CDC 2021 Workshop
“Uncertainty Management in Power System Dynamics”

Physics-Informed Neural Networks for Power System Dynamics

Spyros Chatzivasileiadis
Associate Professor, DTU

Joint work with Jochen Stiasny, Georgios Misyris, Andreas Venzke, Sam Chevalier

Power Systems Are Changing

- Millions of new converter connected resources
  - Transients propagate faster
  - We need to **decide and act faster**

- No clear separation between fast and slow dynamics
  - Need for more EMT models and simulations
  - **Complexity** increases exponentially

- Towards a 100% Renewables System
  - **Uncertainty** in supply and demand

How can we manage uncertainty with increasingly complex power system dynamics? **AI can help.**

Neural Networks for Power Systems

1. **Extremely fast → can assess 100x-1'000x more of critical scenarios**
   - computation within only a **few milliseconds** (100x – 1000x faster than conventional methods)
   - Predict fast and act faster increasing resilience

2. Can handle **very complex systems,** and **infer** from incomplete data

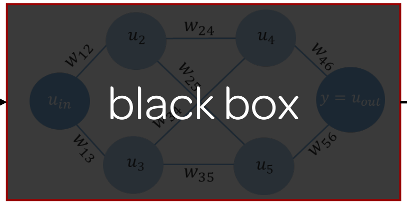
3. Neural networks are **universal function approximators**
   - Can theoretically approximate any function
   - Train **NNs as proxies for complex models** → can give a very fast estimate, boosting simulation speed

But:

Would an operator ever trust AI in the Control Room?

ML Barriers for Power systems

Input:
Operating point



secure/
insecure

1. Why would we use a "**black box**" to decide about **a safety-critical application**?

2. Do we have **enough** (good-quality) **data** to train a neural network that achieves a good performance?

3. Why would we only depend on **discrete and incomplete data**, when we have developed **detailed physical models** over the past 100 years?

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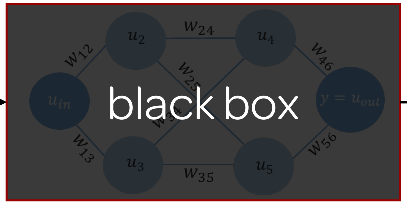

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Physics-Informed Neural Networks

- Integrate power system models in **NN training**
- Potential to replace conventional solvers?

Why Physics-Informed Neural Networks? (PINNs)

1. Make **Neural Networks follow the physics**, by taking advantage of the wide range of models we have available

2. **Drastically reduce** the amount of high-quality **data** that is necessary to train a good-performing neural network
   - No need for external massive datasets; which shall also cover both normal and abnormal situations equally well

3. Turn **from supervised** learning (conventional NNs) **to (semi-)unsupervised** learning
   - Limited amount of data mostly related to initial conditions or discrete events is necessary

4. Possibly, **better interpretability** (no longer a “black-box”)

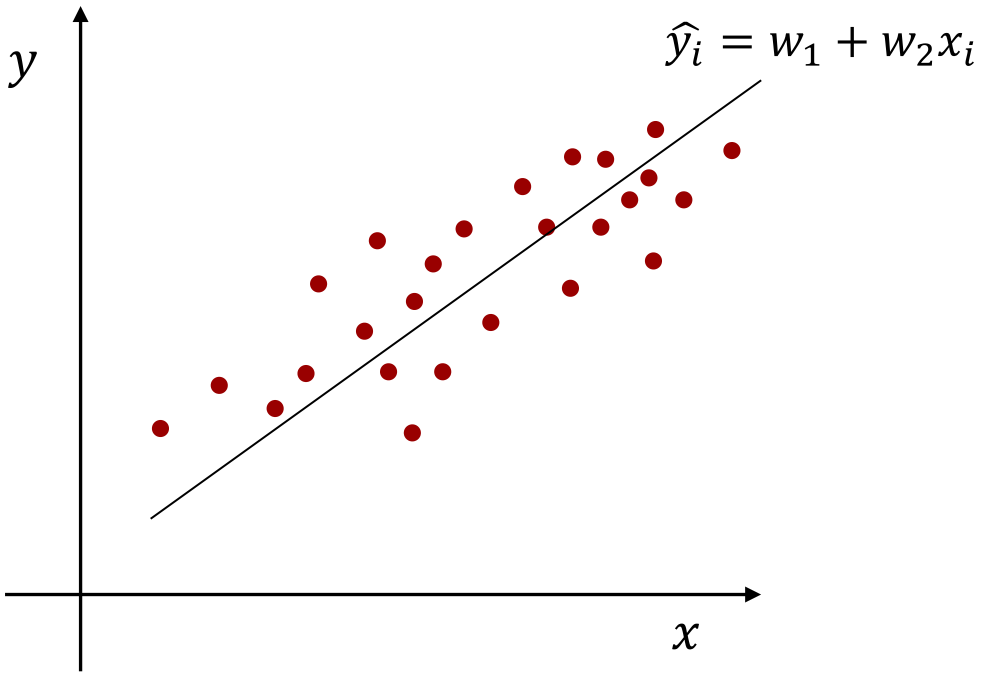
5. Will PINNs **replace conventional solvers?**

Physics-Informed Neural Networks for Power Systems

Neural Networks: An advanced form of non-linear regression

y_i: actual/correct value

$\hat{y}_i$: estimated value



Loss function: Estimate best w_1, w_2 to fit the training data

$$\min_{w_1, w_2} \quad \|y_i - \hat{y}_i\|$$

s.t.

$$\hat{y}_i = w_1 + w_2 x_i \quad \forall i$$

Traditional training of neural networks required no information about the underlying physical model. Just data!

