DTU PES Summer School: Future Energy Systems

Rethinking Power System Dynamic Simulations with Machine Learning

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Why do we need to rethink power system dynamics?

Denmark 1980

Source: Energinet

Why do we need to rethink power system dynamics?

Denmark 1980

Source: Energinet

Each generator is a dynamic system described by **Differential Algebraic Equations (DAEs)**:

$$\mathbf{M}\frac{d\mathbf{x}}{dt} = f(\mathbf{x}, \mathbf{u}, t)$$
$$\mathbf{x}(0) = \mathbf{x_0}$$

- $\mathbf{x}$ Differential & algebraic states
- $\mathbf{u}$ Control inputs & disturbances
- $\mathbf{M}$ Mass-Matrix: determines if the row corresponding to state x is algebraic or differential

Characteristics of **SM-dominated power systems**:

- **SM** dynamics **dominate** system behavior
- Loads are predominantly static (or aggregated with simple dynamics)

» **Established analytical and time-domain methods for system-level stability analysis**

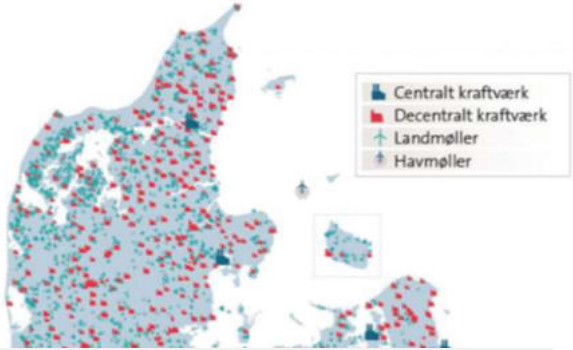
SM: Synchronous Machine

Why do we need to rethink power system dynamics?

Denmark 1980

Source: Energinet

Denmark Today

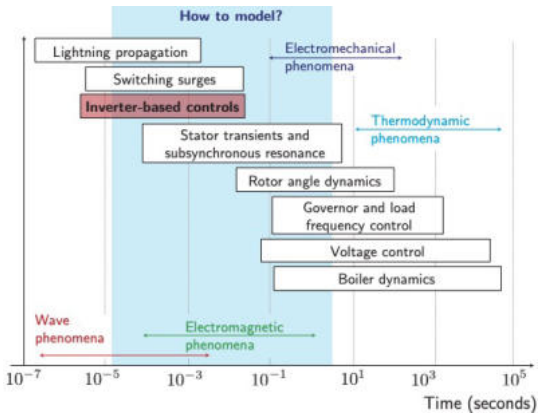


Source: Energinet

Complexity of dynamic system analysis is drastically increasing!

How do we assess the behavior of such a system after a disturbance?
Can we still do this effectively?

There is Another Problem: Time-Scale Separation



Source: N. Hatziargyriou et al, doi: 10.1109/TPWRS.2020.3041774

In SM-dominated systems, **electromechanical** and **thermodynamic** phenomena were key concerns:

- Frequency stability
- Voltage stability
- Rotor-angle stability

Inverters/ Renewable Generators act on the time-scales of **electromagnetic** and **wave** phenomena:

- **resonance stability & converter-driven stability**[1]
- Faster time-scales, and interaction of different dynamics

How do we study these systems?

- Analytical solutions typically do not scale to system-level stability assessment

» Time-domain simulations

[1] N. Hatziargyriou et al., "Definition and Classification of Power System Stability – Revisited & Extended," in IEEE Transactions on Power Systems, vol. 36, no. 4, pp. 3271-3281, July 2021, doi: 10.1109/TPWRS.2020.3041774

How do we perform a classic time-domain simulation?

Time-Domain Simulations require:

- a **system model**: physics & controls
- a **time-stepping, or integration, algorithm**

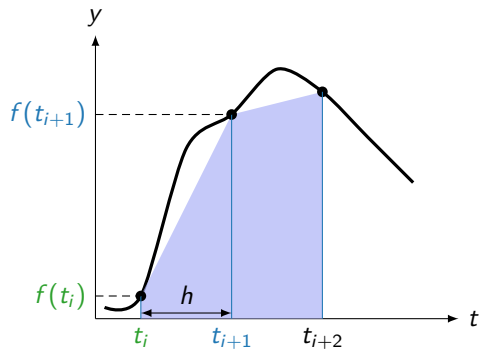
Given the initial condition for the system states $\mathbf{x}_0$, the integration algorithms find the solution for a timeline:

$$\mathbf{x}_{t+h} = \mathbf{x}_t + \int_t^{t+h} f(\mathbf{x}, \tau) d\tau$$

Since we cannot calculate the continuous integral analytically, we discretize it using numerical integration methods. **Example**: Trapezoidal Rule

$$\mathbf{x}_{t+h} = \mathbf{x}_t + \frac{1}{2} h \Big[f(\mathbf{x}, t) + f(\mathbf{x}_{t+h}, t+h) \Big]$$

We use an iterative algorithm to solve the implicit equation for each consecutive timestep.



Computational Complexity for Renewable Grids:

- Step size h must be **small enough** to capture the fastest dynamics
- Simulation time scales with the number of states
- Re-initialization required for discrete events

Classic Time-Domain Simulations are not Error-Free

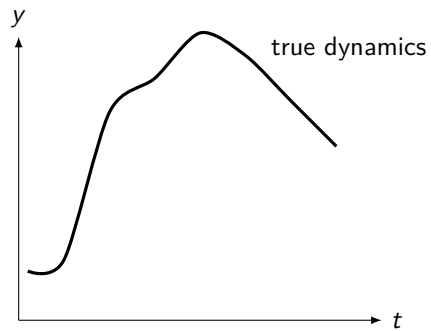
Classic time-domain simulations are subject to several errors. These stem from:

- the **system model**: DAEs are an **approximation** of the true dynamics, called **model error**
- the selected **time-stepping algorithm**

Numerical integration errors include:

- **local truncation error**: error caused by one iteration
- **global truncation error**: cumulative error caused over many time steps

Numerical integration errors depend on the **integration method** and the **time step**.

