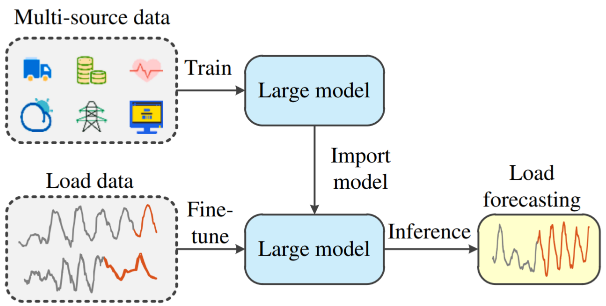


Sampling synthetic data & use real-data

Snapshot sampling



Time-series foundational models



LF ENERGY OpenSynth

[24] https://sgfin.github.io/2020/06/22/Induction-Intro/
[25] 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.
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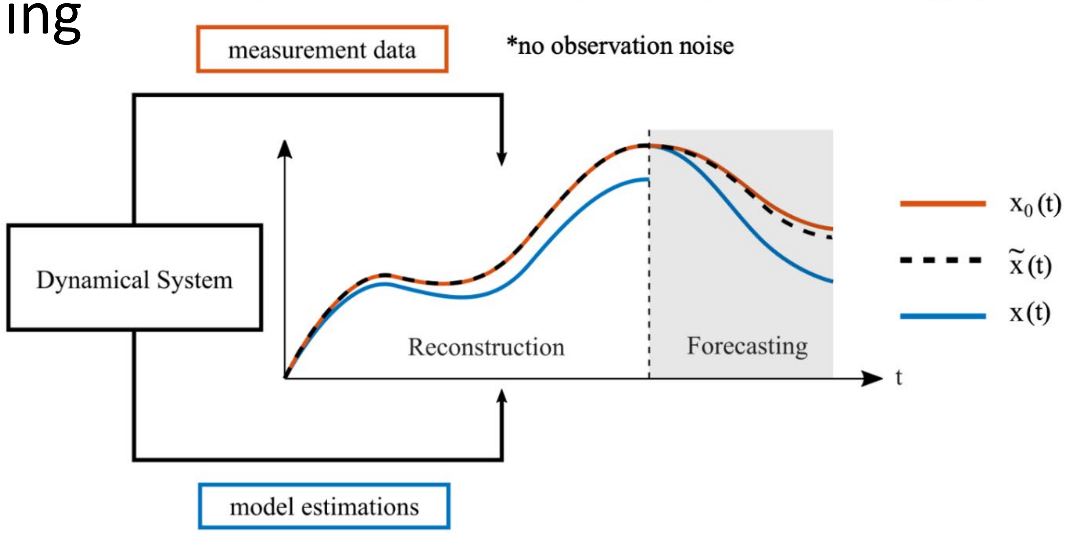
Model error $s \neq m$ (data quality issues)

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

Sim-to-Real Domain Adaptation

- 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



[29] 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

- Let’s work together to realise the potential of AI-based methods
- Let’s develop good representations to learn for grids
- How to train data-efficiently models across system operators?
- Know when your model works and when it does not work (generalisation)
- Future work: Grid foundation models
  - Focus on multiple tasks
  - Enable use cases between tasks
  - Majority of training is on synthetic data

Thank you

Speaker

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Email: j.l.cremer@tudelft.nl

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

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