Εμπιστεύσιμη Τεχνητή Νοημοσύνη στα Ηλεκτρικά Δίκτυα

Σπύρος Χατζηβασιλειάδης
Καθηγητής
DTU Wind

Μερικές διαφάνειες για το 1ο ΣΦΗΜΜΥ

DTU Department of Wind and Energy Systems

Working for a sustainable future

Management
Head of Department
Morten Jeppesen

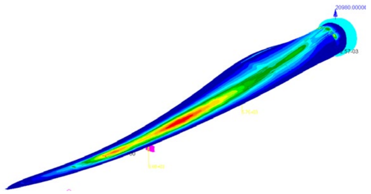
Administration
Head of Administration
Søren Knudsen

Wind Energy Materials & Components (WMC)
Head of Division
Ignacio Martí

Wind Turbine Design (WTD)
Head of Division
Kenneth Thomsen

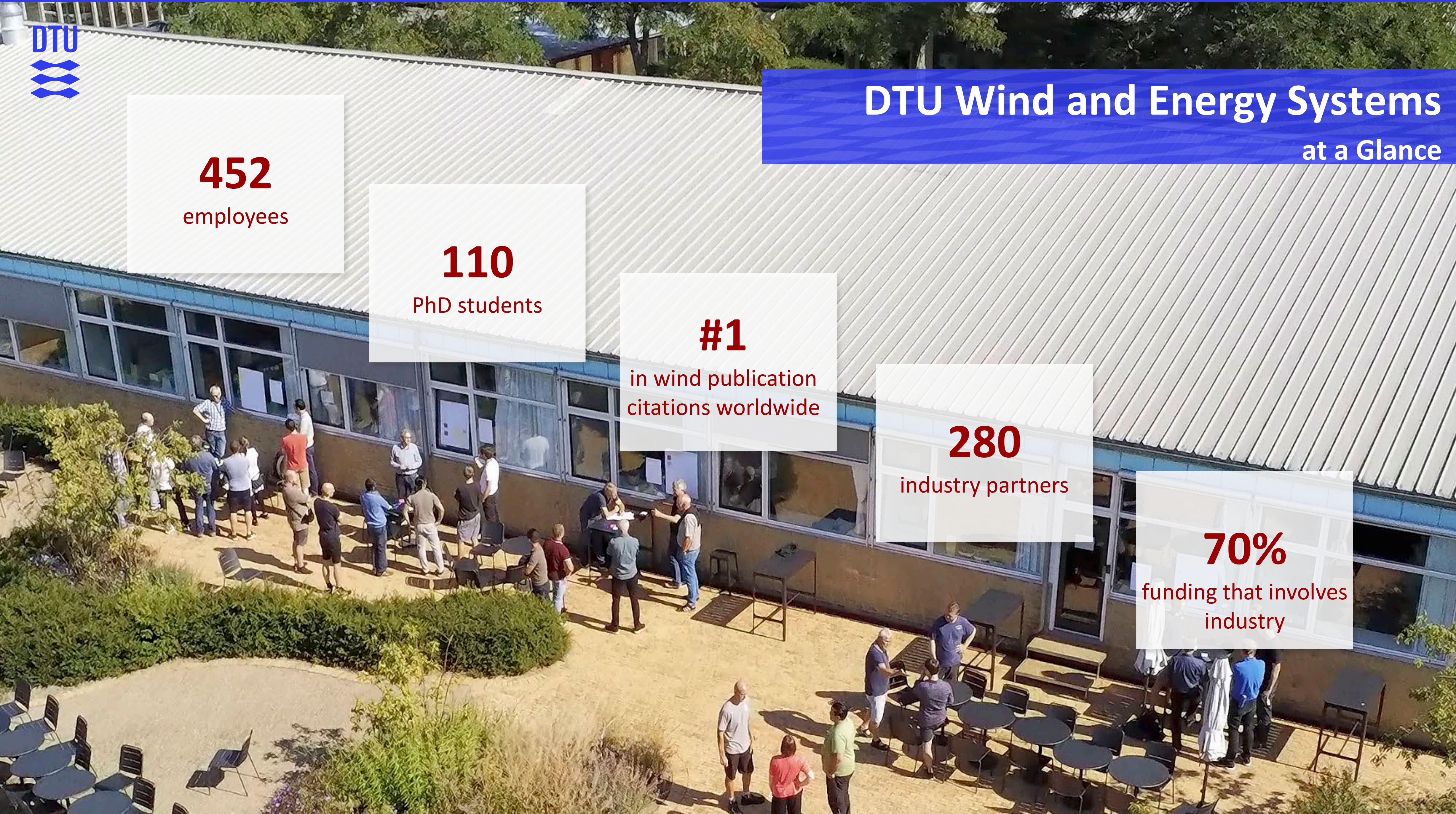
Wind Energy Systems (WES)
Head of Division
Lena Kitzing

Power and Energy Systems (PES)
Head of Division
Jacob Østergaard



DTU Wind and Energy Systems

at a Glance



452
employees

110
PhD students

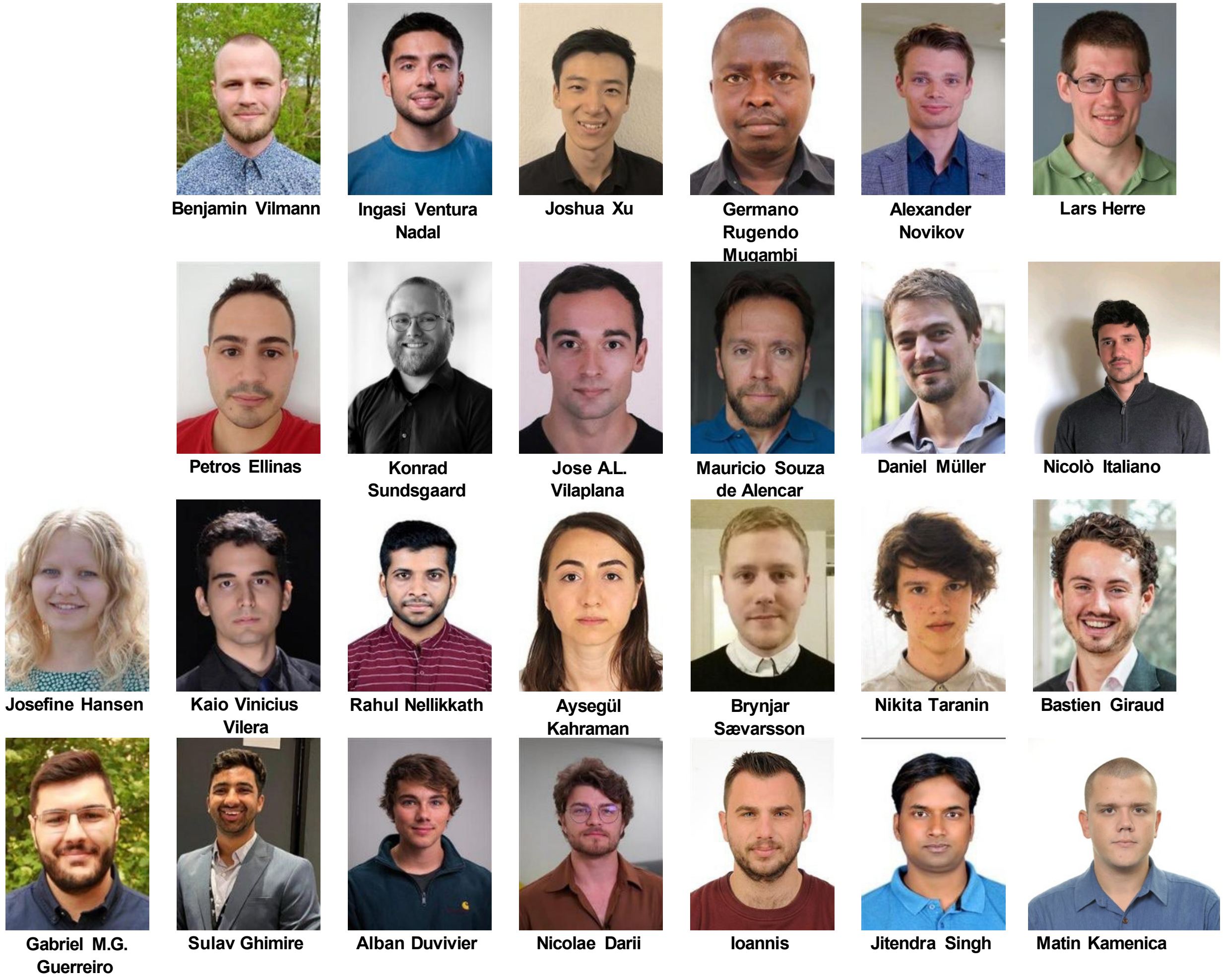
#1
in wind publication citations worldwide