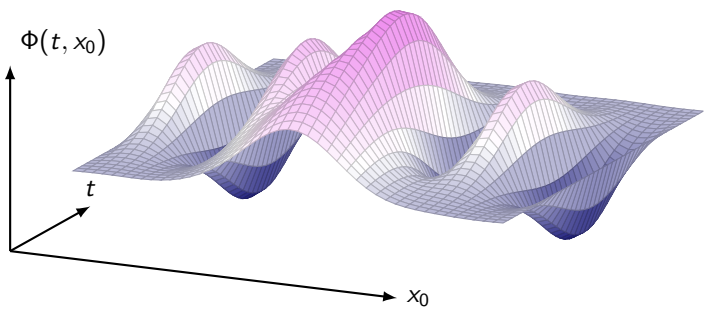


Let us Change The Perspective: Geometrical Interpretation

DAE System

$$\mathbf{M}\frac{d\mathbf{x}}{dt} = f(\mathbf{x}, t)$$
$$\mathbf{x}(0) = \mathbf{x_0}$$

Flowmap of a DAE System



The **flowmap** $\phi(t, x_0)$ contains all trajectories for all initial conditions $\mathbf{x}_0$.

A time-domain simulator computes **only one trajectory on the flowmap**.

What if we knew the flowmap?
A closed-form $\phi(x_0, t + h) \rightarrow x(t + h)$ would let us advance in time in one shot

- no repetitive iterations per step
- no recalculation for a different initial condition

Idea: Can we capture the flowmap with Machine Learning?

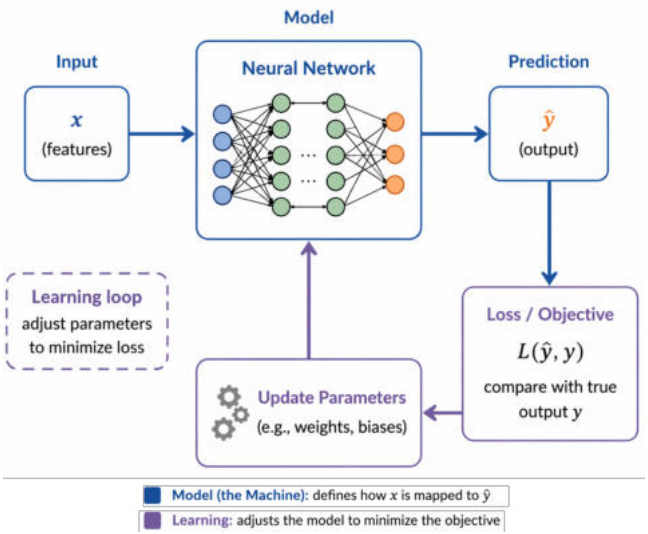
What is Machine Learning?

Machine Learning consists of two parts:

- the **Machine:** a mathematical model, e.g., a Neural Network (NN)
- the **Learning**: the calibration of the mathematical model to fit an objective

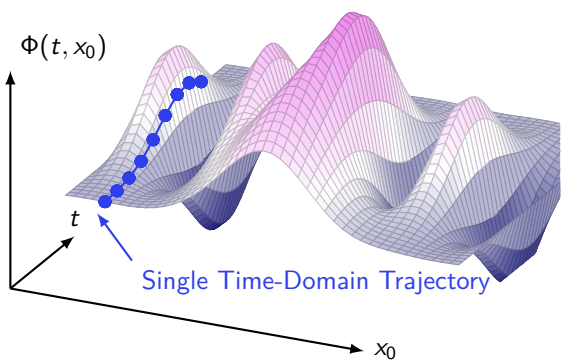
Benefits of using an ML Model:

- We can obtain a continuous function $\widehat{\mathbf{y}}(\mathbf{x})$
- Prediction is a sequence of simple parallel multiplications



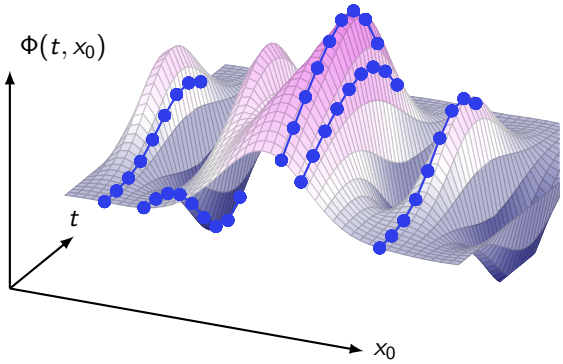
Goal for ML: Learning the Flowmap of the DAE System

Time-Domain Solver solves **iteratively** for **one** initial condition during each simulation



Evaluation per trajectory is computationally expensive. Execution of iterative algorithm per time-step and trajectory.

Goal for ML Algorithm: learn **a continuous representation of the flowmap**



Main computational burden for **learning of the flowmap**, but **fast evaluation of trajectories**.

Motivation to Use Machine Learning for Power System Dynamics

Simulation Speed-Up

Faster inference of the time-domain simulation

- Replace components that slow classic simulation down
- Full ML-based simulator

Accurate Aggregate Models

Dynamic behavior of **multiple/ complex components** in one ML surrogate

- External system
- Complex components
- Accurate dynamics: e.g learn EMT dynamics to represent in RMS domain

Intellectual Property (IP) Protection

ML-models are black-boxes and **provide IP protection inherently**

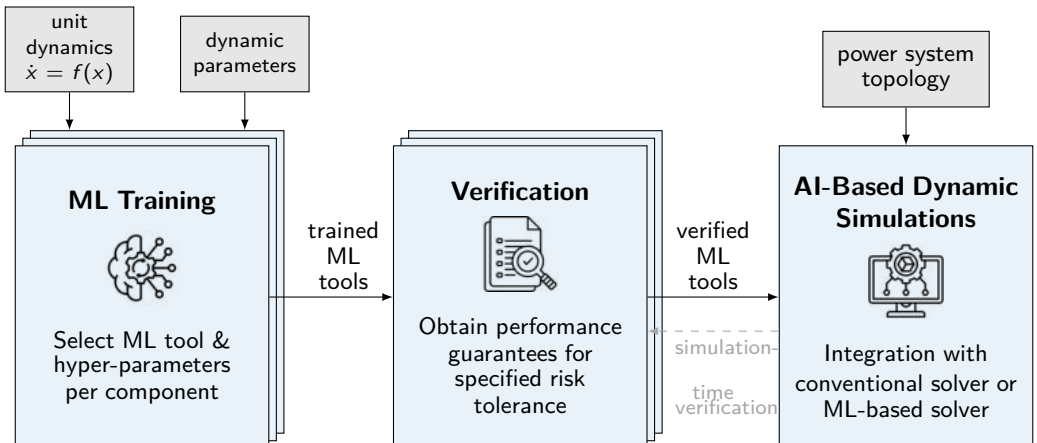
- Protect true dynamic model and parameters
- Potentially reduction of encryption needs
- No known methods for exact reverse engineering

RMS-Simulation: Root-Mean-Square Simulation with Phasor Approximation, EMT: Electromagnetic Transient Simulation

Images on this slide are AI generated (Copilot, 2.20260511.18.0)

How can we make it happen?