Physics Informed Neural Networks

- Automatic differentiation: derivatives of the neural network output with respect to the input can be computed during the training procedure
- A differential-algebraic model of a physical system can be included in the neural network training*
- Neural networks can now exploit knowledge of the actual physical system
- Machine learning platforms (e.g. Tensorflow) enable these capabilities

*M. Raissi, P. Perdikaris, and G. Karniadakis, Physics-Informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations", Journal of Computational Physics, vol.378, pp. 686-707, 2019

Physics-Informed Neural Networks for Power Systems

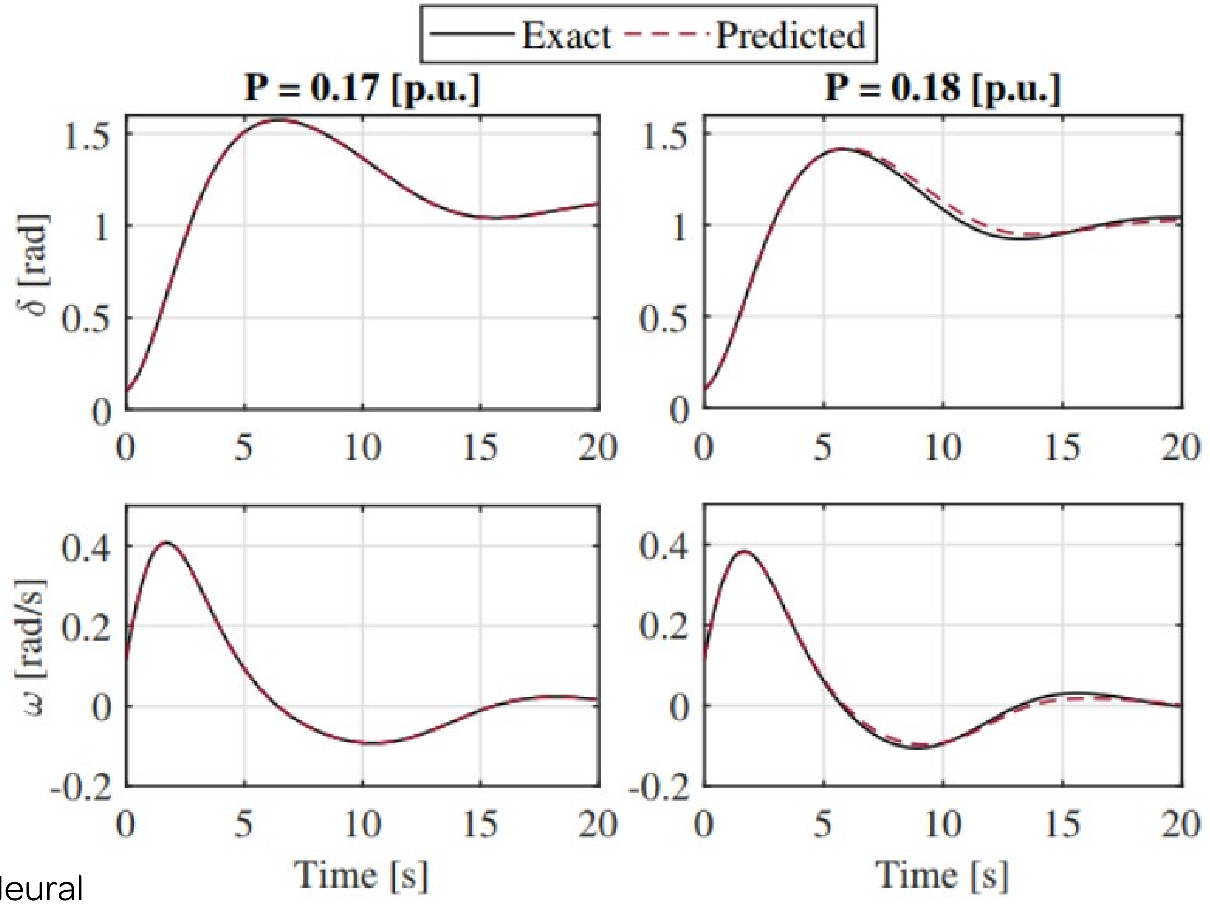
"Original"
Loss function

$$\boxed{\min_{\mathbf{W},\mathbf{b}} \quad \frac{1}{|N_\delta|}\sum_{i\in N_\delta}|\hat{\delta}-\delta^i|^2} + \frac{1}{|N_f|}\sum_{i\in N_f}|f(\hat{\delta})|^2 \tag{6a}$$

$$s.t. \qquad \hat{\delta} = NN(t, P_m, \mathbf{W}, \mathbf{b}) \tag{6b}$$

$$\dot{\hat{\delta}} = \frac{\partial\hat{\delta}}{\partial t}, \qquad \ddot{\hat{\delta}} = \frac{\partial\dot{\hat{\delta}}}{\partial t} \tag{6c}$$

$$f(\hat{\delta}) = M\ddot{\hat{\delta}} + D\dot{\hat{\delta}} + A\sin\hat{\delta} - P_m \tag{6d}$$



G. S. Misyris, A. Venzke, S. Chatzivasileiadis, Physics-Informed Neural Networks for Power Systems. Presented at the Best Paper Session of IEEE PES GM 2020. https://arxiv.org/pdf/1911.03737.pdf

Physics-Informed Neural Networks for Power Systems

"Original" Loss function

"Physics-Informed" term

$$\min_{\mathbf{W},\mathbf{b}} \quad \frac{1}{|N_\delta|}\sum_{i\in N_\delta}|\hat{\delta}-\delta^i|^2 + \boxed{\frac{1}{|N_f|}\sum_{i\in N_f}|f(\hat{\delta})|^2} \tag{6a}$$

