Regional-scale day-ahead wind power forecasting using deep learning

Mathilde Lepetit, Frederik Kurzrock, Pierre Aillaud, Nicolas Sebastien, and Nicolas Schmutz

EGU General Assembly 2022

UNION EUROPÉENNE

REGION REUNION
www.regionreunion.com

Wind power

- Wind turbines convert the kinetic energy of wind into electricity

- Production depends on meteorological conditions

  → non-dispatchable

- Wind farms contain many turbines, leading to air turbulence

  → physical model is complex

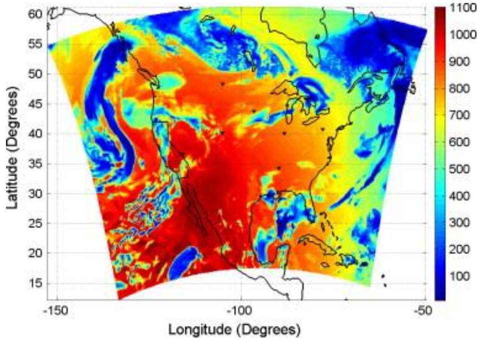
Grid stability and forecasts necessity

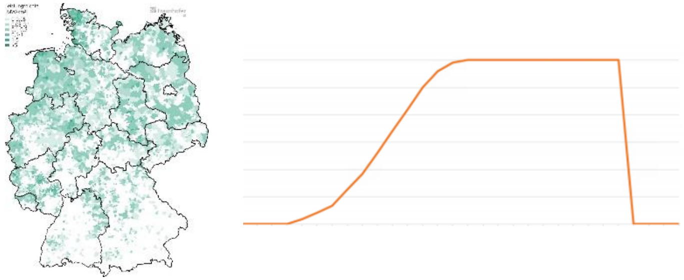
→ Production forecasts needed to manage the network

Two approaches

Physical approach

NWP model output (wind speed, etc.)





Turbine locations and characteristics
→ upscaling from single site forecasts

Power

Machine learning

Training

Statistical approach

Our approach: Deep learning

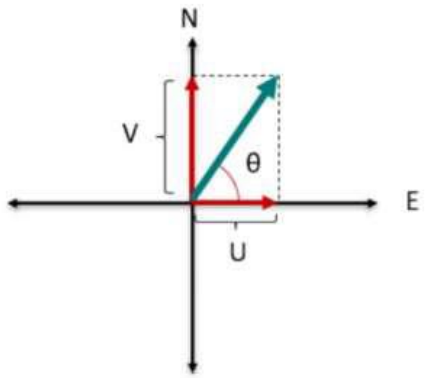
- Supervised deep learning
- Day-ahead forecasts (horizons 24 to 48 hours)
- For a German TSO (regionscale)

- Inputs:
  - Forecasts from a physical model: EuroWind GmbH
  - Historical meteorological forecasts (IFS-ECMWF and GFS)
  - Power production measures (available from Entso-E)

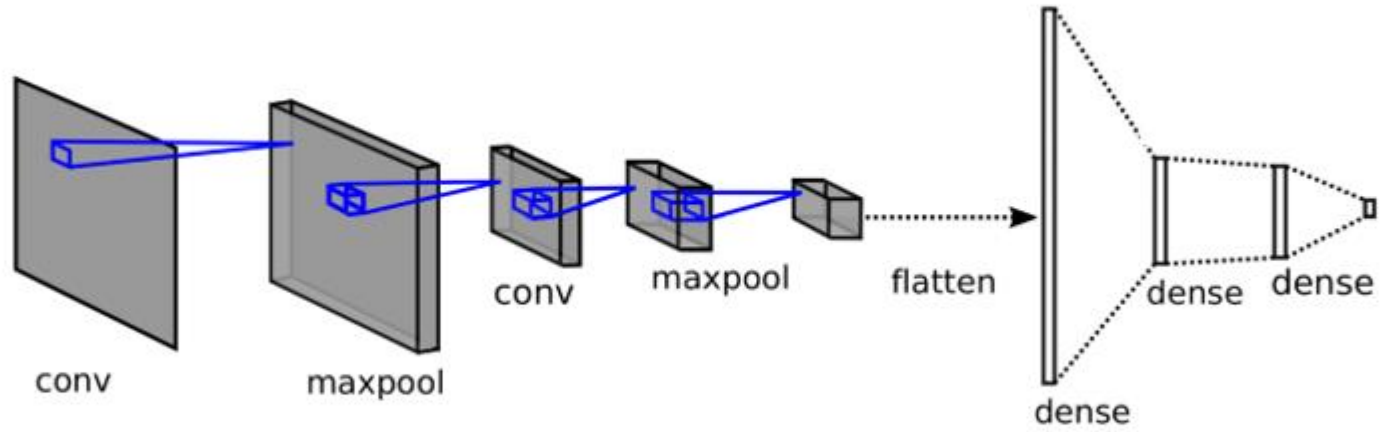
- Goal: To qualify the method in terms of performances

