Evaluation of neural networks performance for regional-scale day-ahead wind power forecasting in Germany

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Context

Historically, electricity was provided by dispatchable sources that can be adapted to demand variations. Adding an irregular source to the network is a challenge for the grid stability. Especially, wind turbine production varies depending on meteorological conditions. At a regional or country scale, Transmission System Operators (TSOs) are responsible to maintain supply demand equilibrium in their network.

In this context, wind power production forecast is one of the tools needed to manage the network. Traditionally, physical models are used to predict power production based on turbine characteristics and numerical weather prediction models. Indeed, wind power production is strongly correlated to wind speed at turbine hub height and other meteorological parameters. One limit of those physical approaches is that they require precise knowledge on turbines characteristics and locations, in particular at a regional scale.

To overpass this limit, a statistical approach such as Artificial Neural Network (ANN) can be used but needs to be qualified in terms of performances. In this study, two ANN models are explored. These models do not require information on turbine location or characteristics but require historical samples of weather parameters and associated production. We will focus on day-ahead forecasting using meteorological forecasts as main data source.

Case study

Germany has seen a massive deployment of renewable energies over the past 20 years. In 2022, the share of renewables in net electricity generation was ~50% [Fraunhofer ISE, 2023]. Wind energy was the main electricity source (see Figure 1).

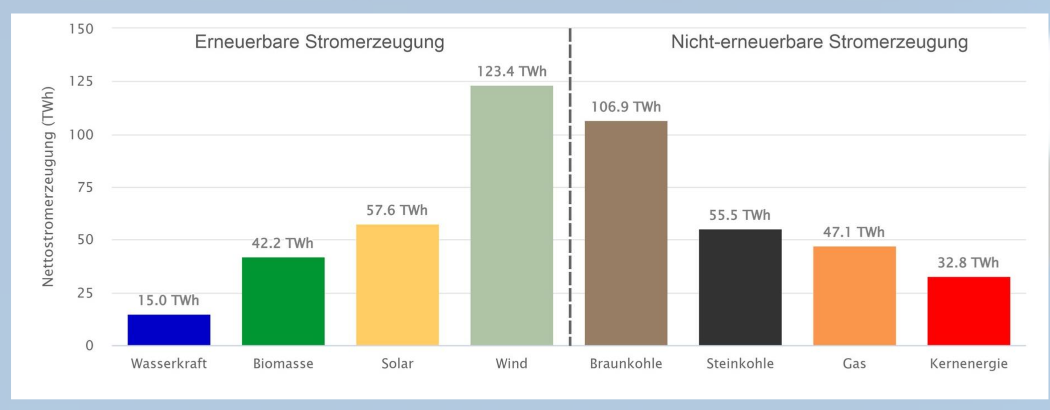

Figure 1: Public net electricity generation in Germany in 2022
Source [Fraunhofer ISE, 2023]

The German power network is managed at a regional scale by four TSOs. Our work focuses on the territory managed by Amprion. Its high voltage network extends over 11,000km covering from the North Sea to the Alps (see Figure 2). This area is home to 29 million people and around a third of Germany's economic output.

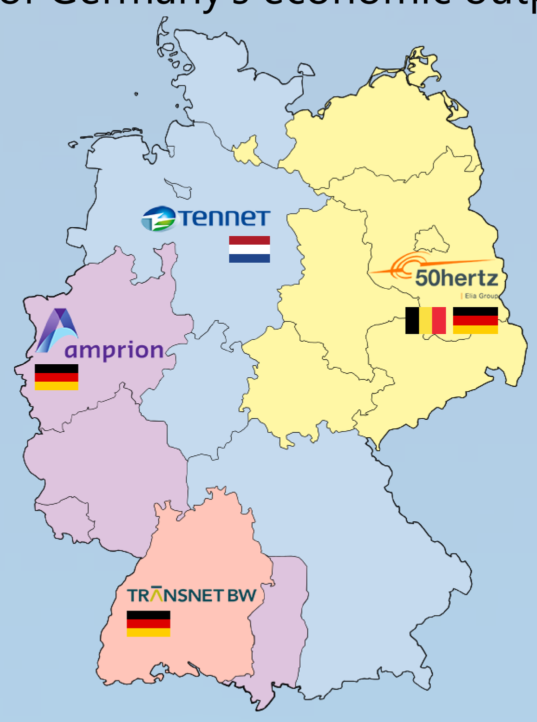

Figure 2: Geographical repartition of German Transmission System Operators
Source Wikipedia.org

Data

A dataset of 27 months have been considered to both train and evaluate our model. The dataset covers from 2021-03 to 2023-05.