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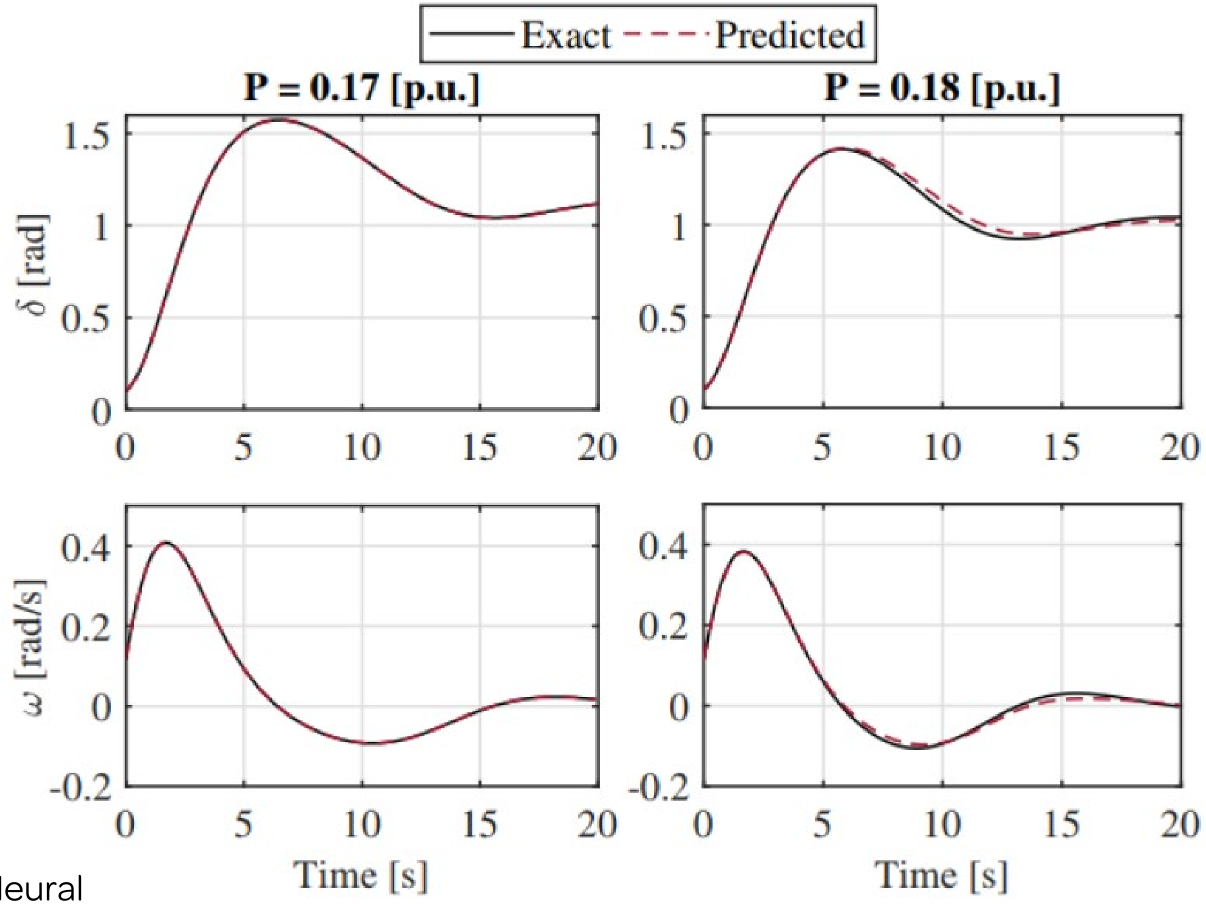
Swing equation



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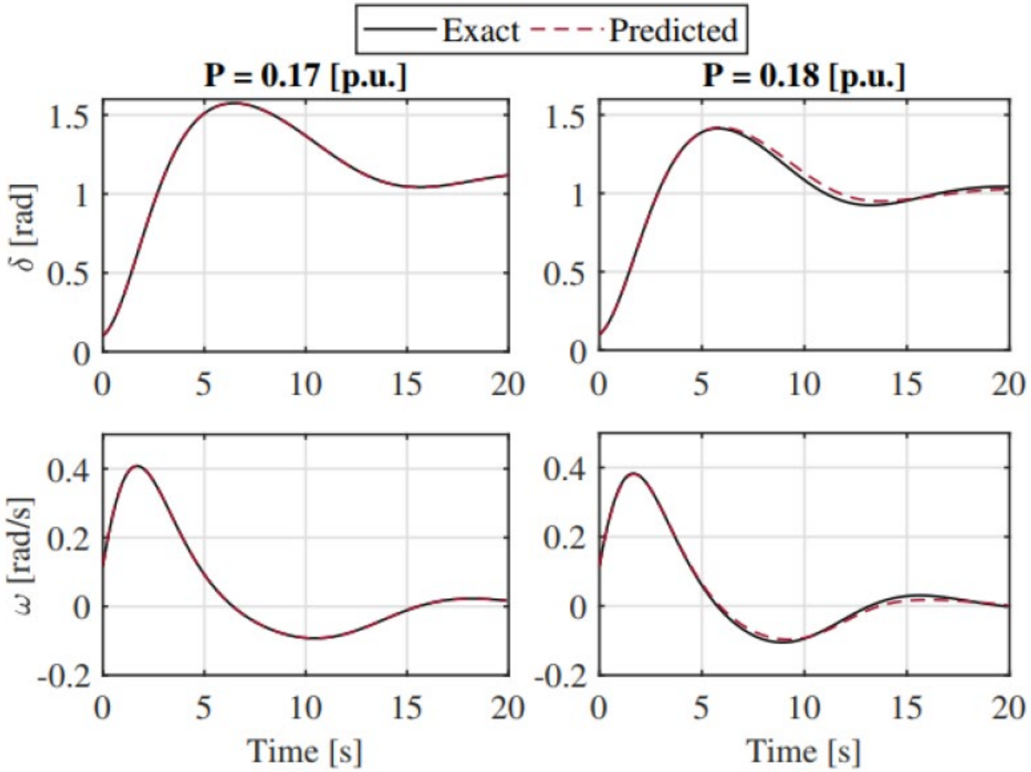
Physics-Informed Neural Networks for Power Systems