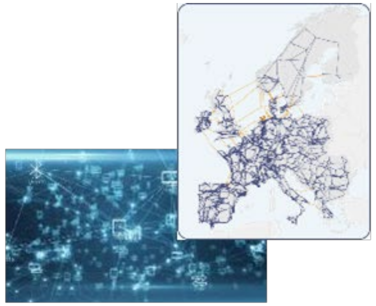
280
industry partners

70%
funding that involves industry

Power Systems Section

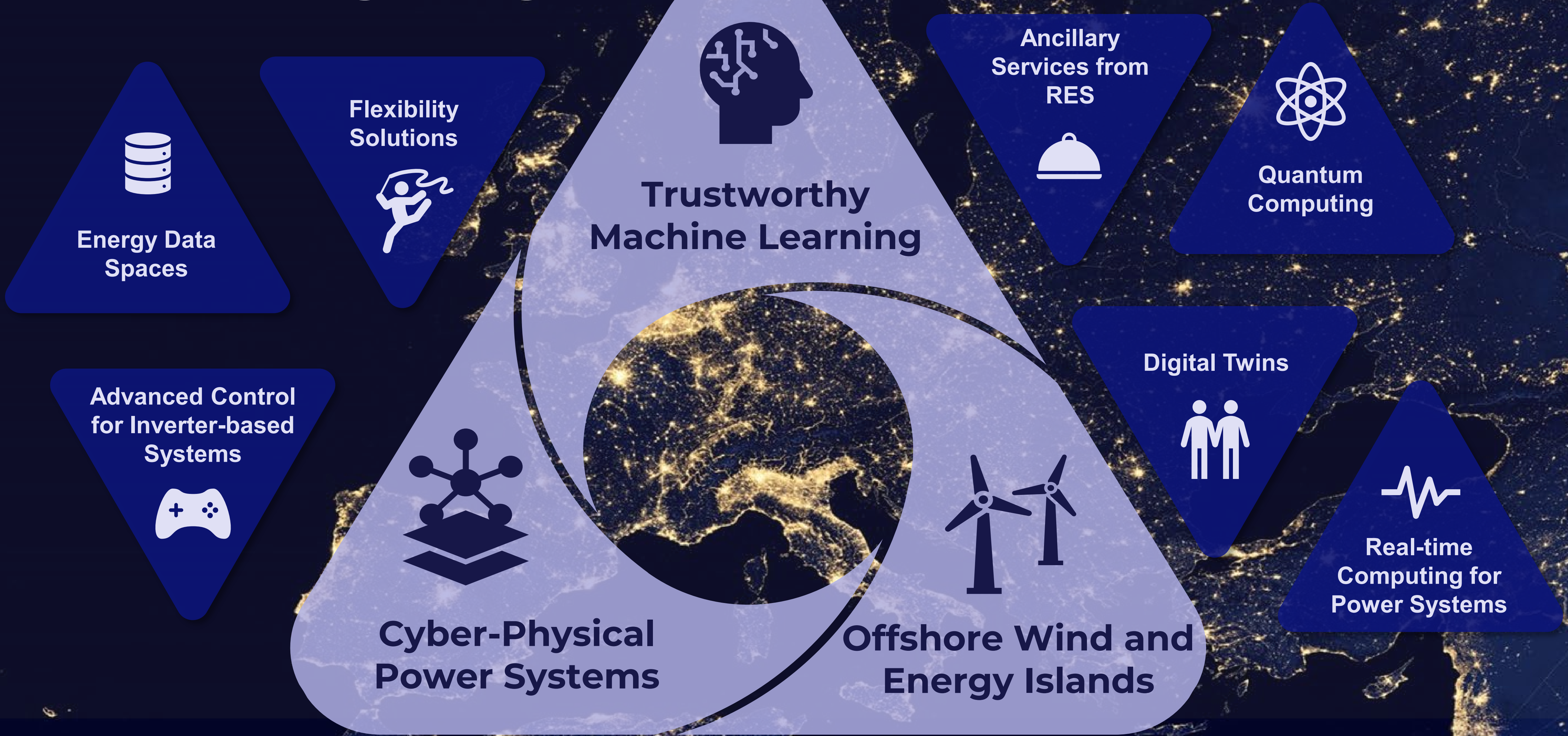
PWR – 32 members; 20 nationalities





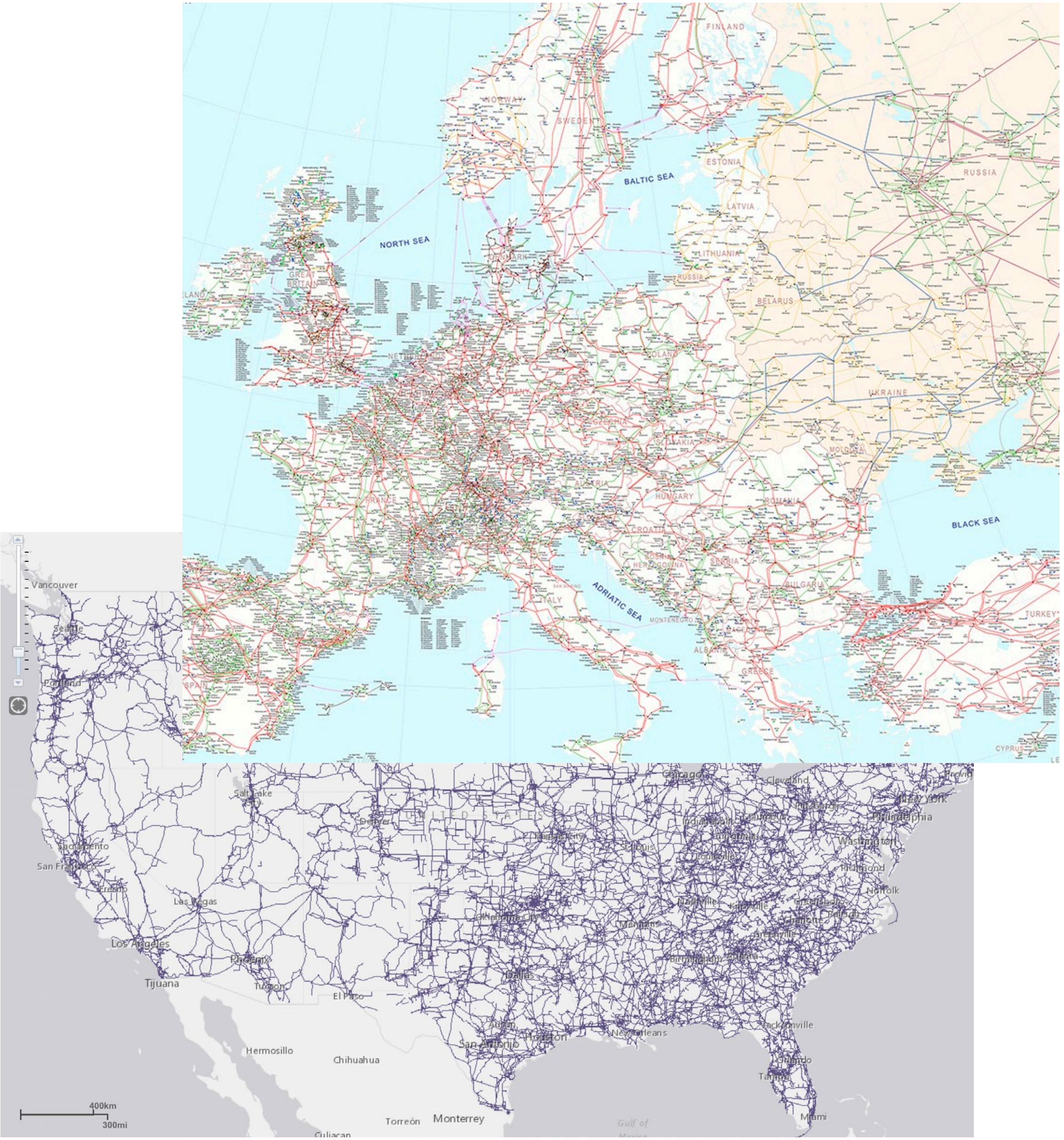
PowerLab.dk

Keeping the lights on in 100% RES Power Systems!



The electric power grid: Probably, the largest machine humans ever built

- Millions of loads
- Thousands of generators
- Very large machines
  - Human lives can be in danger
- All interconnected
  - If a fault happens in Portugal, it can affect lives in Sweden
- Extreme economic value
  - A blackout for a day means billions of Euros in economic loss



What is the goal?