Forecasting method

- Pre-processing
  - Regional mask
  - Transformation of variables wind speed
  - Input standardization
  - Output rescaling



- Deep learning model: CNN



- Post-processing
  - thresholding

Validation strategy: « Sliding window »

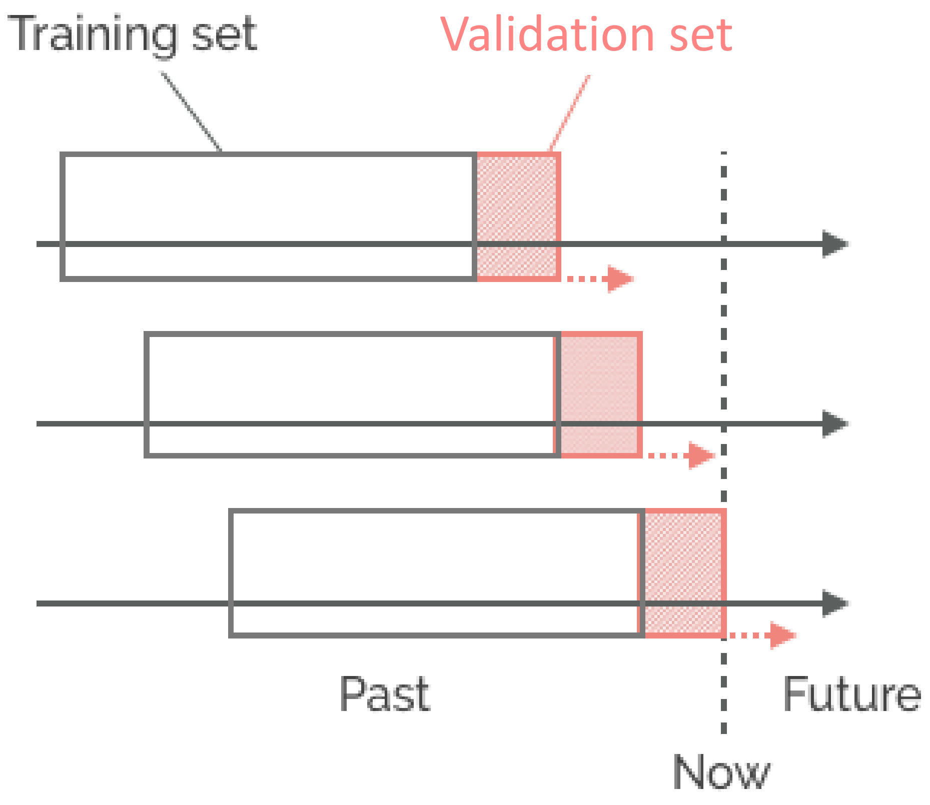
In order to :

- Select input features
- Adjust model architecture
- Tune hyper-parameters

Strategy:

- Training window: parameter to set (example: 1 year)
- Validation window: 1 month
- Do it for the 12 months of year