- Physics-Informed Neural Networks (PINN) could potentially replace solvers for systems of differential-algebraic equations in the long-term
  - **Probable power system application: Extremely fast screening of critical contingencies**

- In our example: PINN 87 times faster than ODE solver

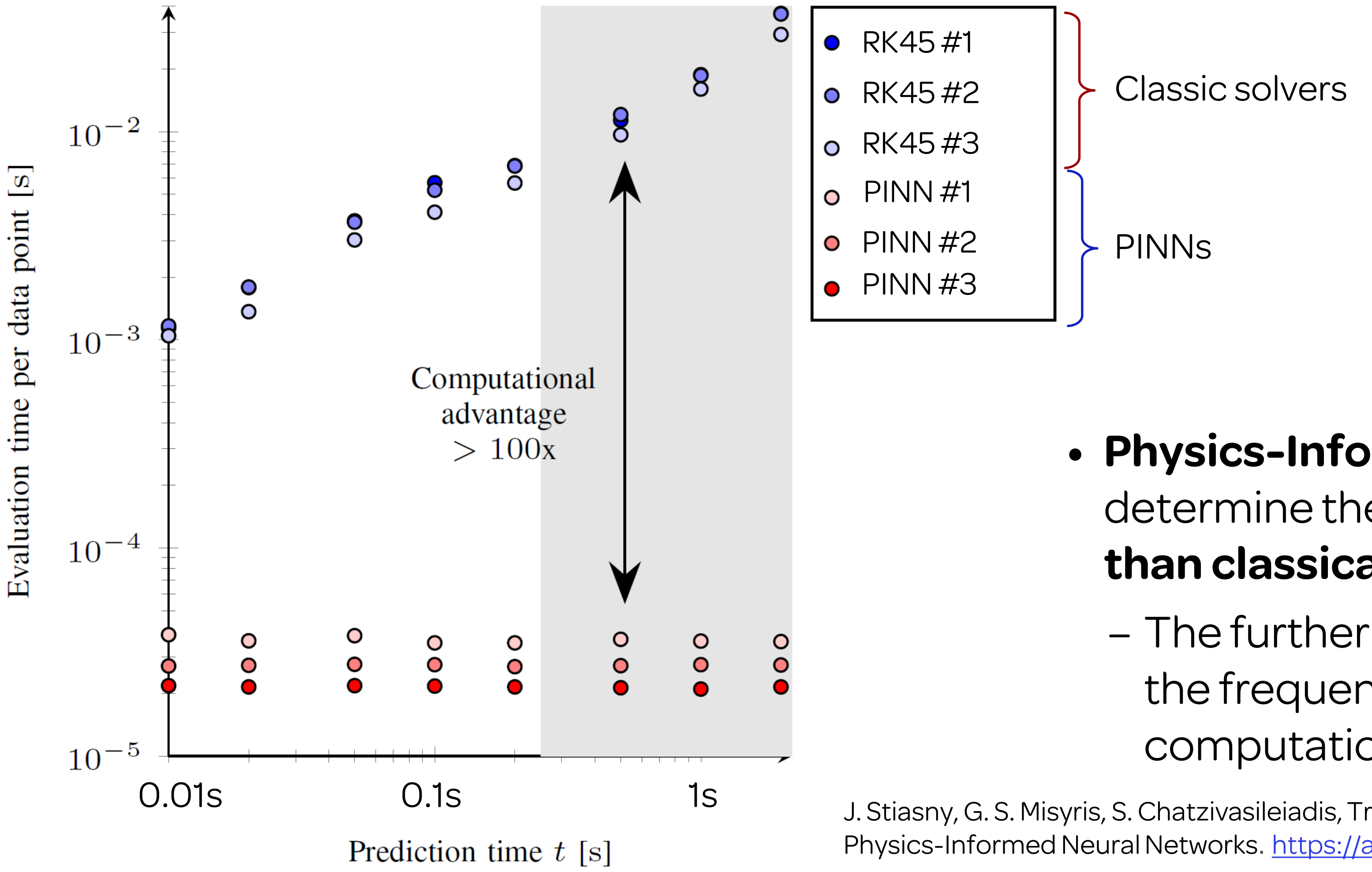
- Can **directly estimate** the rotor angle at **any** time instant



Code is available on GitHub: https://github.com/jbesty

G. S. Misyris, A. Venzke, S. Chatzivasileiadis, Physics-Informed Neural Networks for Power Systems. Presented at the Best Paper Session of IEEE PES GM 2020. https://arxiv.org/pdf/1911.03737.pdf

Computation time: Classical numerical solvers vs. Physics-Informed NNs



- **Physics-Informed Neural Networks** can determine the outputs more than **100x faster than classical numerical solvers**
  - The further ahead we look in time, e.g. what is the frequency at t=1s, the larger the computational advantage is

J. Stiasny, G. S. Misyris, S. Chatzivasileiadis, Transient Stability Analysis with Physics-Informed Neural Networks. https://arxiv.org/abs/2106.13638 [code]

Do Physics-Informed Neural Networks really work?

