Machine learning for power systems: present and future

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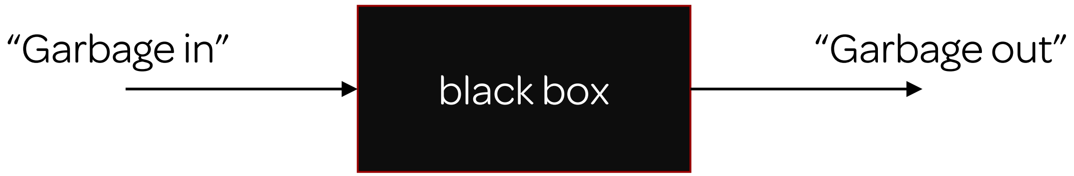
Machine learning is not a calculation.
It is an estimation.

- Machine learning will **never be as accurate** as a model that fully describes a system or process.
  - Why: ML does not calculate a function. It estimates its result.

- Then, **why** shall we apply Machine Learning?
  1. **extremely fast**
  2. good alternative if we do not have full knowledge of the actual model
     - Handle **very complex systems**
     - **Infer** from incomplete data

- **Data is key**



https://en.wikipedia.org/wiki/Garbage_in,_garbage_out

ML Opportunities and Barriers for Power systems

- ML can work well for forecasting/predicting
  - Weather/wind/PV or load forecasting, prediction of electricity prices, prediction of failures

Barriers

1. Why would we use a "black box" to decide about **a safety-critical application**?
   - Example #1: ML for security assessment
   - Example #2: ML for any type of power system optimization/optimal power flow

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

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

Why accuracy is not enough?

- Example: Power System Security Assessment; Classify SAFE or UNSAFE

Total operating points = 1000	Actually Safe (Total = 20)	Actually Unsafe (Total = 980)
Predicted safe	1	30
Predicted Unsafe	19	950

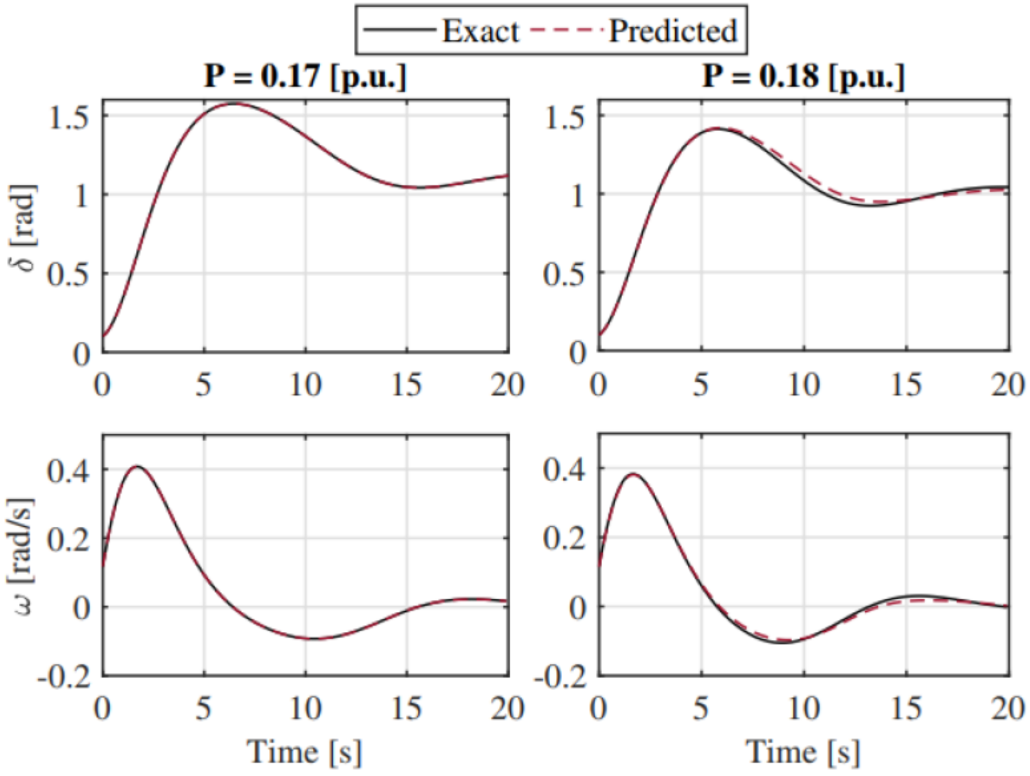
$$\text{Accuracy} = \frac{1+950}{1000} = 95\%$$

- 95% accurate but we have misclassified almost all truly safe points!

- **We need Neural Network Verification** for safety-critical applications
  - Formal guarantees about the classification over *continuous* input regions
  - We no longer rely on statistical performance metrics
  - Systematic identification of adversarial examples

Why use incomplete datasets when we have detailed physical models?

- **Physics-Informed Neural Networks**
  1. Include the physical models inside the NN training → need for less data, probably smaller NN sizes
  2. **Extremely fast:** can potentially replace solvers for systems of differential-algebraic equations
  3. Turn **NN training** from supervised to **unsupervised learning**



Single Machine Infinite Bus Example: Physics-Informed NN is 87x faster than ODE solver

Takeaways

1. **Extremely fast** (up to 1'000x faster): Revolutionize power system computation → replace non-linear and differential-algebraic solvers for e.g. OPF, sec. assessment, etc.

2. **Data is key:** Sampling beyond statistics
   - Use physical modeling (e.g. convex relaxations of OPF) to accelerate generation of high-quality data

3. We need **Verification of Neural Networks** for safety-critical applications

4. **Physics-Informed Machine Learning**: Use the already available models in the NN training

5. **Interpretable AI**: we need to better understand how ML behaves to remove the barriers for its application in power systems

6. **From NN to MILP**: Decision Trees/Neural Networks can capture previously intractable constraints and convert them to a MILP

7. Before you apply ML/RL on power systems: Think! **ML/RL is an estimation, not a calculation!**
   - Given infinite time or data ML/RL will converge to the correct decision/optimal strategy. Do you have solid reasons why spending so many resources for ML/RL training will lead to a better performance than a Linear Program or Kalman filter? If not, then better stick to the conventional approach.

Thank you!

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Some datasets and code on Machine Learning for Power systems (e.g. Physics-Informed ML, NN verification, etc)

available at:

www.chatziva.com/downloads.html