1. Make sure that **everyone always has electricity**
   (e.g. whenever & wherever you plug your smartphone)
2. Make sure that **nothing, never goes wrong**
3. You cannot really store any electricity (yet)

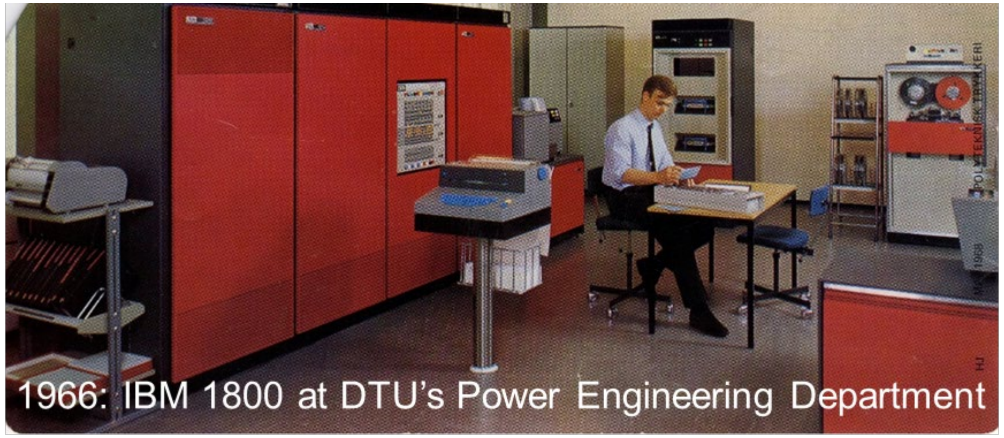
How?

1. We need to **run millions of scenarios**, to make sure we are prepared for anything going wrong

2. We need to take **good decisions fast** (real-time)

What is the goal?

1. Make sure that **everyone always has electricity**
   (e.g. whenever & wherever you plug your smartphone)
2. Make sure that **nothing, never goes wrong**
3. You cannot really store any electricity (yet)



How?

1. We need to **run millions of scenarios**, to make sure we are prepared for anything going wrong
2. We need to take **good decisions fast** (real-time)

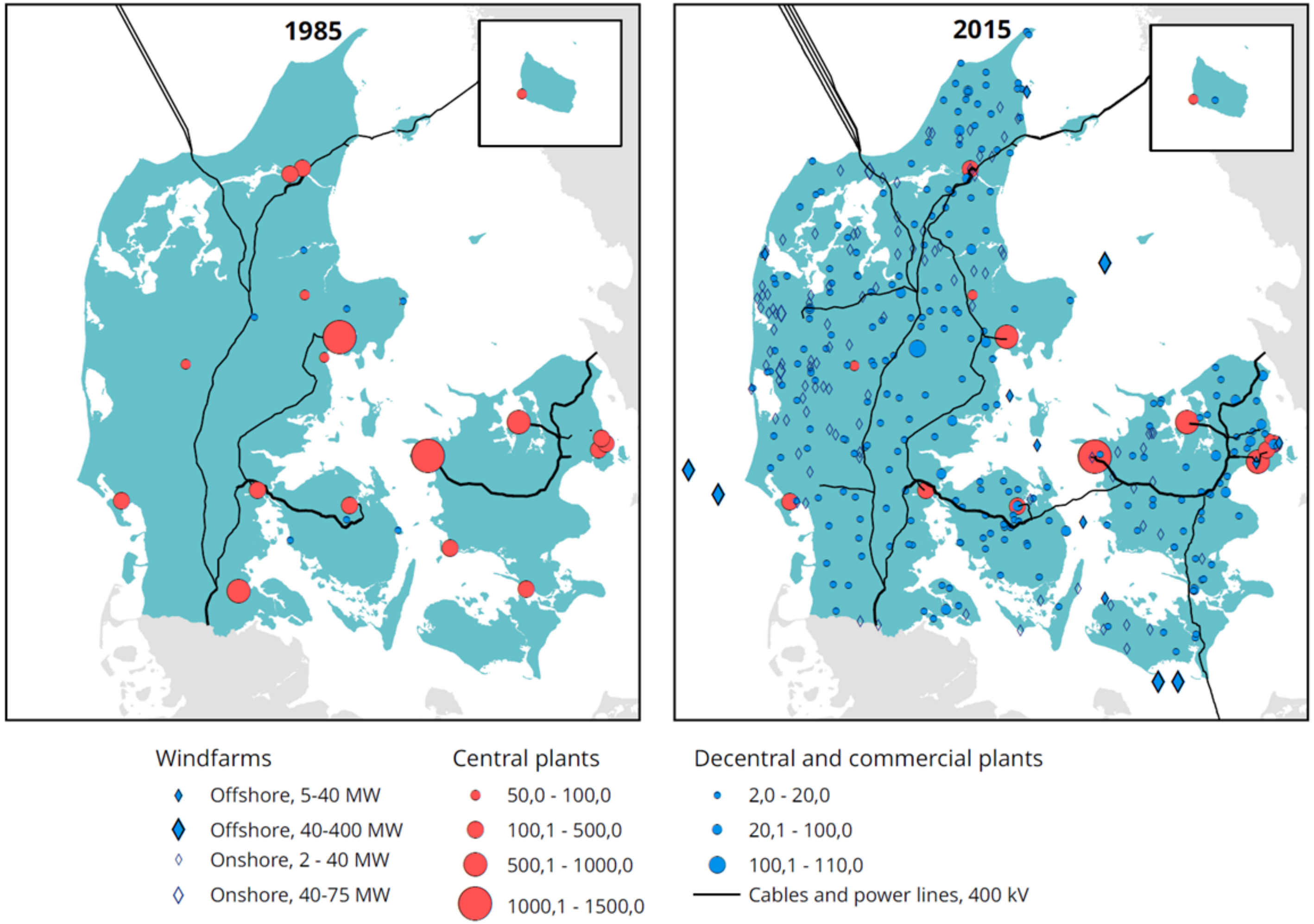
Towards the Green Transition

What is the challenge?

1. We need to run a grid on (ideally) 100% Renewable Energy Sources

2. We need to electrify carbon intensive sectors, e.g. transportation, heating in buildings, etc.

Towards the Green Transition: What is the challenge?



From centralized to decentralized power production, the Danish Energy Agency 2017, ens@ens.dk

Towards the Green Transition

What is the challenge?

1. We need to run a grid on (ideally) 100% Renewable Energy Sources

2. We need to electrify carbon intensive sectors, e.g. transportation, heating in buildings, etc.

What does this mean?

1. Millions of new injection points
2. Orders of magnitude higher complexity (due to power electronic converters)
3. A lot of uncertainty (e.g. wind, solar, electric vehicles)

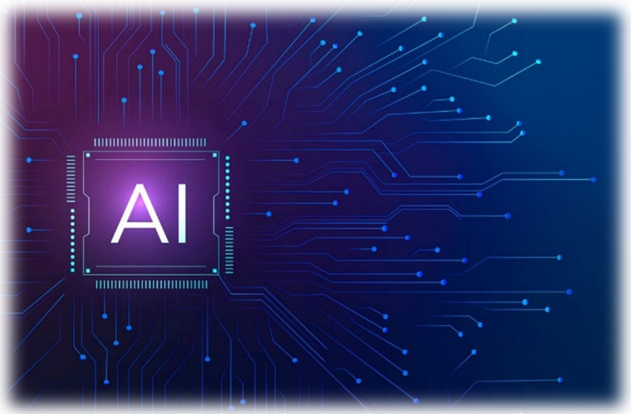
Towards the Green Transition

Towards the Green Transition

Current Computational Tools are no longer sufficient

We need tools that are 10x-100x-1’000x faster to capture much higher complexity and thousands of more scenarios

Could AI or Quantum Computing help?



AI and Energy:
two of the Sectors with the
highest growth potential

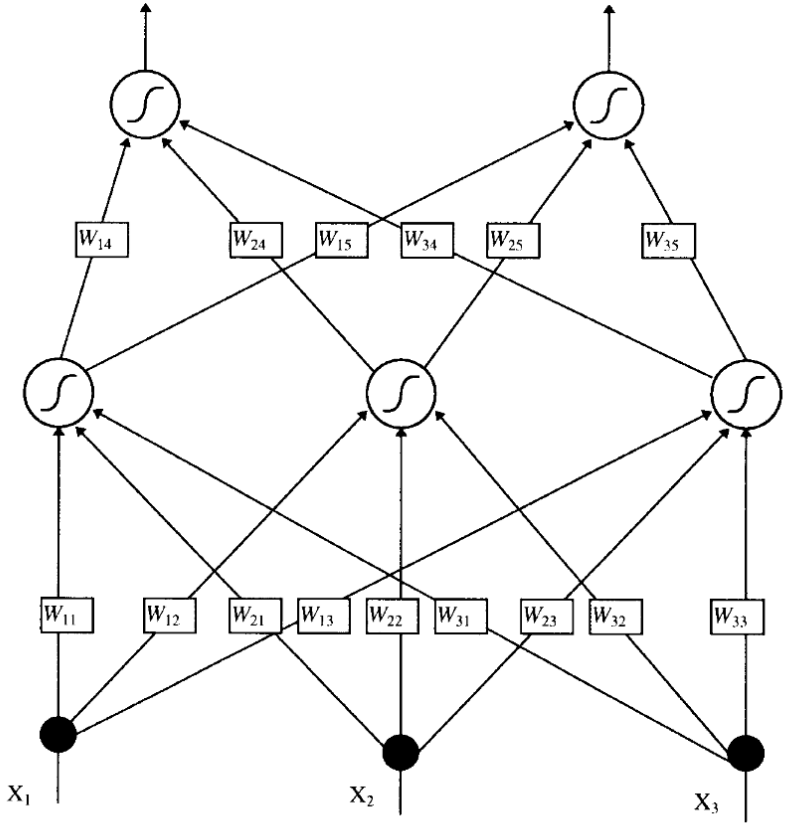
and Quantum Computing is
rapidly emerging