- To understand what is the impact of physics inside NN training, we designed a new training procedure → dtNN

$$\min_{\mathbf{W},\mathbf{b}} \frac{1}{|N_\delta|} \sum_{i \in N_\delta} |\hat{\delta} - \delta^i|^2$$

NN: standard training procedure

NN uses an external training dataset

$$\min_{\mathbf{W},\mathbf{b}} \frac{1}{|N_\delta|} \sum_{i \in N_\delta} |\hat{\delta} - \delta^i|^2 + \frac{1}{|N_\delta|} \sum_{i \in N_\delta} |f(\hat{\delta})|^2$$

dtNN: check if NN output satisfies physics

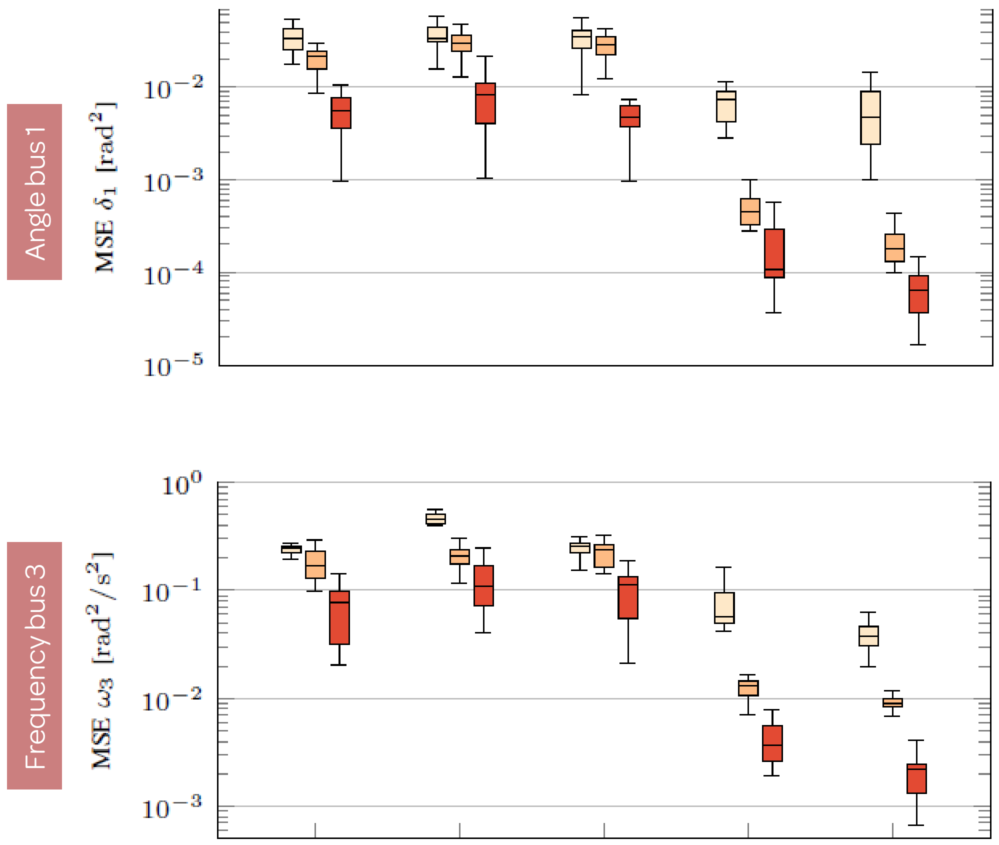
NN uses an external training dataset

$$\min_{\mathbf{W},\mathbf{b}} \frac{1}{|N_\delta|} \sum_{i \in N_\delta} |\hat{\delta} - \delta^i|^2 + \frac{1}{|N_\delta|} \sum_{i \in N_\delta} |f(\hat{\delta})|^2 + \frac{1}{|N_f|} \sum_{i \in N_f} |f(\hat{\delta})|^2$$

PINN: check if NN output satisfies physics

NN uses an external training dataset and randomly generated inputs (collocation points)

Do PINNs really work?