Learning the dynamics of an entire system is **infeasible** and extremely complex. Hence, we can learn **components or clusters of components** use them in ML-assisted time-domain simulations.

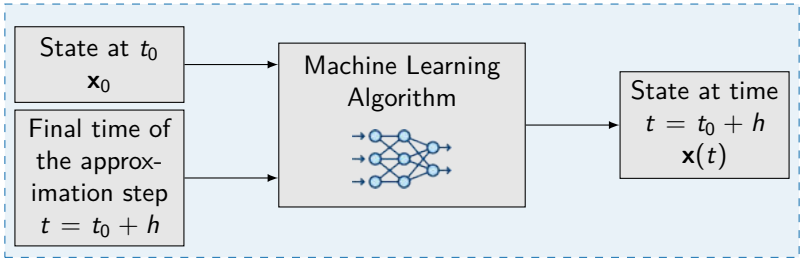


P. Ellinas, I. Karampinis, I. Ventura Nadal, R. Nellikkath, J. Vorwerk, S. Chatzivasileiadis "*Physics-informed machine learning for power system dynamics: A framework incorporating trustworthiness*", SEGAN, Volume 43, 2025, www.doi.org/10.1016/j.segan.2025.101818, presented at IREP 2025

Topic 1:

Overview of ML Tools for Power System Dynamic Applications

Our Goal: Learning an Initial Value Problem



The Initial Value Problem consists of a set of DAEs and an initial condition:

$$\mathbf{M}\frac{d\mathbf{x}(t)}{dt} = f\Big(\mathbf{x}(t), \mathbf{u}(t)\Big)$$
$$\mathbf{x}(t=0) = \mathbf{x}_0$$

Nomenclature from now on:

$\mathbf{x}$	true DAE solution
$\hat{\mathbf{x}}_{NN}$	NN output prediction for input
$\mathbf{x}_0$	initial condition, NN input

Classic Machine Learning Task

Classic machine learning approximates the mapping from features $\mathbf{x}_0$ to predictions $\hat{\mathbf{x}}$

- Supervised learning task
- Minimize a specified loss term during training

Given the true outputs $\mathbf{x}$, we train all model parameters θ, including the weights and biases, by optimizing

$$\min_{\theta} \mathcal{L}((\mathbf{x}_0, \theta), \mathbf{x}(t))$$

For the MSE (Mean-Squared Loss) and N samples:

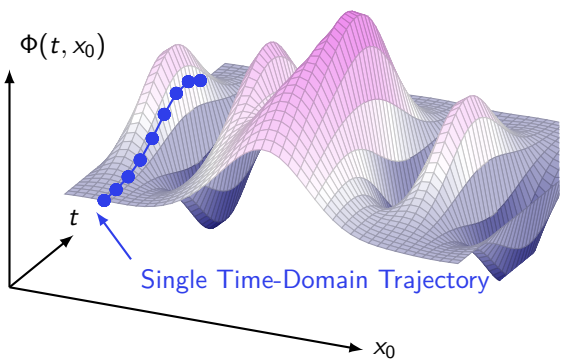
$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} (\mathbf{x}_i - \hat{\mathbf{x}}_{NN,i})^2$$

The model architecture and activation functions (g, f in our example) are selected during hyper-parameter tuning.

While classic ML fits the data, it may **violate physics**!

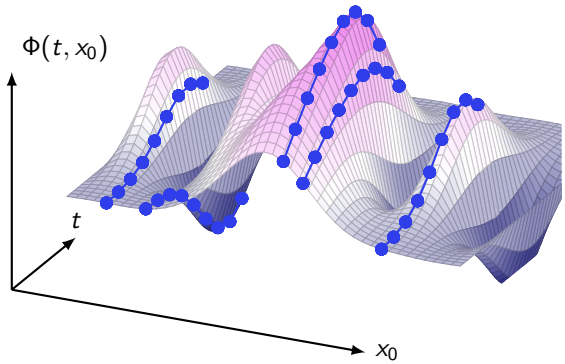
Vanilla Neural Network

$$\hat{\mathbf{x}}_{NN} = f\Big(\mathbf{W}_2 \cdot g(\mathbf{W}_1 \cdot \mathbf{x}_0 + \mathbf{b}_1) + \mathbf{b}_2\Big)$$



Shaping the Loss Function: Integrating Physics

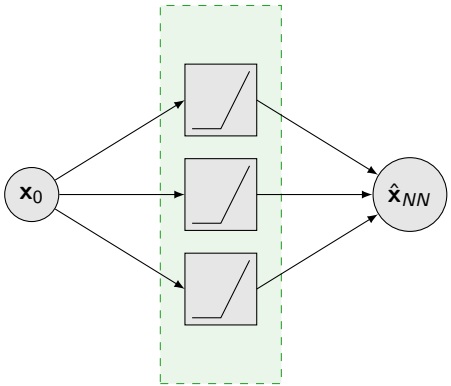
We change the minimization objective during training:



$\hat{x}_{NN}$: NN output, X: true solution, since X is unavailable, we use the NN output $\hat{x}_{NN}$ to evaluate the source term for the residual $\mathcal{R}_p$

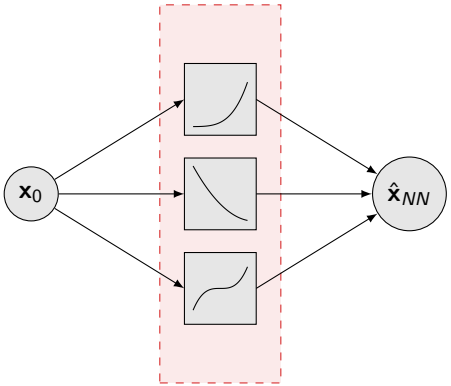
Shaping Activation Functions: Achieving Smaller Neural Networks

Classic (Vanilla) Neural Networks



- Classic activations: ReLU, tanh, linear, sigmoid
- Need large models to capture highly nonlinear behaviors

Learnable Activation Function



- Kalmogorov Arnold Networks (KAN) use B-splines for learnable activation
- Smaller neural network architectures can capture highly nonlinear systems

B-Splines: The Foundation of Kalmogorov Arnold Networks

Key Idea: Any multivariate, continuous function on a bounded domain is a sum of u univariate (1D) functions (**Kalmogorov-Arnold Presentation Theorem**).