AI is already creating value in Energy Systems

- Load Forecasting
- Weather Forecasting
- Predictive Maintenance
- Energy Trading (forecasting of prices or quantities)

AI is already creating value in Energy Systems

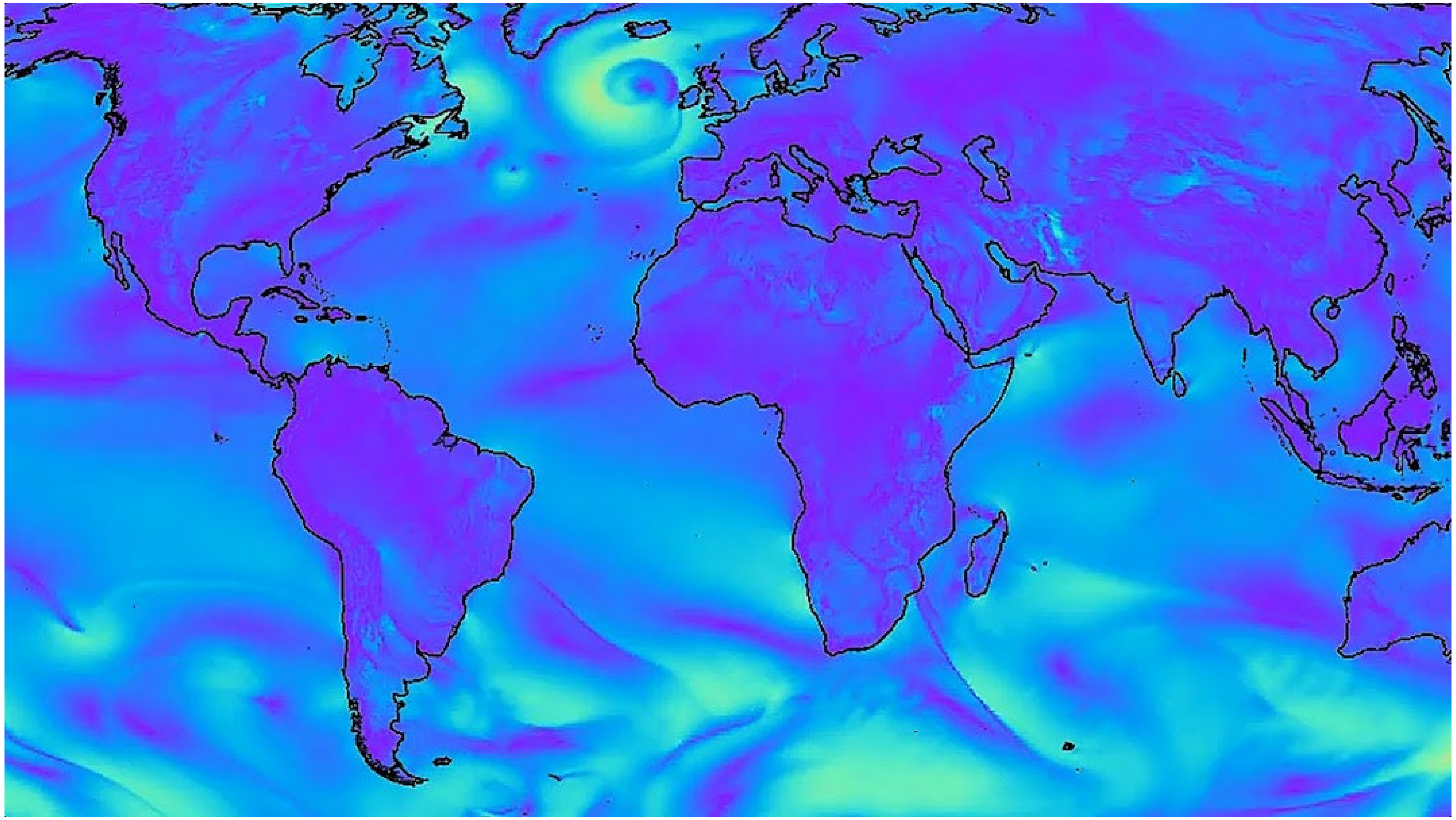
- **Load Forecasting**
- Weather Forecasting
- Predictive Maintenance
- Energy Trading (forecasting of prices or quantities)



- **ANNSTLF**: Probably the **first tool based on Machine Learning** in Power Systems
- Developed by EPRI (Electric Power Research Institute) in the US
- First deployed in 1992 in Texas. Deployed to 32 utilities by 1997

AI is already creating value in Energy Systems

- Load Forecasting
- **Weather Forecasting**
- Predictive Maintenance
- Energy Trading (forecasting of prices or quantities)



Google Graphcast: AI is already better than physical models for global weather forecasting

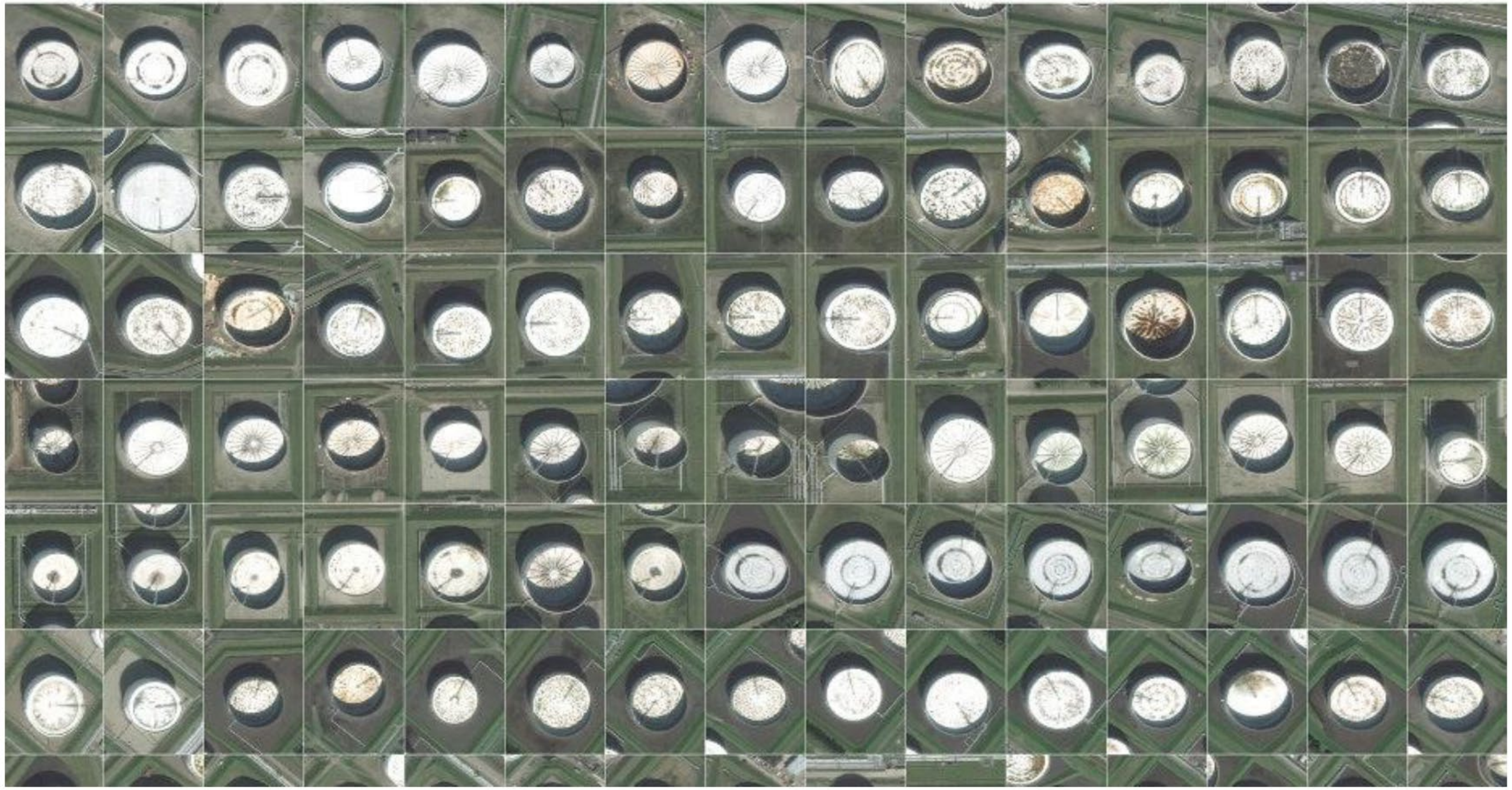
AI is already creating value in Energy Systems