- The introduction of physics reduces the estimation error in all cases

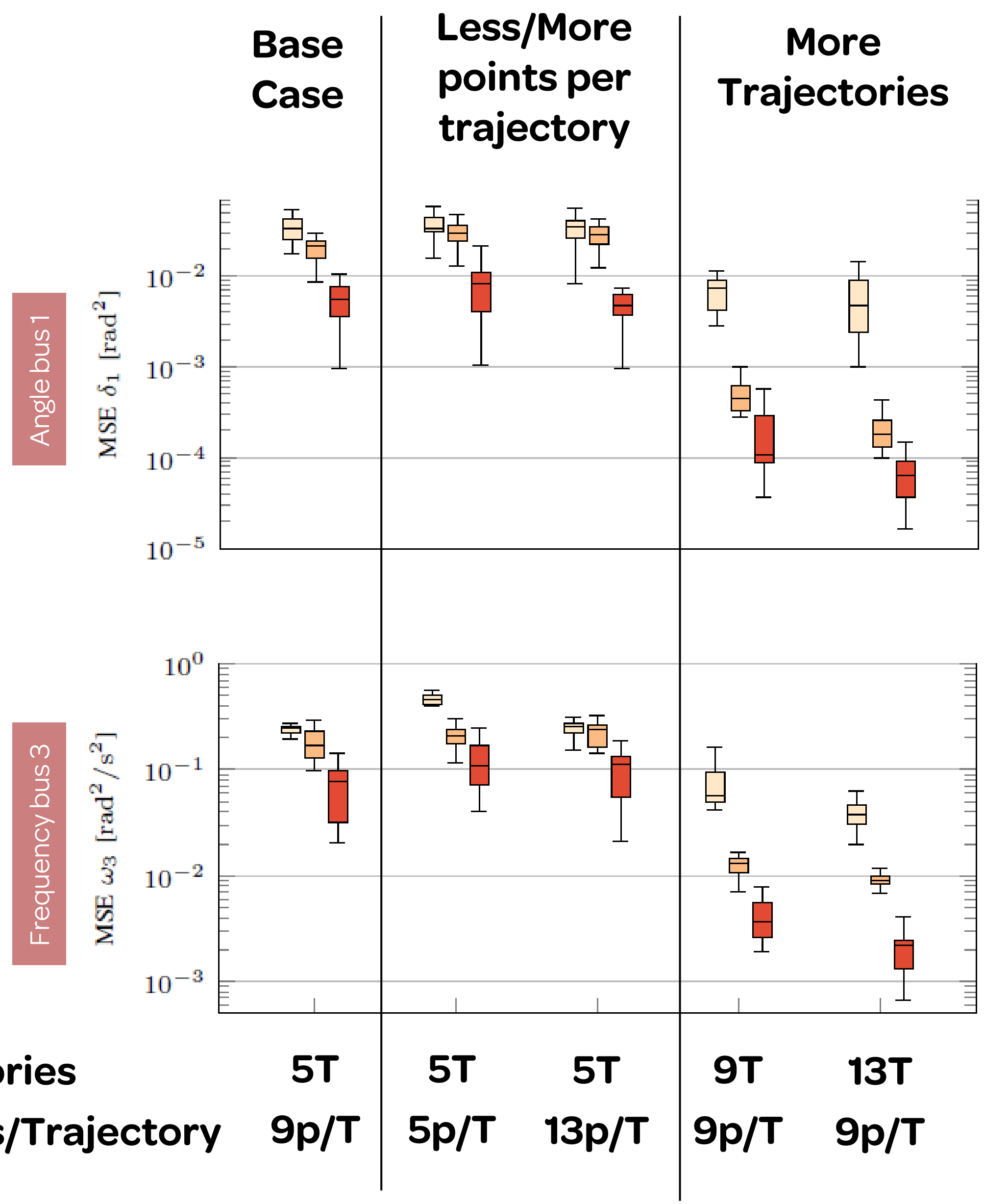
- PINNs assess if the physics hold in an additional, large set of randomly generated inputs (without us providing any external info)
  → this helps

standard NN: no physics

dtNN: physics on the external training dataset

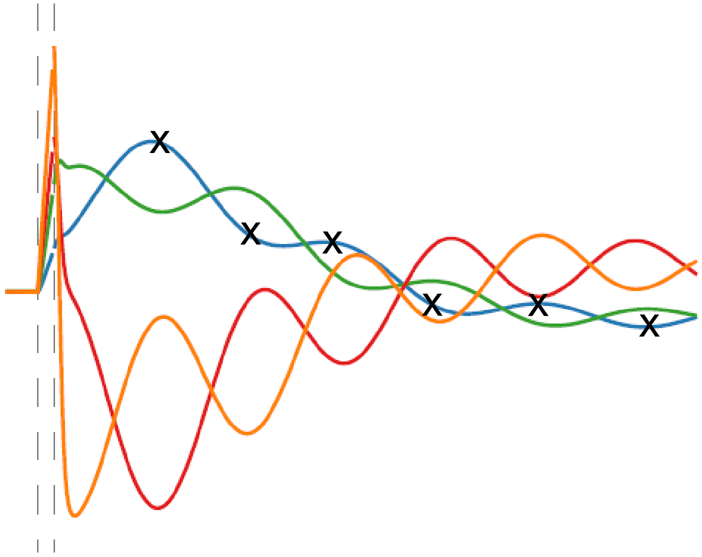
PINN: physics on external dataset and a lot of randomly generated inputs

What types of data are important?