For the day-ahead forecast, we used IFS (Integrated Forecasting System) meteorological forecast provided by ECMWF (European Centre for Medium-Range Weather Forecasts) (see Figure 3):

- Cycle: 00h
- Horizon: from t+24h to t+48h
- Temporal resolution: 1h
- Geographical resolution: 0,1°
- Parameters: U and V wind components at level 133_HYBL (~100m)

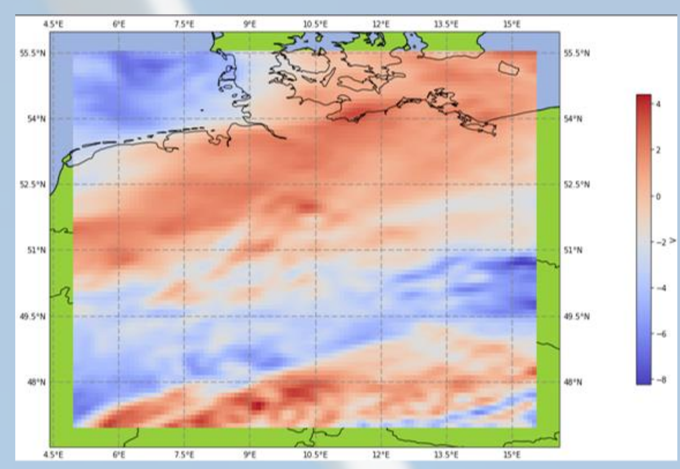

Figure 3: Visualisation of V-component (latitudinal) IFS forecast over Germany

Historical timeseries of wind-production on Amprion's territory is available on the ENTSO-E Transparency website (https://transparency.entsoe.eu) (see Figure 4).

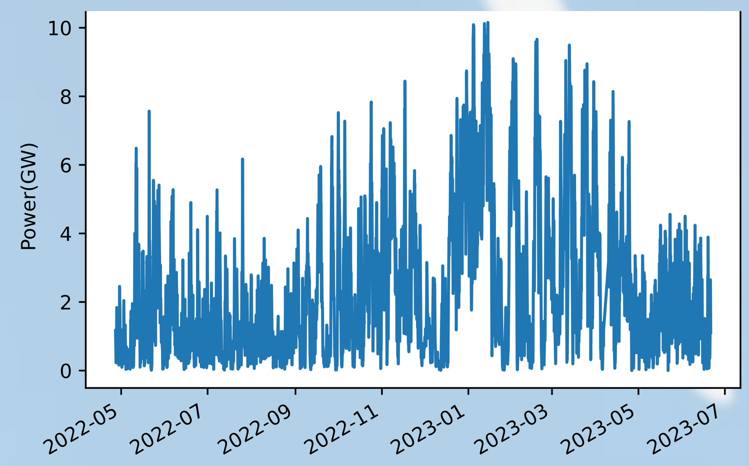

Figure 4: Wind production over Amprion's territory

Models

Our reference model is a physical model developed by a private company which has been operating for many years on Amprion's territory. This model has been finely tuned to take into account the installed capacity.

Two ANN models have been developed. They both use Convolutional Neural Network (CNN) layers [LeCun, 2015] but differ in the way they are parameterized:

- pvNET:
  - ~2M trainable parameters
  - Use Hyperband for automatic hyperparameters search [Li, 2018]
- eoleNET:
  - ~4M trainable parameters
  - Hyperparameters have been manually chosen (manual sensitivity analysis)

A sliding window of the previous 12 months is used to train the model before forecasting the considered month.

The models take U and V wind components at time t+xh as input and provide aggregated wind production at time t+xh as output, with t being the date/cycle used (00h) and xh the time horizon (in hours) being comprised between 24h and 48h.