- Load Forecasting
- Weather Forecasting
- **Predictive Maintenance**
- Energy Trading (forecasting of prices or quantities)

- Combination of images with other sensor data to predict failures
- IEA: digitalization can help lower maintenance costs of electricity grids by 5% = **80 billion EUR**

AI is already creating value in Energy Systems

- Load Forecasting
- Weather Forecasting
- Predictive Maintenance
- **Energy Trading** (forecasting of prices or quantities)

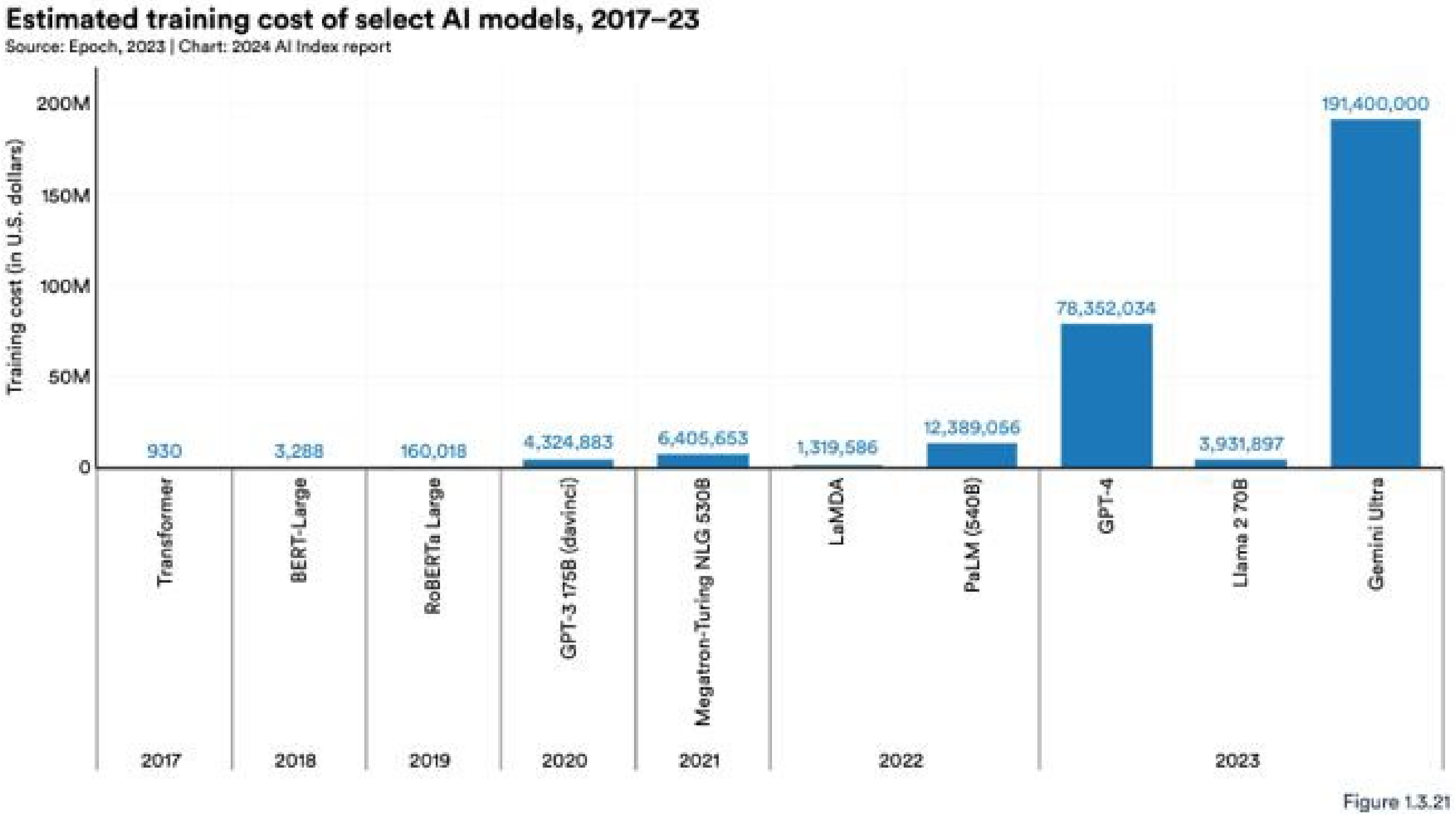


But AI can do a lot more things

1. Virtual assistant
2. Live interpreter/translator
3. Creative writing
4. Support for decision making

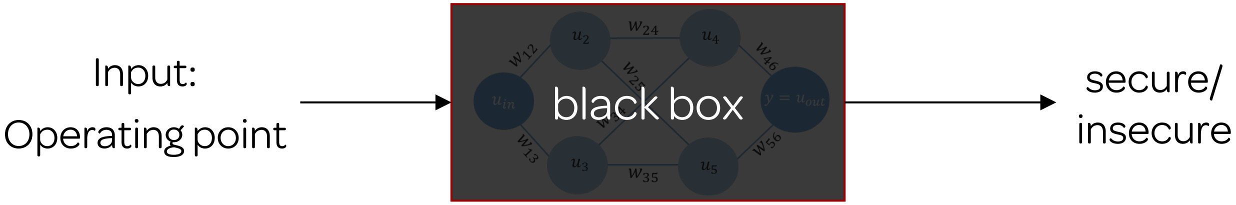
And many more

Costs of training Generative AI models (e.g. ChatGPT) 2017-2023



But: Would you ever trust AI to run your electricity network?

Machine Learning (ML) Barriers for Power systems

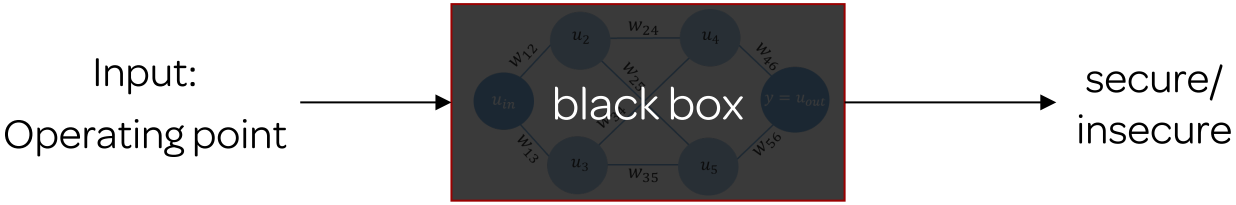


1. Why would we use a “**black box**” to decide about **a safety-critical application**?

2. Neural Networks performance metric is “Accuracy”. **Accuracy is** a **purely statistical** performance metric. Who guarantees that the Neural Network can handle well previously unseen operating points?

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

Machine Learning (ML) Barriers for Power systems



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

2. Neural Networks performance metric is “Accuracy”. **Accuracy is** a **purely statistical** performance metric. Who guarantees that the Neural Network can handle well previously unseen operating points?

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

Neural Network verification: guarantees for the NN performance!

Physics-Informed Neural Networks: potential to deliver tools that are 10x-100x-1000x faster!

A lot of recent developments for trustworthy AI

- **April 2021:** The EU is promoting rules for Trustworthy AI

- Visit of Ms. Margrethe Vestager at DTU
  - EU Commissioner of Competition, Executive Vice President of "A Europe Fit for the Digital Age”
  - In April 2021, Ms. Vestager proposed new rules and actions aiming to turn Europe into the global hub for trustworthy Artificial Intelligence

A lot of recent developments for trustworthy AI

- World-leading optimization tool: Starting with Gurobi 10.0, Gurobi supports Neural Network verification since 2023

Gurobi Optimizer

Gurobi 10.0 also includes the following advances in the underlying algorithmic framework:

- **New network simplex algorithm** – Greatly speeds up solving LPs with network structure.
- **New heuristic for QUBO models, which can arise in quantum optimization** – Improves Gurobi's ability to quickly find good feasible solutions for quadratic unconstrained Boolean optimization problems.
- **Significant performance gains on MIPs that contain machine learning models** – Results in a more than 10x improvement on certain models that contain embedded neural networks with ReLU activation functions.