T: Trajectories

p/T: points/Trajectory



- standard NN: no physics
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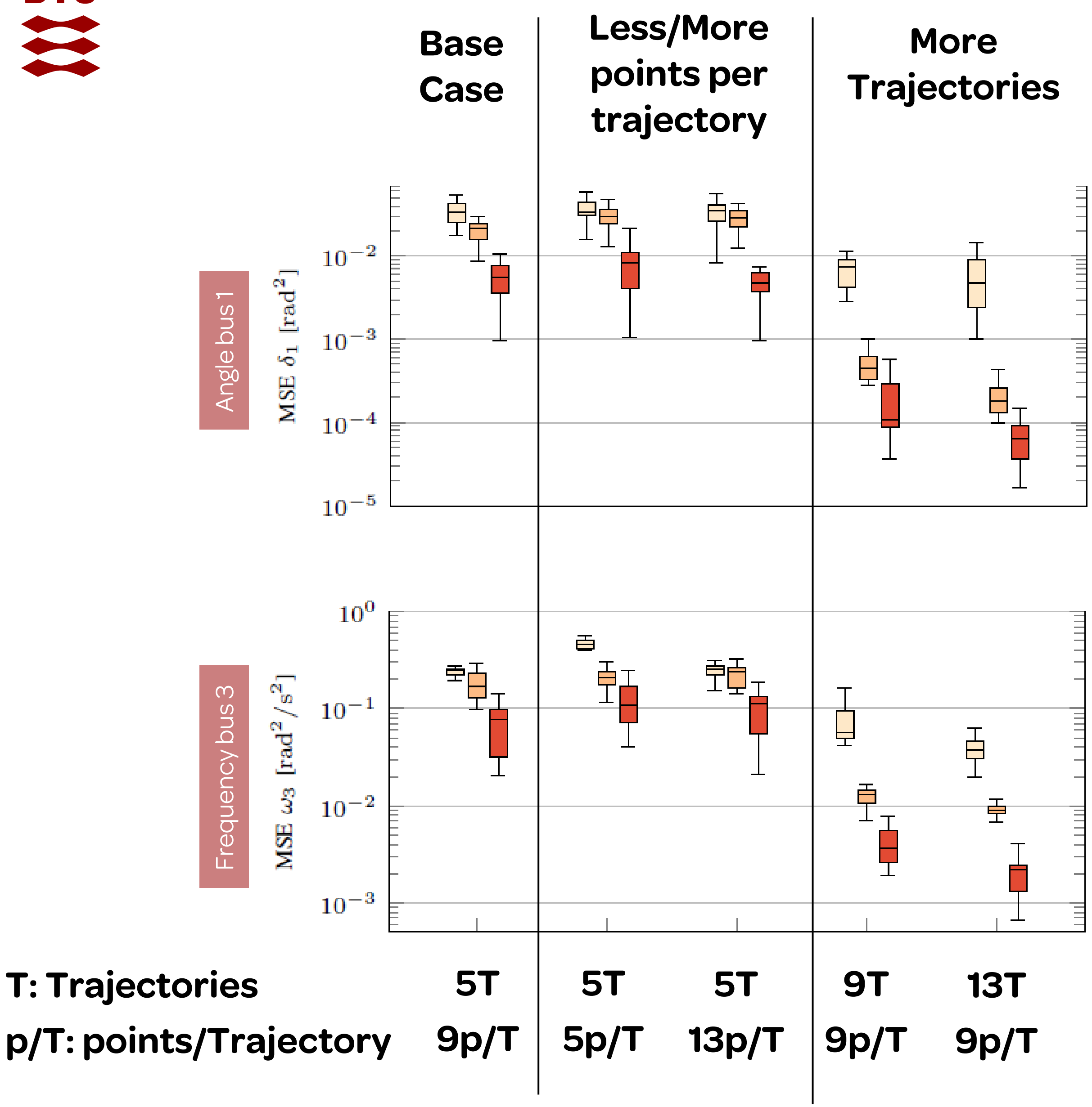
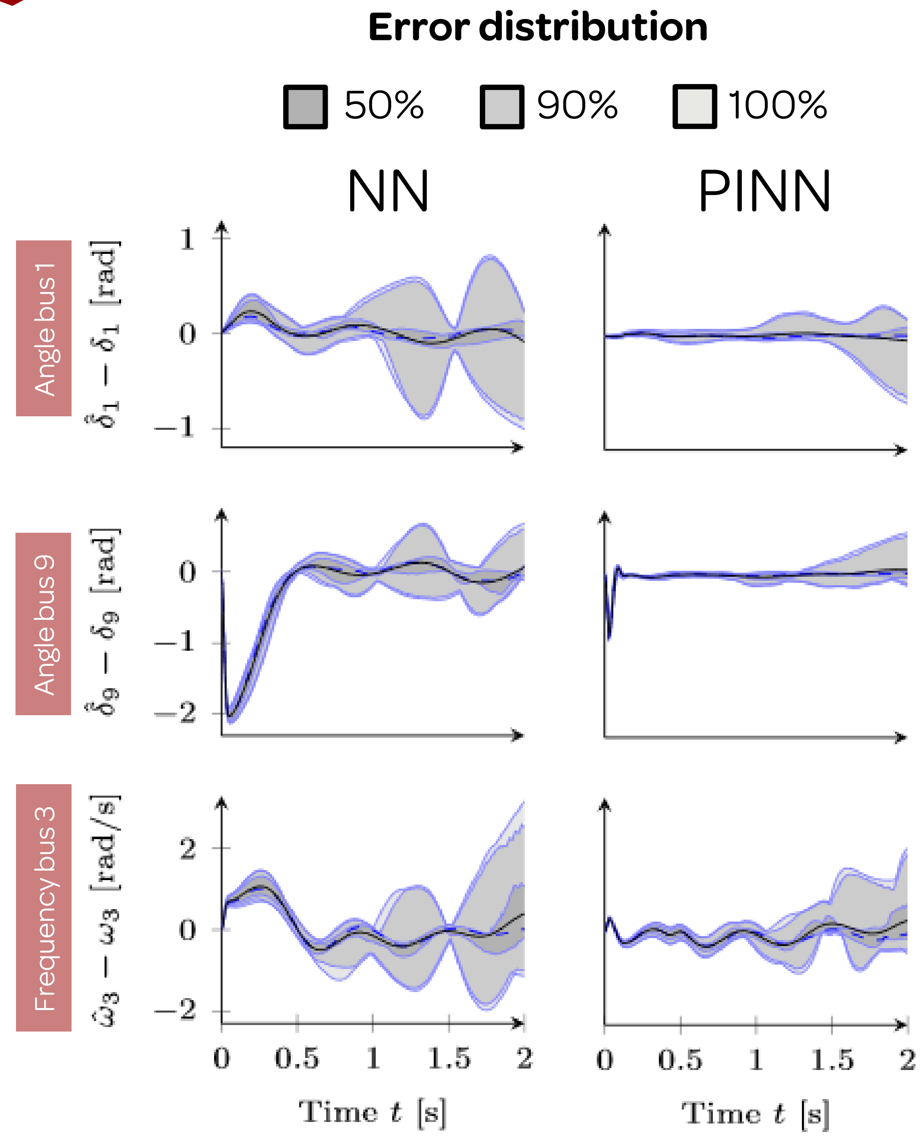