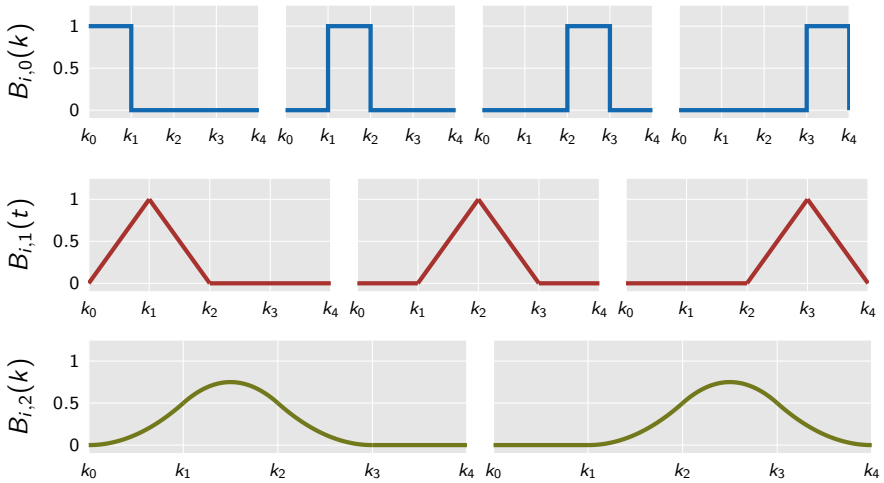
De Boor's Recursive Algorithm for B-Splines: Example with $k = 5$ uniformly distributed control points

0-th order basis function:

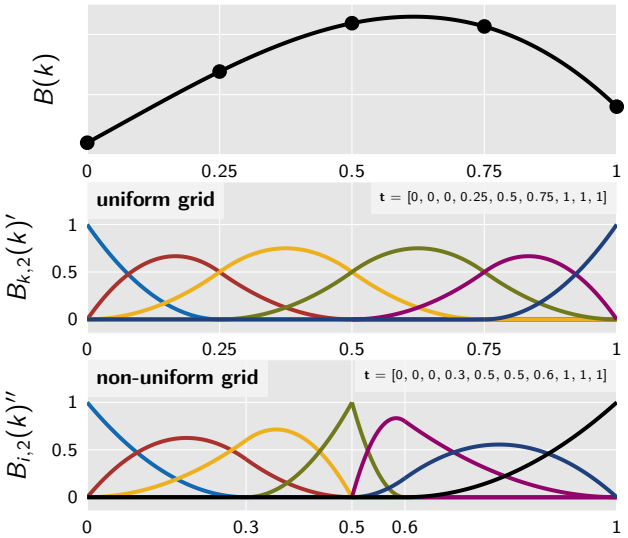
$$B_{i,0}(k) = \begin{cases} 1 & \text{if } k_i \leq k < k_{i+1}, \\ 0 & \text{otherwise.} \end{cases}$$

n-th order basis function:

$$B_{i,n}(k) = \frac{k - k_i}{k_{i+n} - k_i} B_{i,n-1}(k) + \frac{k_{i+n+1} - k}{k_{i+n+1} - k_{i+1}} B_{i+1,n-1}(k)$$



KAN-Layers: Weighted Sum of B-Splines provide Flexible Activation



The **final KAN activation** $\phi(\mathbf{x})$ is:

$$\phi(\mathbf{x}) = \mathbf{w} \cdot \underbrace{\mathbf{c} \cdot \mathbf{B}(x)}_{\text{weighted sum of B-Splines}} + \boldsymbol{\alpha} \cdot \text{base}(\mathbf{x}),$$

where

$\mathbf{w}, \boldsymbol{\alpha}$	weights
$\mathbf{B}(x)$	B-splines
$\text{base}(\mathbf{x})$	pre-defined base activation

KANs are Challenging to Train

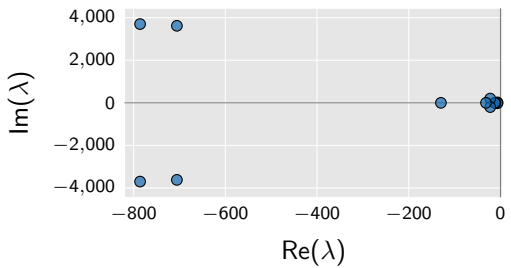
- trainable parameters: $\boldsymbol{\alpha}, \mathbf{c}, \mathbf{w}$
- hyper-parameters: grid (number and location of control points)
- one **recursive evaluation of splines per neuron**, hindering parallelization
- more **prone to overfitting**
- BUT they can provide a **compact closed-form solution**

Supporting Multi-Time Scales: ActNET Layers

Eigenvalue Spectrum of Power System Components

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{A}\,\mathbf{x}(t) + \mathbf{B}\,\mathbf{u}(t)$$

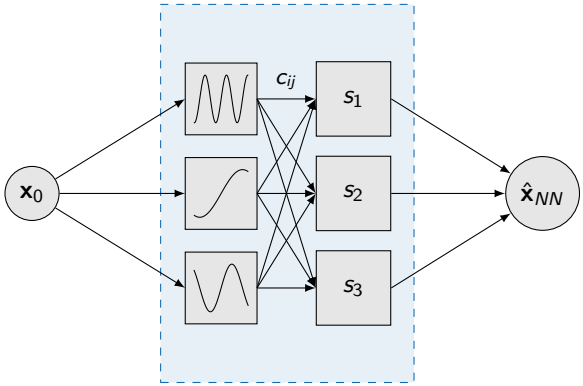
$$x_i \propto e^{-\lambda_{A,i} t} = e^{-(\sigma_i \pm j\omega_i)t}$$



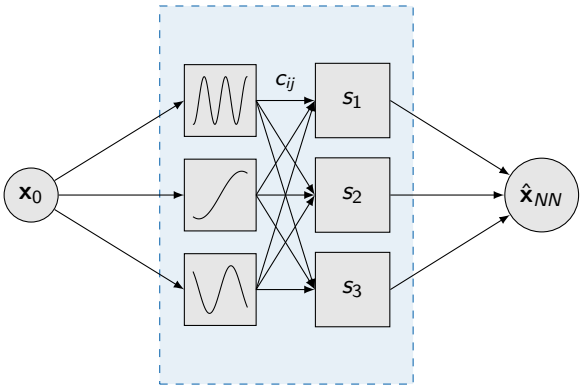
Challenges for ML:

- Dynamic behavior of one state x is superposition of multiple eigenmodes λ on multiple time-scales
- Learning modes across all required time-scales is computationally challenging

ActNET Layer: each input channel is a **sum of learnable sinusoidal components with different frequencies**



ActNET Layers: Decomposition into Multiple Frequency Components



Sinusoidal Activation Function

$$\phi_i(t) = \frac{\sin(\omega_i t + p_i) - \mu_i}{\sigma_i + \varepsilon}$$

- ω_i and p_i are **trainable frequency and phase parameters**
- μ_i, σ_i **normalize** the output for numerical stability

Given input vector $\mathbf{x}$, ActNET layers compute the mixed response of channel/neuron i:

$$\widehat{\mathbf{x}}_{NN} = \sum_{i=1}^{m} s_i(\mathbf{x})), \qquad s_i(\mathbf{x}) = \sum_{j=1}^{n} c_{ij}\, \phi_i(x_j)$$

This ActNET structure aligns the **architecture with the multi-timescale nature of power system dynamics!**

Note: We can learn all these advanced architectures with classic loss terms, or **physics-informed losses**.

Results: Capturing Different Frequency Components

Case Study Setup

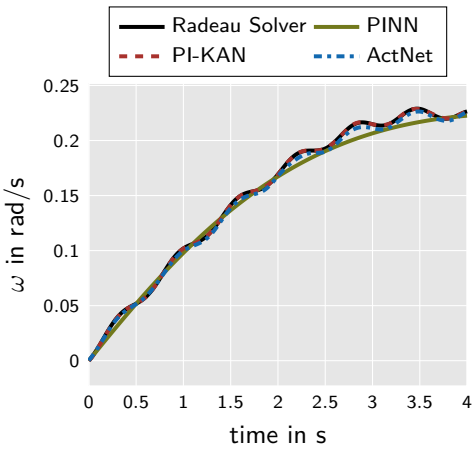
Learning the dynamics of a **single-machine-infinite bus (SMIB) system** with oscillatory voltage inputs:[2]

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & H & 0 \\ 0 & 0 & \tau \end{bmatrix} \frac{d}{dt} \begin{bmatrix} \delta \\ \omega \\ V \end{bmatrix} = \begin{bmatrix} \omega \\ P_m - EV\sin(\delta) + P_L(t) - D\omega \\ V_{\text{ref}} - V + k\sin(\delta) \end{bmatrix}$$

System Parameters and States

H	system inertia
δ, ω, V	dynamic states: angle, frequency and voltage
E	internal voltage of the synchronous machine
P_m, P_L	mechanical and electric load of the synchronous machine
D	damping coefficient
V_{ref}, k	shaping terminal voltage

Dynamic Response of a Vanilla PINN, PI-KAN and ActNET



[2] P. Ellinas, J. Vorwerk, S. Chatzivasileiadis, "*Tools to Explain Neural Networks for Power System Dynamics*"

Results: Accuracy and Runtime Comparison

Case Study Setup

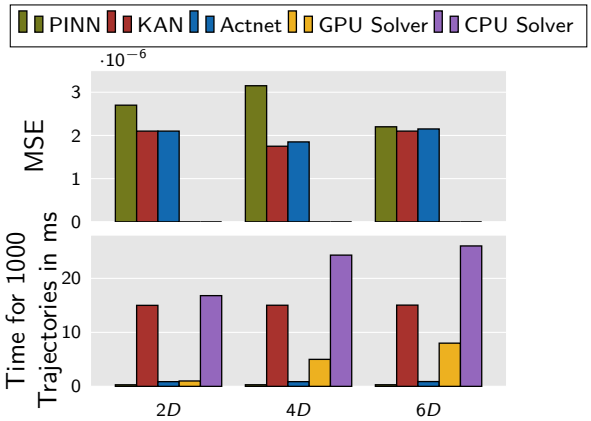
Learning the dynamics of an **SMIB system** of different orders:

- 2nd order SM model → 2D
- 4th order SM model → 4D
- 6th order SM model → 6D

Details in:

P. Ellinas, J. Vorwerk, S. Chatzivasileiadis, "*Tools to Explain Neural Networks for Power System Dynamics*"
www.github.com/elpetros99/tools_explaining_power

I. Karampinis, P. Ellinas, I. Ventura Nadal, R. Nellikkath, S. Chatzivasileiadis, "*Toolbox for Developing Physics Informed Neural Networks for Power Systems Components*," 2025 PowerTech
www.github.com/radiakos/PowerPINN



Key Results

- **Architectures with learnable activation** improve **accuracy** compared to vanilla PINN, while **KANs** significantly reducing architecture size
- Runtime of **ActNET** is comparable to vanilla PINN, since it is more parallelizable than **KANs**
- **KAN** are expensive during inference, **ActNET** provide good trade-off

Neural Operators: Encoding Information into Different Networks

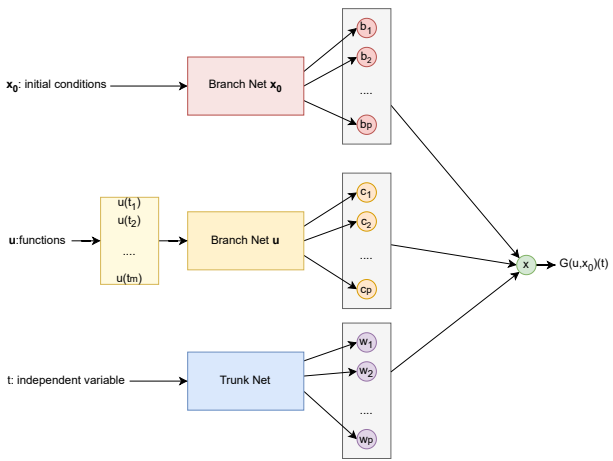
Conceptual Shift of DeepONet (Deep Operator Network):

- **separate encoding of spatial and temporal information** into different neural networks, weighted multiplication to obtain the final result
- **disturbances u(t) are variable in time**, rather than fixed for previously discussed NNs

Stacked DeepONet

- **Branch Nets** encode initial condition and disturbances into one neural network each
- **Trunk Net** encodes temporal information
- **Output**: dot product of spatial and temporal evaluation