Provable Worst-case Guarantees

Venzke, G. Qu, S. Low, S. Chatzivasileiadis, Learning Optimal Power Flow: Worst-case Guarantees for Neural Networks. **Best Student Paper Award** at IEEE SmartGridComm 2020. https://arxiv.org/pdf/2006.11029.pdf

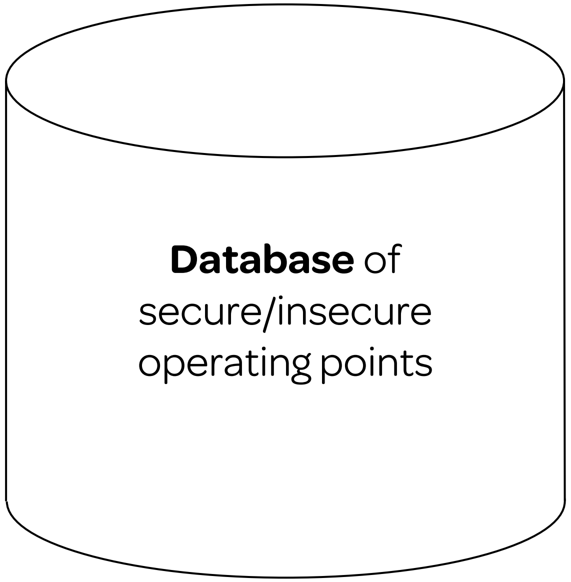
R. Nellikkath, S. Chatzivasileiadis, Physics-Informed Neural Networks for Minimising Worst-Case Violations in DC Optimal Power Flow. In IEEE SmartGridComm 2021, Aachen, Germany, October 2021.

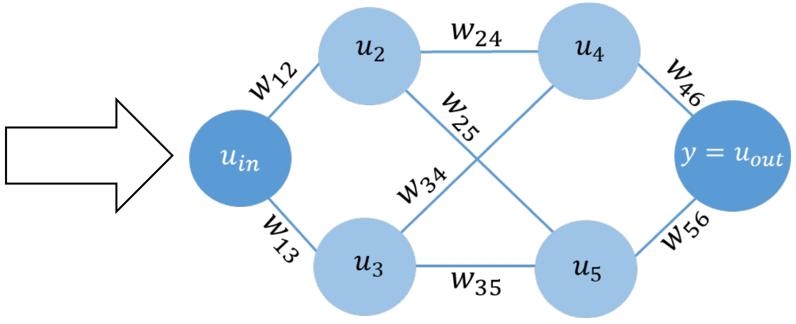
R. Nellikkath, S. Chatzivasileiadis. Physics-Informed Neural Networks for AC Optimal Power Flow. 2021.

Guiding Application:
Optimal Generator Setpoints with Neural Networks

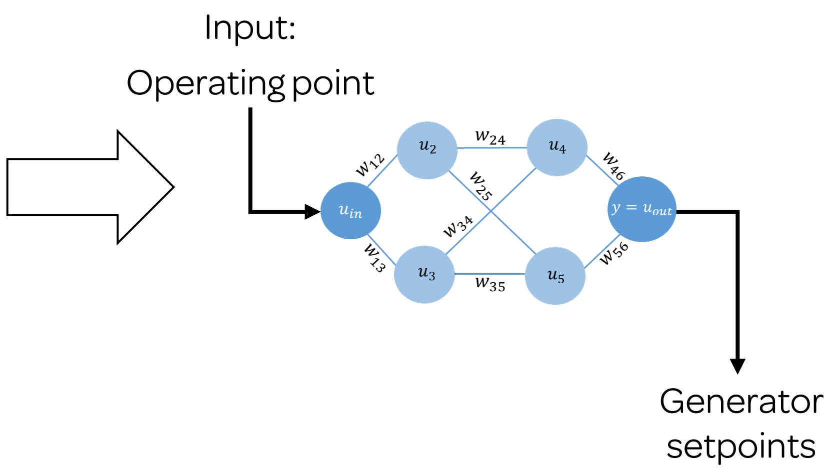
European Research Council

Approaches proposed up to now





5. Use the NN



1. Split the database in a training set and a test set

2. Train a neural network

3. Test the neural network

4. Is accuracy high enough?

NN Output:

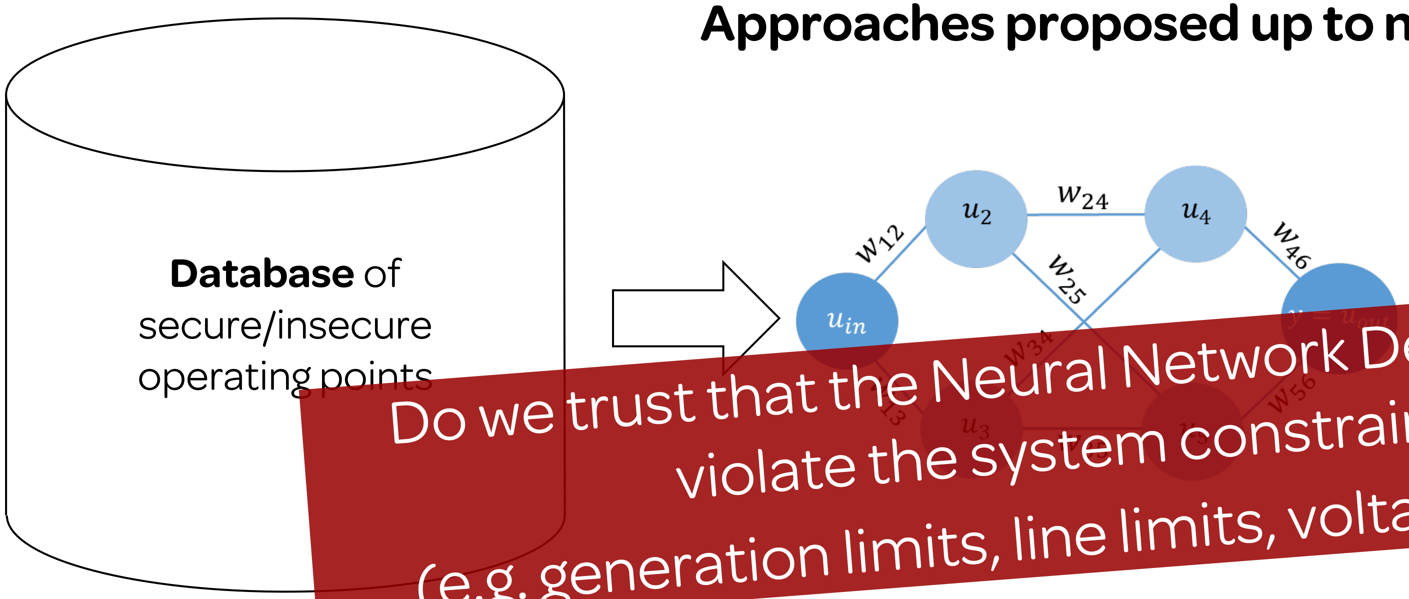
Set of **lowest-cost generators that cover the demand**

Extremely fast: up to 100x faster

Guiding Application:
Optimal Generator Control with Neural Networks

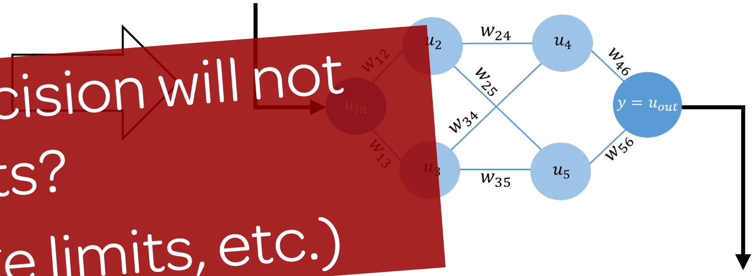
European Research Council

Approaches proposed up to now



5. Use the NN

Input:
Operating point



Generator
setpoints

Do we trust that the Neural Network Decision will not violate the system constraints?
(e.g. generation limits, line limits, voltage limits, etc.)