→ Global score on a whole year



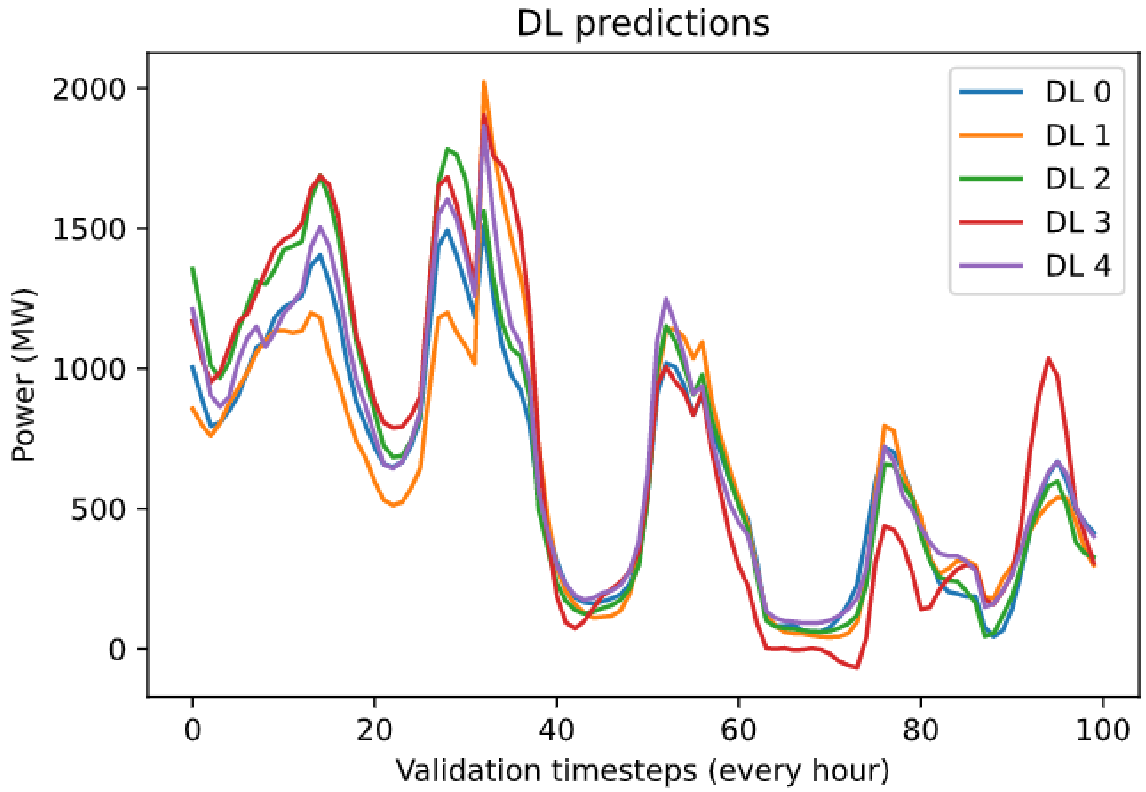
Several deep learning models

Different configurations possible:

- Architecture parameters (nb of layers, filters etc.)
- Training parameters (epochs, batch sizes etc.)
- Input variables
- …

Remark:

For the same configuration, each training leads to a different model



Examples of forecasts for a set of different CNNs

Combination of models

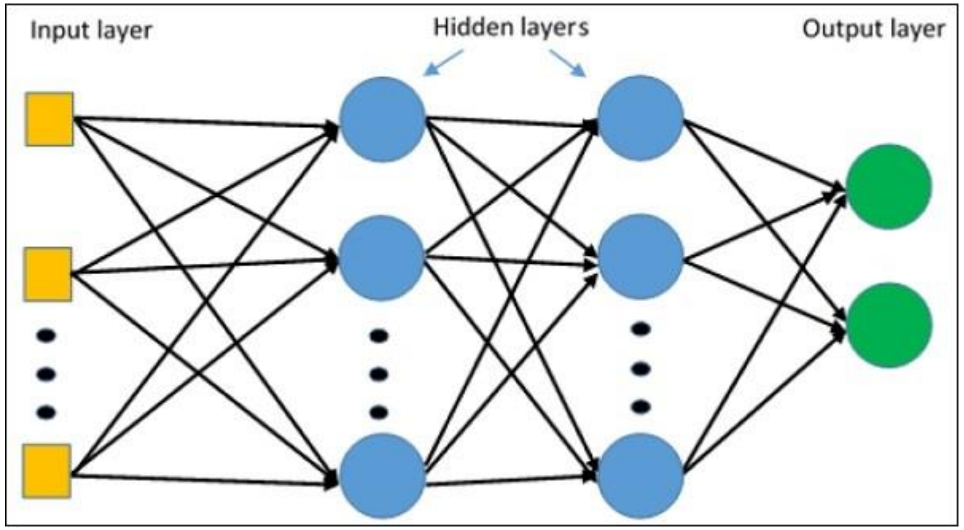
Inputs:

- Several deep learning predictions
- Physical model prediction

→ Multi-Layer Perceptron

→ New power production forecast

"Hybrid"



Multi-Layer Perceptron (MLP)

Reuniwatt

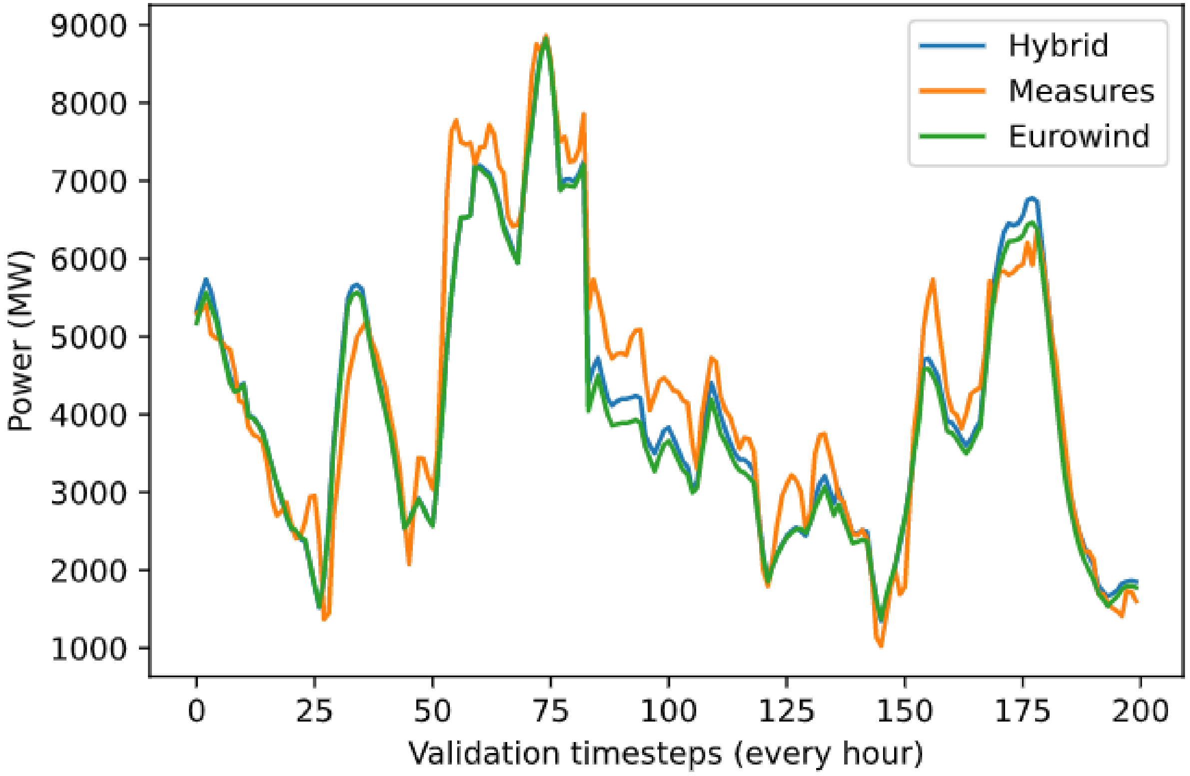
Hybrid results

Validation on 2020

	MAE	FSS	RMSE	FSS
Physical model	370	-	521	-
Hybrid	**342**	**+8%**	**482**	**+7%**

Test on 2021

	MAE	FSS	RMSE	FSS
Physical model	336	-	451	-
Hybrid	**316**	**+6%**	**430**	**+5%**



Example of measures and forecasts

Conclusion

- Different approaches (physical and statistical) provide similar results

Needs are different:

  - historical samples
  - details on turbines characterisics and locations

- Combining several deep learning models and a physical model:
  - 6% MAE improvement on 2021 (test year) compared to the physical model alone

- Open question:
  - Can we easily transpose the method to other regions?

UNION EUROPÉENNE

REGION REUNION
www.regionreunion.com

The present work is carried out as part of the RIWind project. The RIWind project is co-financed by the European Union and the regional council of La Réunion.

Reuniwatt

Excellence in forecasting