Stacked DeepONet



Results: Comparing DeepONets to Vanilla PINNs

Case Study Setup:

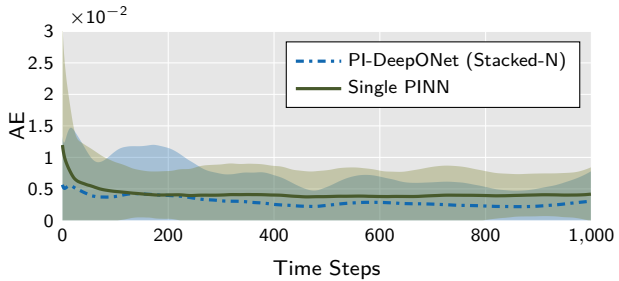
- 4th order SMIB system with varying voltage
- Time-varying input signal $\mathbf{u}(t)$: 1st or 2nd order ODE represents disturbance

Details provided in:

I.Karampinis, P. Ellinas, J. Vorwerk, S. Chatzivasileiadis, "*Neural Operators for Power Systems: A Physics-Informed Framework for Modeling Power System Components*", to be presented at PSCC 2026, www.arxiv.org/abs/2511.05216

www.github.com/radiakos/PowerDeepONet

DeepONet shows more stable errors over the prediction horizon



Inference Times and SpeedUp (in ms)

	Single Trajectory	1000 Trajectories
ODE solver	15.517	15516.834
PINN	0.189 (80×)	6.861 (2260×)
Stacked-N DeepONet	0.485 (30×)	2.415 (6430×)

ODE solver trajectories are evaluated sequentially, DeepONet and PINN simulations are parallelized

Topic 2:

Trustworthiness of ML Tools

How exact is the ML model?
What did the ML model learn?
Can we understand the ML model results?

Verification: How exact is the ML model?

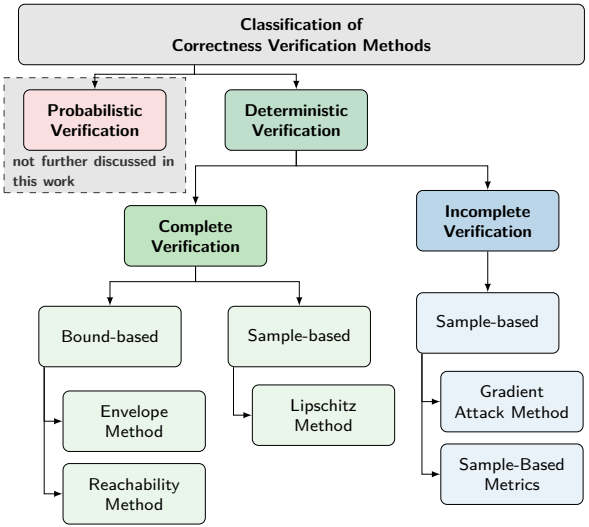
Verification finds the **maximum discrepancy** of the ML model to the **true solution** and checks it agains an error specification ε

$$\max_{(\mathbf{x}_0,t)\in\mathcal{U}} ||\mathbf{x}(\mathbf{x}_0,t) - \widehat{\mathbf{x}}_{NN}(\mathbf{x}_0,t)|| \leq \varepsilon$$

- $\widehat{\mathbf{x}}_{NN}$ is continuous and in close form
- $\mathbf{x}$ is potentially discretized and not in closed form

More details:
P. Ellinas, et al., "*Physics-informed machine learning for power system dynamics: A framework incorporating trustworthiness*", SEGAN, Volume 43, 2025, www.doi.org/10.1016/j.segan.2025.101818, presented at IREP 2025

Verification toolbox:
P. Ellinas, I. Chaudhuri, J. Vorwerk, S. Chatzivasileiadis, "*Verification and Validation of Physics-Informed Surrogate Component Models for Dynamic Power-System Simulation*", in review, www.arxiv.org/abs/2603.17836



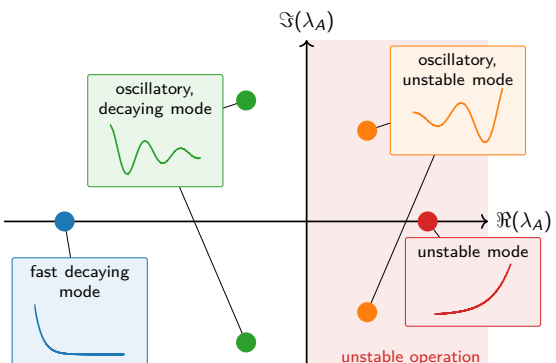
Neural Tangent Kernel (NTK): Insights into Training Dynamics

Small-Signal Stability Analysis

The locations of the eigenvalues $\boldsymbol{\lambda}_A$ of the state-space matrix $\mathbf{A}$ provide insights into the dynamic mode behavior:

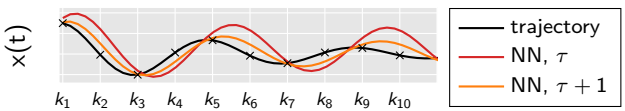
$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{A}\,\mathbf{x}(t) + \mathbf{B}\,\mathbf{u}(t)$$

$$x_i \propto e^{-\lambda_{A,i} t} = e^{-(\sigma_i \pm j\omega_i)t}$$



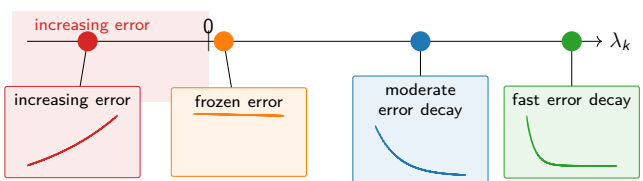
NTK Analysis

NTK provides insights into how fast dynamics are learnt by an ML model. Consider the following trajectory with 10 collocation points:



The NTK eigenvalues $\boldsymbol{\lambda}_k$ indicate how quickly the training error decays per collocation point. The training losses over epochs τ decay with learning rate η:

$$\mathcal{L}_k(\tau) \approx \mathcal{L}_k(0) e^{-\eta \lambda_k \tau}$$



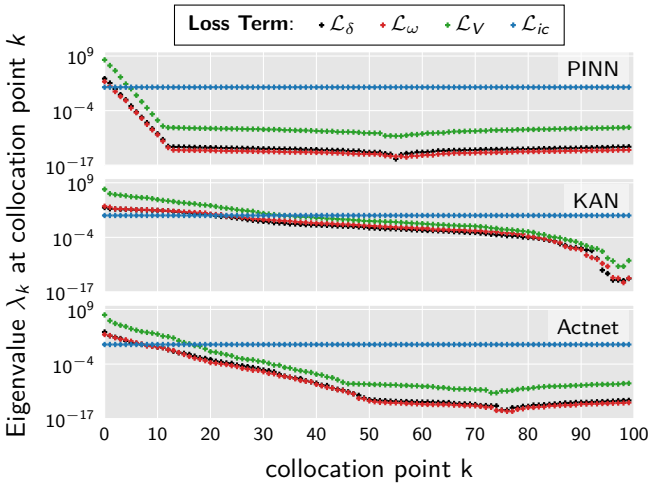
Neural Tangent Kernel (NTK): Insights into Training Dynamics

Case Study: Modified SMIB system from before, 2nd order SM with voltage dynamics
We monitor the different **physics-based loss terms**:

- rotor angle: $\mathcal{L}_\delta$
- rotor speed: $\mathcal{L}_\omega$
- terminal voltage: $\mathcal{L}_V$
- initial condition: $\mathcal{L}_{ic}$

A **flat NTK spectrum** indicates that all collocation points are learnt at an equal rate.

More details: P. Ellinas, J. Vorwerk, S. Chatzivasileiadis, "*Tools to Explain Neural Networks for Power System Dynamics*"



Main Findings:

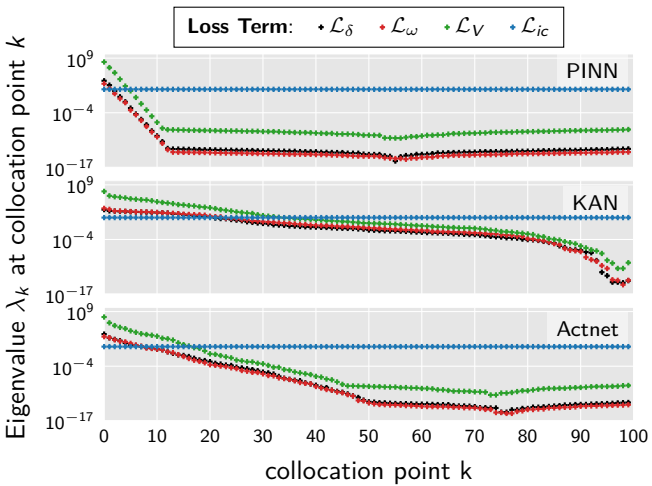
- Losses of fast-changing components (V) are always higher than slow components (δ, ω)
- KAN provides better learning (flatter profile) across the NTK spectrum

Neural Tangent Kernel (NTK): Updated Learning Weights

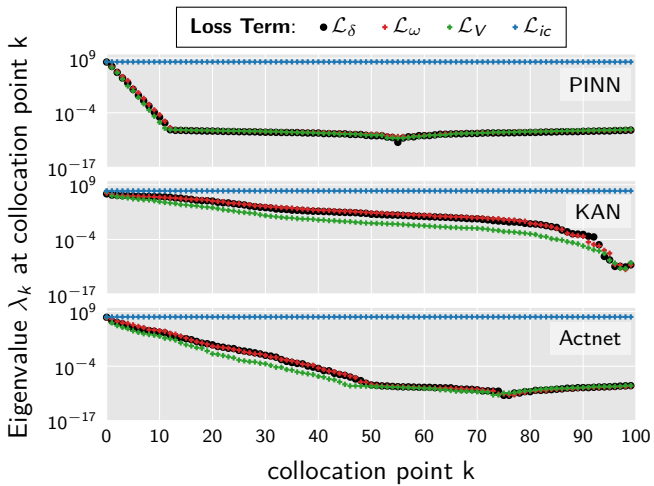
To promote **uniform convergence across loss components**, we integrate an **adaptive weighting scheme** during training:

$$\mathcal{L} = \mathbf{w}_\delta \mathcal{L}_\delta + \mathbf{w}_\omega \mathcal{L}_\omega + \mathbf{w}_V \mathcal{L}_V + \mathbf{w}_{ic} \mathcal{L}_{ic}$$

Classic Physics-Informed Training



Training with Adaptive Weights



Neural Tangent Kernel: Insights into Learning Inverter Dynamics

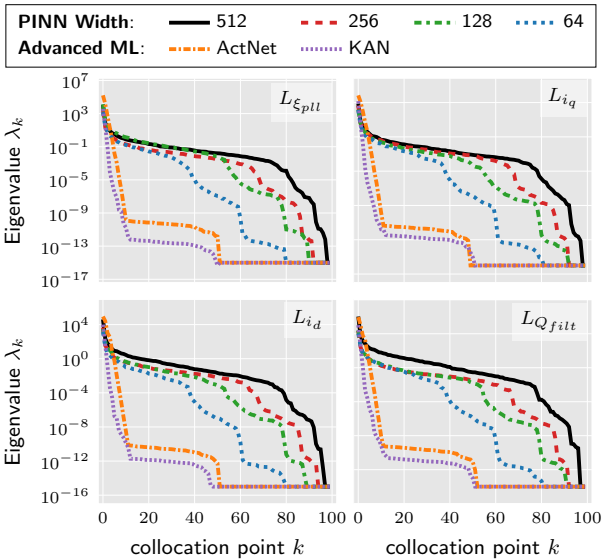
Case Study: **11th order inverter model** with nested control loops
We monitor the different **physics-based loss terms** for each of the 11 dynamics states.

- rotor angle: $\mathcal{L}_\delta$
- rotor speed: $\mathcal{L}_\omega$
- terminal voltage: $\mathcal{L}_V$
- initial condition: $\mathcal{L}_{ic}$

More details: P. Ellinas, J. Vorwerk, S. Chatzivasileiadis, "*Tools to Explain Neural Networks for Power System Dynamics*"

Main Findings:

- Spectra of some inverter states are very uneven: span a large range of magnitude across the entire spectrum
- No balanced learning across the different inverter states observed