1. Split the database in a training set and a test set

2. Train a neural network

3. Test the neural network

4. Is accuracy high enough?

NN Output:

Set of **lowest-cost generators that cover the demand**

Extremely fast: up to 100x faster

Worst-Case Guarantees for Neural Networks

European Research Council

- **Determine the worst-case performance = provable worst-case guarantees**
  - **Across the continuous input domain**
  - No Sampling
  - Once “certified”, we can use directly the Neural Network (no need to re-run the verification)

Worst violation over the **whole training dataset** (training+test set)

Our algorithm: **provable** worst-case guarantee over the **whole input domain**

European Research Council

	Empirical lower bound		Exact worst-case guarantee	
Test cases	ν_g (MW)	ν_{line} (MW)	ν_g (MW)	ν_{line} (MW)
case9				
case30				
case39				
case57				
case118				
case162				
case300				

ν_g Maximum violation of generator limits

ν_{line} Maximum violation of line limits

Worst violation over the **whole training dataset** (training+test set)

Our algorithm: **provable** worst-case guarantee over the **whole input domain**

	Empirical lower bound		Exact worst-case guarantee	
Test cases	ν_g (MW)	ν_{line} (MW)	ν_g (MW)	ν_{line} (MW)
case9	2.5	1.8	2.8	1.9
case30	1.7	0.6	3.6	3.1
case39	51.9	37.2	270.6	120.0
case57	4.2	0.0	23.7	0.0
case118	149.4	15.6	997.8	510.8
case162	228.0	180.0	1563.3	974.1
case300	474.5	692.7	3658.5	3449.3

ν_g Maximum violation of generator limits

ν_{line} Maximum violation of line limits

Over the whole input domain **violations can be much larger** (here ~7x) compared to what has been estimated empirically on the dataset

European Research Council

DTU

Worst violation over the **whole training dataset** (training+test set)	New algorithm: **provable** worst-case guarantee over the **whole input domain**

	Empirical lower bound		Exact worst-case guarantee	
Test cases	ν_g (MW)	ν_{line} (MW)	ν_g (MW)	ν_{line} (MW)
case9	2.5	1.8	2.8	1.9
case30	1.7	0.6	3.6	3.1
case39	51.9	37.2	270.6	120.0
case57	4.2	0.0	23.7	0.0
case118	149.4	15.6	997.8	510.8
case162	228.0	180.0	1563.3	974.1
case300	474.5	692.7	3658.5	3449.3

European Research Council

ν_g Maximum violation of generator limits

ν_{line} Maximum violation of line limits

We can now provide **guarantees that no NN output will violate the line limits** over the whole input domain

Trustworthy AI for Power Systems: Vision

AI Testing and Experimentation Facility for Energy

- Establish a platform that verifies AI tools and certifies that they comply with power system safety specifications

AI Standards: Create Standards for AI tools in Energy

Design a Neural Network Training Algorithm that simultaneously delivers guarantees of the worst-case NN performance

- Example: "Neural Network Training finished. Accuracy 99.2%. Worst-case violation of critical constraints: 10%."

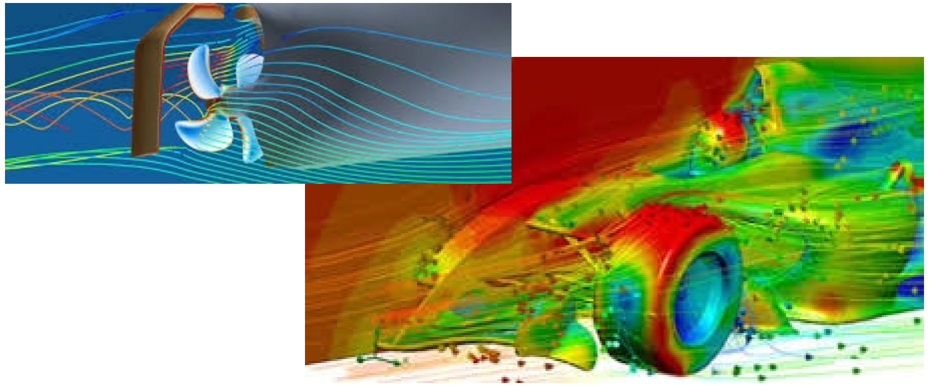
Physics-Informed Neural Networks for Power Systems

Physics-Informed Neural Networks (PINNs)

- **Why can Neural Networks be faster than conventional simulation tools?**
  - Conventional tools need to run iterative methods to approximate the solution of differential equations
  - For Neural Networks, it is a matrix multiplication (as long as they are accurate enough)
- **What is the benefit of PINNs over standard NNs?**
  - **PINNs do not need large amounts of training data.** They learn from the physical models included in training.
  - No need to spend (a lot of) time on generating data or depend on incomplete data

10x-100x-1’000x faster solution, depending on the application

Seem to be achieving significant speedups for partial differential equations (e.g. computational fluid dynamics)

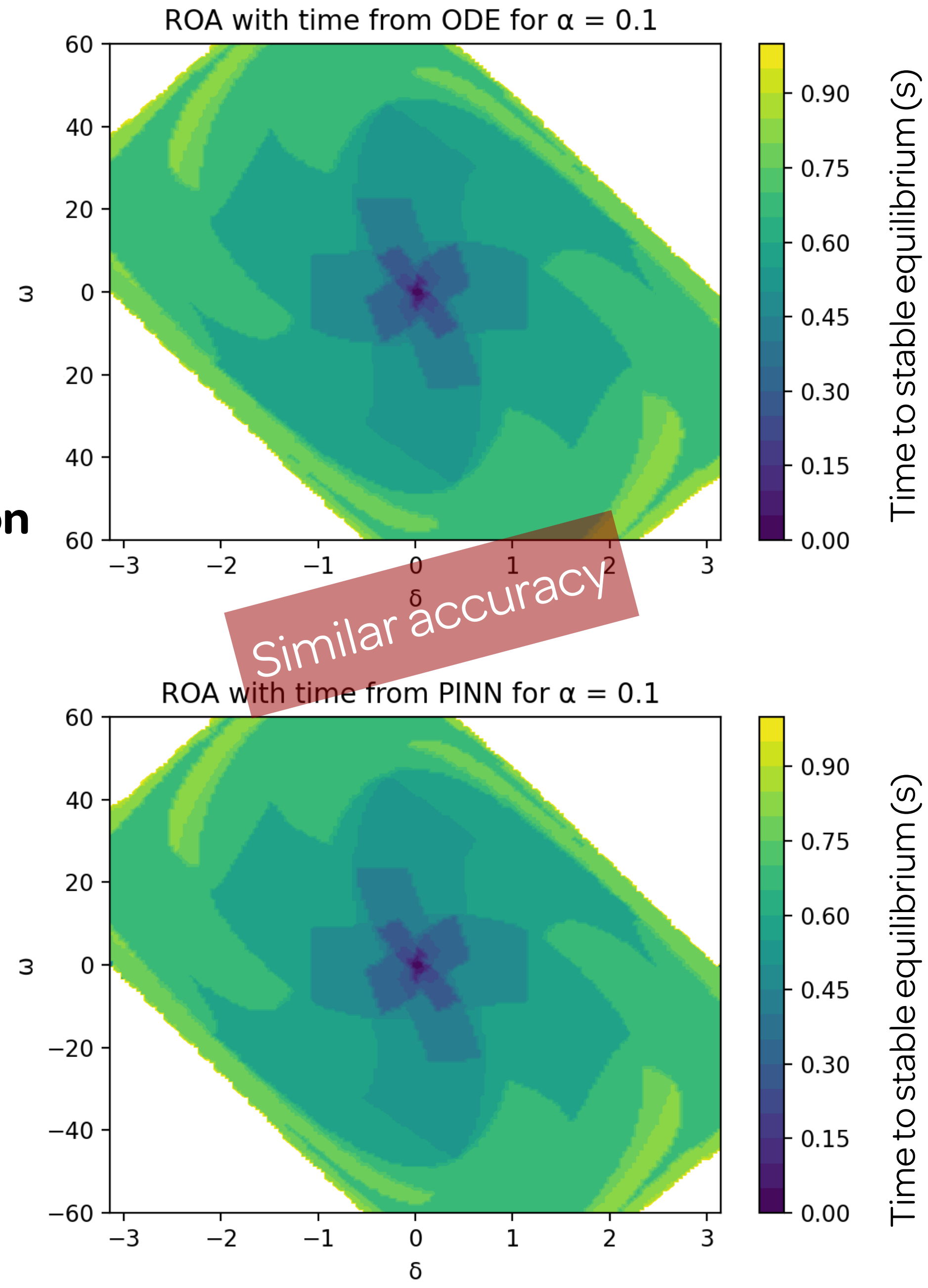


Simulations for Wind Farms:

Estimating the Region of Attraction of a Wind Farm Controller

Conven-tional simulation

PINN



- Collaboration with Ørsted
  - Estimating the region of attraction of controllers is an important part of the wind farm design process
- Goal: Determine the best set of controller parameters (controller tuning)
- Training PINNs with GPUs
  - collaboration with NVIDIA