- The estimation errors differ based on the type of data we include in the external training database
- **Including more trajectories reduces error**
- If physics are included (PINNs), additional external data are not necessary for a given trajectory; **given the initial conditions, the NN can infer the rest of the trajectory from physics**

standard NN: no physics

dtNN: physics on the external training dataset

PINN: physics on external dataset and a lot of randomly generated inputs



Prediction horizon: Standard Neural Networks (NN) vs. Physics-Informed NNs (PINN)

- The error increases as we look further into the future
- **PINNs result in lower errors** than standard neural networks across time
- PINNs can deliver an excellent screening tool, i.e. to very quickly assess if critical scenarios are secure or not.
  - To determine the exact numerical values, classic solvers are still very valuable

J. Stiasny, G. S. Misyris, S. Chatzivasileiadis, Transient Stability Analysis with Physics-Informed Neural Networks. https://arxiv.org/abs/2106.13638 [code]

Computation time

1. PINNs computation time is longer
   - For the same level of accuracy, in our tests (Kundur 11-bus system) PINNs required 4 times longer computation time per epoch than standard NNs (220 ms vs 55ms)

2. A few points to consider:
   - PINNs require substantially less input data → substantially less time to generate the training database
   - PINNs accuracy can improve further without additional data. They can continue training on the physical models

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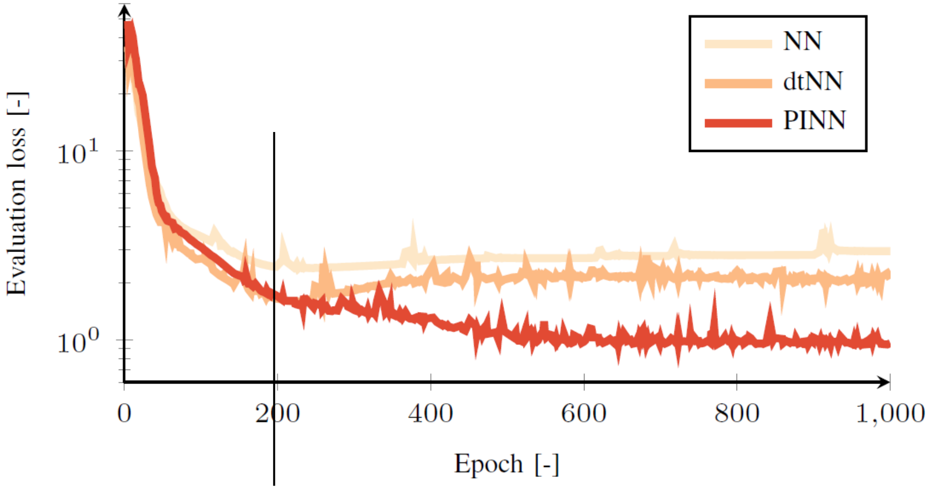
- For standard NNs and dtNNs, the estimation error plateaus after Epoch 200 → input data do not contain any more info

- PINNs continue reducing the error beyond Epoch 200 → they take advantage of the info in the physical models



Capturing Power System Dynamics by Physics-Informed Neural Networks and Optimization

- PINNs can help us determine key characteristics of non-linear dynamic systems
  - E.g. critical clearing time of a fault in power systems
- PINNs capture the non-linear dynamic behavior
- Through an **exact transformation**, **convert PINNs to a tractable optimization program** → its constraints capture the dynamic behaviour of the system
- Solve the optimization problem to **determine key critical indices**, e.g. what is the critical clearing time?
  - **Avoid exhaustive time domain simulations**

Interested to learn more?
Check out Jochen Stiasny's CDC talk on Thursday, Dec 16, Paper ThA03.4!
(13.45-14.00 CDT)

G. S. Misyris, J. Stiasny, S. Chatzivasileiadis, Capturing Power System Dynamics by Physics-Informed Neural Networks and Optimization. Accepted in IEEE Conference on Decision and Control 2021. [.pdf]

Topics I did not talk about

- PINNs to replace ODE solvers
  - Runge-Kutta PINNs
  - Extremely fast; use of neural networks as solvers

J. Stiasny, S. Chevalier, S. Chatzivasileiadis, Learning without Data: Physics-Informed Neural Networks for Fast Time-Domain Simulation. In IEEE SmartGridComm 2021, Aachen, Germany, October 2021. [paper | code]

- PINNs for parameter estimation
  - E.g. system inertia or damping
  - Kalman filters can do an excellent job for this task
  - When non-linearities increase, PINNs appear to have a better performance

J. Stiasny, G. S. Misyris, S. Chatzivasileiadis, Physics-Informed Neural Networks for Non-linear System Identification applied to Power System Dynamics. In IEEE Powertech 2021, Madrid, Spain, pages 1-6, June 2021. [.pdf]

Wrap-up

- Neural Networks are 100x-1000x faster than conventional methods
  – Increasing uncertainty: we can assess 100-1’000 more critical scenarios at the same time we would have only assessed a single one

- Physics Informed Neural Networks (PINNs) can take advantage of the rich information about existing power system models inside neural network training

- PINNs are more accurate
- PINNs require substantially less data; and are more robust against bad or incomplete data

- Still a number of challenges to be addressed:
  – Most important of them is scalability

Thank you!

Spyros Chatzivasileiadis
Associate Professor, PhD
www.chatziva.com
spchatz@elektro.dtu.dk

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Some code available at:

www.chatziva.com/downloads.html