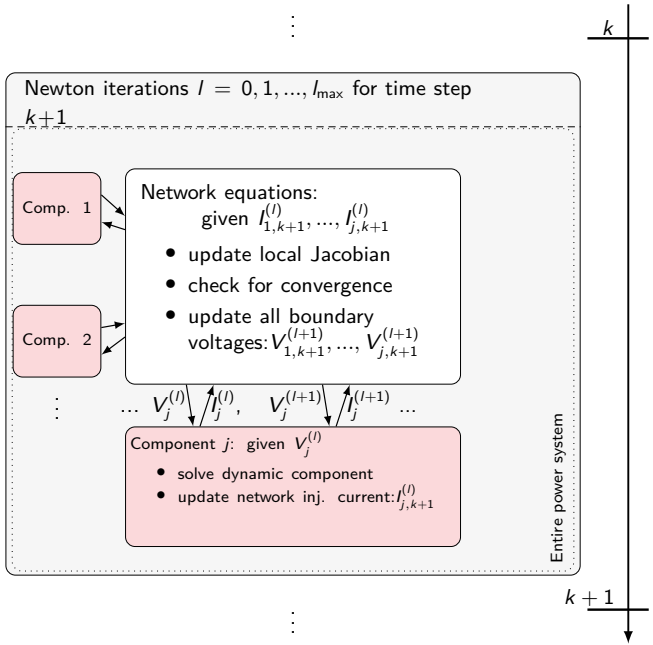
Topic 3:

System-Level Time-Domain Simulations with ML Support

How can we integrate the trained models into existing time-domain simulators?

Classic Time-Domain Simulations

- ODEs describe component dynamics: e.g. synchronous machine, converter, etc.
- Algebraic equations describe the network
- During one time-step, Newton iterations are solved until the network and dynamic equations match
- **Dynamic components** can be computed and updated in **parallel**, convert the terminal voltage to currents
- **Network equations** take current injections from components, solve the network, and update terminal voltages



Integration of Neural Surrogates into Time-Domain Solvers

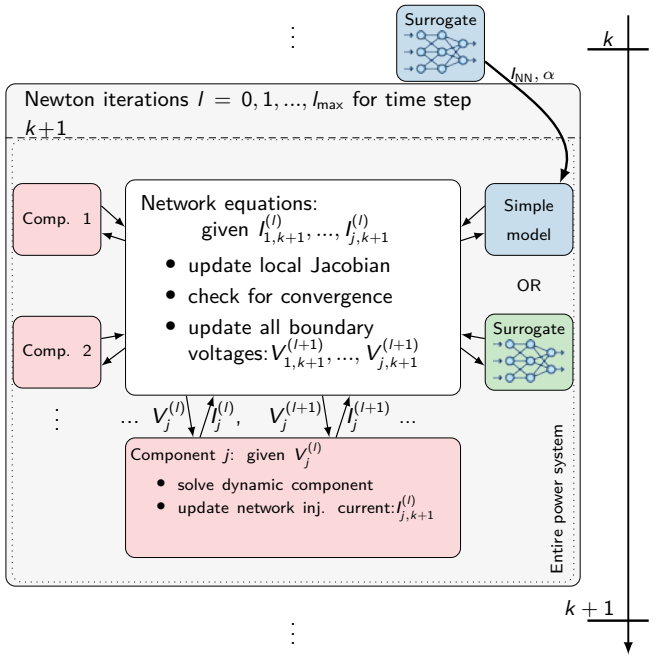
"Once-a-Newton-Iteration" Approach

- The ML surrogate is solved instead of the DAEs in the component
- Requires high accuracy ML surrogate for the Newton iteration to work

"Once-a-Time-Step" Approach

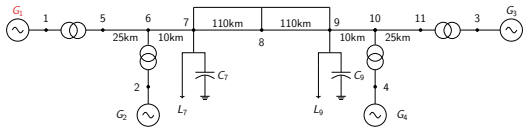
- The ML surrogate is solved **once per time-step**
- We use a simple model that represents the information retrieved from the ML surrogate in the Newton iterations, e.g. a constant

For both approaches, we need to **convert the terminal voltages into the input required** by our neural surrogate.



Example: Integration into Ramses/ STEPSS

Case Study: Replace G1 in the 11-bus Kundur system with a neural surrogate

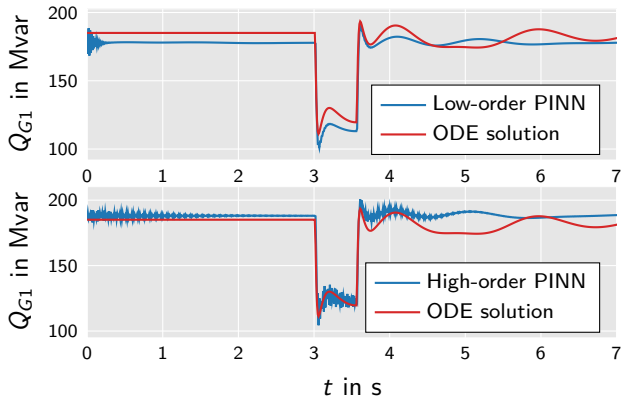


Details:

B. Gelfort, I. Karampinis, M. Desai, P. Aristidou, G. Hug, J. Vorwerk, "*Embedding Neural Surrogates into Established Dynamic Power System Simulators*", to be presented at PowerUp 2026, Boulder

www.github.com/BrunoGelfort/RamsesNN

Results: Once-a-Time-Step Approach



Main findings:

- "Once-a-Newton" Approach not successful: NN errors need to remain below the Newton tolerances
- "Once-a-Time-step" Approach successful, but **drift** in steady-state and oscillations observed

» enhance training procedures to reduce errors

Key Takeaways

ML can aid time-domain simulations through **speed-up**, **representation of complex dynamics** (within one or across simulation domains), and **improved IP**

Engineering activation functions together with **physics-informed learning** are interesting pathways for learning DAEs

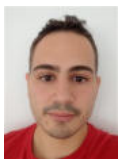
Verification and explainability tools like the **Neural Tangent Kernel (NTK)** analysis are key to enhance **trustworthiness and validity** of ML Tools

Neural surrogates can be **integrated into standard time-domain tools** through once-a-time-step evaluations (advancements needed for Newton iterations)

- We need to **consider downstream tasks when designing ML Tools**, e.g. accuracy requirements for time-domain simulations restrict acceptable training error
- **Improve training error**: integrate (real-world) data into the learning process to reduce overall modeling error, learning complex, high-order models
- Improve **neural surrogate representation in time-domain simulations** and conduct assessment integrated into final application
- Study **steady-state and stability properties** of neural surrogates

Thank you for joining us!

The main body of the research presented in this presentation was conducted by:



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- Maitraya Desai, ETH Zürich
- Gabriela Hug, ETH Zürich
- Petros Aristidou, Cyprus University of Technology

You are more than welcome reach out for discussions and follow-up!

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