U and V wind components are normalized before being provided to the models as inputs. One input value is obtained by subtracting the mean and dividing the result by the standard deviation. This best practice eases convergence during the learning phase.

The output value of the model is the square root of wind production. This reduces the spread of output values and, by such, takes better account of extreme values.

Results and discussions

The performance has been evaluated on the period [2022-04-01; 2023-05-31] using the normalized Mean Absolute Error (nMAE) (see Figure 5). Normalization has been done using the average production over the set of measurements.

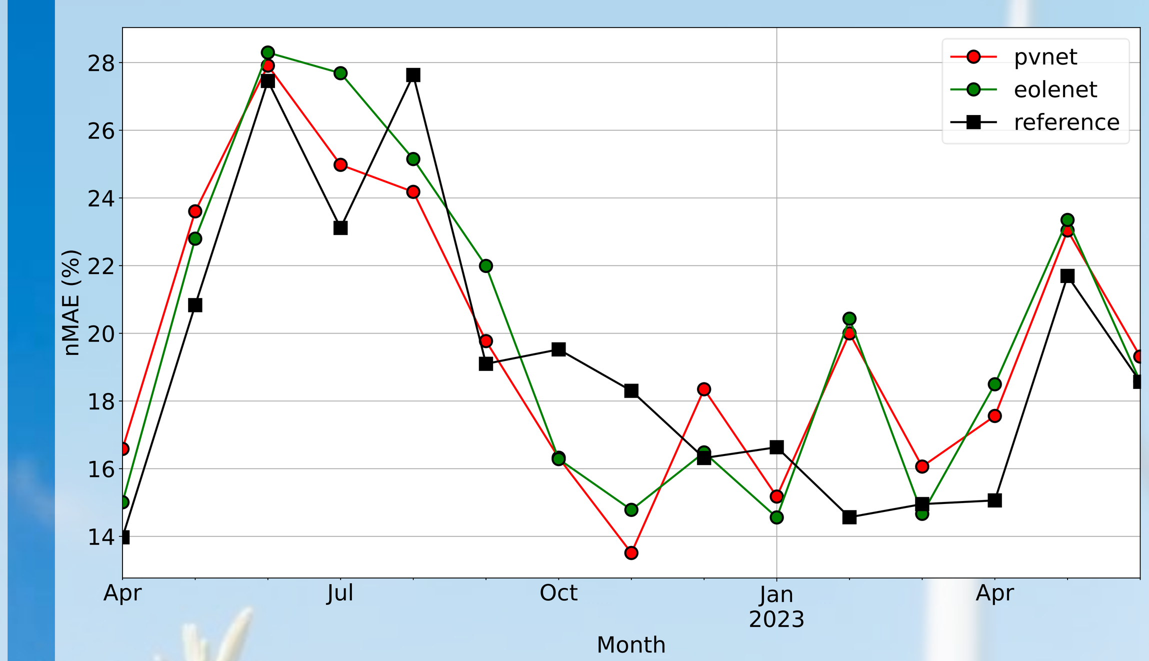

Figure 5: Performance comparison between Reference model (deterministic) and ANN models (pvNET and eoleNET)

The performances between the two ANN models are similar. The automatic approach can be interesting to reduce human-induced optimization time. It can be deployed relatively quickly with new case studies.

The performances between physical and statistical models are relatively consistent. We postulate that a precise description of wind farms location and characteristics is a must for an efficient physical model.

Whatever the model, there is a marked difference in performances between the May-September and October-April periods. There seems to be a seasonal effect which is not modelled in the reference model nor has been captured by the ANN models.

Conclusion

In this study, a comparison between a physical model and two ANN models is made in the context of wind energy forecasting at a regional scale. It is shown that the ANN models are capable of producing forecasts that reach the performance of the reference model.

Deterministic and statistical approaches can be complementary as they do not have the same requirements:

- The physical model requires technical information on the wind farms, but does not require historical data.
- Our ANN models require only historical production data, but no detailed technical information is necessary.

For regions where both detailed technical information and historical data are available, a hybridization of both physical and statistical models could further improve performance.

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