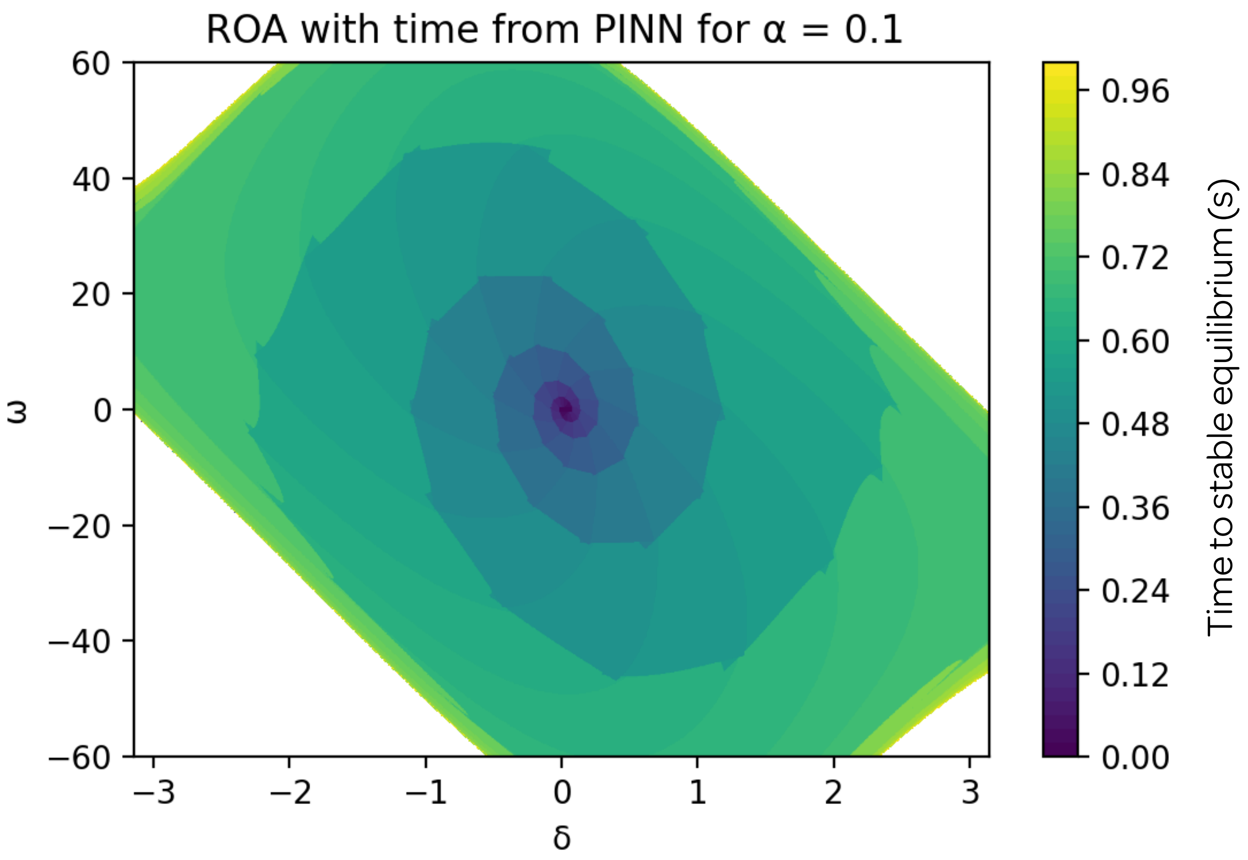
R. Nellikkath, A. Venzke, M. K. Bakhshizadeh, I. Murzakhanov, S. Chatzivasileiadis, Physics-Informed Neural Networks for Phase Locked Loop Transient Stability Assessment [https://arxiv.org/abs/2303.12116]

Simulations for Wind Farms:

DTU Wind

Estimating the Region of Attraction of a Wind Farm Controller

5 million points with PINN



- Evaluation of 5 million points
- **EMT: ~2 days @ DTU HPC**
- **PINNs: 90 minutes for training and 30 minutes for evaluation**

25x – 100x faster

- **Added benefit: once trained, PINN can run on a laptop**

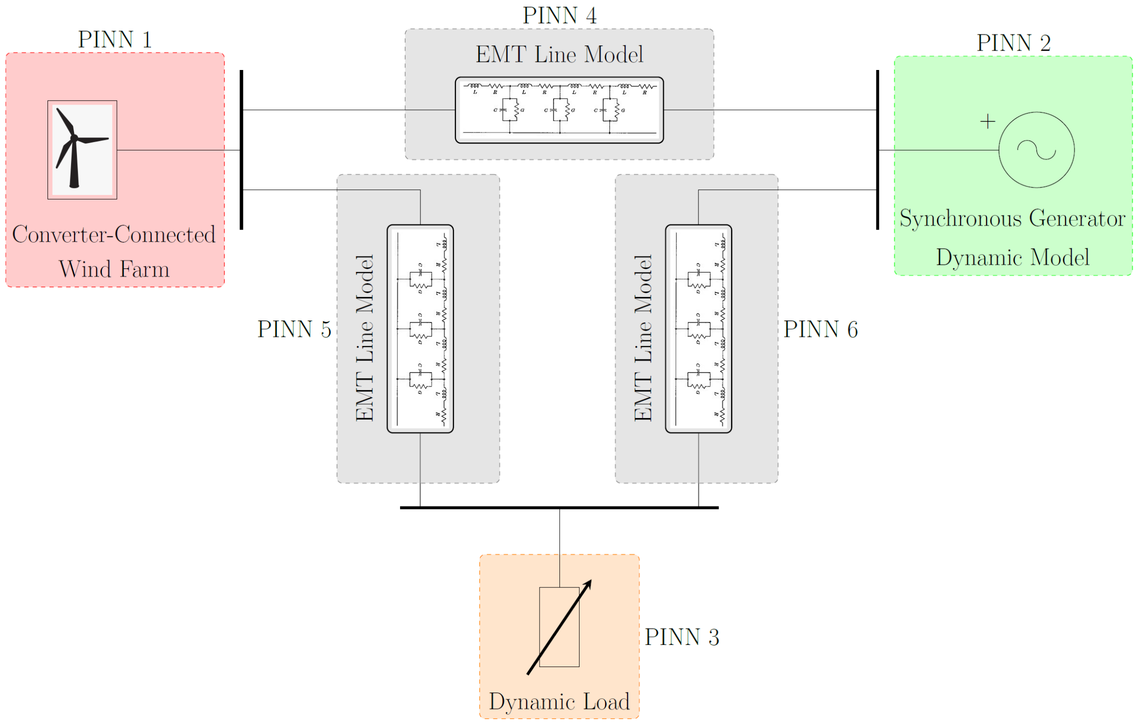
R. Nellikkath, A. Venzke, M. K. Bakhshizadeh, I. Murzakhanov, S. Chatzivasileiadis, Physics-Informed Neural Networks for Phase Locked Loop Transient Stability Assessment [https://arxiv.org/abs/2303.12116]

Physics-Informed Neural Networks for Power Systems: Vision

- **PINNSim: A modular power system time-domain simulator**
  - A library of component models implemented with Neural Networks
  - Drag'n'drop to create your system
  - Integrate/interface PINNSim with conventional power system simulation tools

- A completely new way of simulation which can be 10x-100x faster.
  - What does this mean? Instead of assessing 100 scenarios leading to a blackout within 1 hour, I can now assess 10,000 scenarios

- Possibility to verify PINNs (?) → validate/guarantee model performance



Some Thoughts

- **If we want to accelerate processes by 10x-100x-1000x we need to think differently**
  - Conventional methods reach their limits (?)
  - Could AI or Quantum Computing become the disruptive technology?

- AI is already creating value for applications where there is no other good option, e.g. forecasting

- **AI could potentially be disruptive for energy systems if it becomes trustworthy**
  - Offer 10x-100x-1000x speedups
  - We need standards and AI certification
  - Tradeoff between AI size and interpretability/trustworthiness

- **Physics Informed Neural Networks** can offer new types of simulation tools
  - 10x-100x speedup
  - Potentially run on a laptop (after training)
  - Still a lot of exciting challenges to address
  - Can we verify the PINN models?

Μερικές τελευταίες σκέψεις

- Για να μπορέσουμε να αναπτύξουμε τις εφαρμογές που συζητήσαμε σήμερα δε χρειάζεται μόνο η γνώση των ηλεκτρικών δικτύων. Χρειάζονται γνώσεις από:
  - Αριθμητική ανάλυση, μιγαδικοί, διαφορικές εξισώσεις, γραμμική άλγεβρα, λίγο από ηλεκτρομαγντικά πεδία, συστήματα αυτομάτου ελέγχου, βάσεις δεδομένων, τεχνικές βελτιστοποίησης, αλγόριθμοι τεχνητής νοημοσύνης, και άλλα!
  - Όλα αυτά τα μαθαίνουμε σε μια οποιαδήποτε Σχολή/Τμήμα Ηλεκτρολόγων Μηχανικών και Μηχ. Υπολογιστών στην Ελλάδα!

- Η καινοτομία χρειάζεται όραμα κι ευρύ πεδίο γνώσεων. Εκμεταλλευτείτε τις ευκαιρίες που σας δίνονται στη σχολή! Και αν δεν είναι αρκετές δημιουργήστε καινούριες!

- Εμπιστευτείτε τις δυνάμεις σας!

Thank you!

Spyros Chatzivasileiadis
Professor
Head of Section Power Systems
www.chatziva.com
spchatz@dtu.dk