PO.180

Wind Power Forecasting techniques in complex terrain: ANN vs. ANN-CFD hybrid approach

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Abstract

Thanks to the technological developments, renewable energies are becoming competitive against fossil sources and also wind farms are growing more and more integrated into intelligent power grids. For this reason, accurate power forecast is needed and often operators are charged with penalties in case of imbalance. Yet, wind is a stochastic and very local phenomenon. Time and space variability therefore conspire and wind power forecast is still challenging. Statistical (typically Artificial Neural Networks - ANN) methods are often employed for power forecast but they have some shortcomings: they require vast data sets and are not fit for capturing tails of distributions.
In this work a pure ANN power forecast is compared against a hybrid method, based on the combination of ANN and a physical method as Computational Fluid Dynamics (CFD). The test case is a wind farm sited in southern Italy in a very complex terrain, and having a vast layout.

Objectives

Study the performance of two different techniques in forecasting the wind energy production; both are set using the same feeds from a mesoscale model WRF[1] extracted at different heights a.g.l..
The goal is to detect the performance on the day ahead forecast windows, morning feeds are used in the period from 18 to 32 hours. The standard errors are calculated and the behaviour of the time series is inspected.

Method

The two approaches employed in this study can be summarized as follows:

- A single ANN is applied to the output of the NWP (Numerical Weather Prediction) model to calculate the power production of the single turbine or the whole wind farm. This is called the pure ANN approach.
- An ANN connects the wind, as predicted by the NWP model, to observed wind conditions on site. The result is used as input to the CFD model in order to transfer the forecast from the wind measurement position to the positions of the turbines. The nominal power curve is employed for estimating the power output. This is called the hybrid approach.

The first approach is a purely statistical approach: the ANN stores the correlation between wind speed and wind direction from NWP and the power production. Such an approach can be seen as an Artificial Neural Network Power Curve (ANN wind-power).
The second approach is more complex, a hybrid of statistical and deterministic methods. The ANN acts as an MCP (Measure Correlate Predict)[2], detecting and using the correlation of the wind data between two time series (ANN wind-wind + CFD).

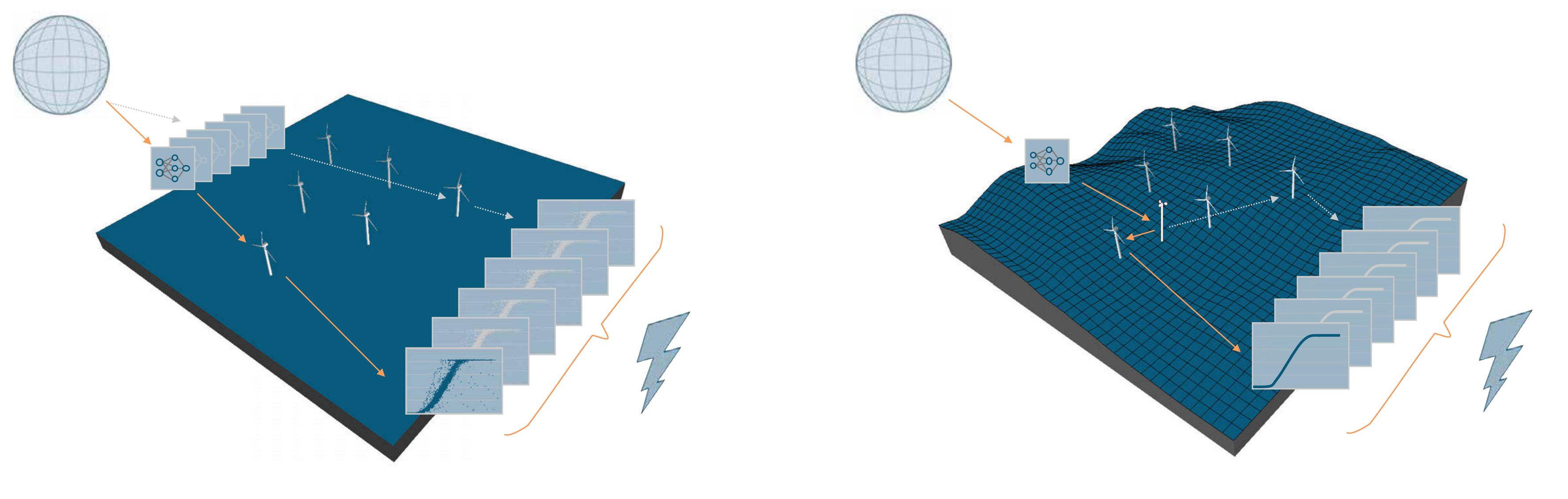

Fig. 1: Methods sketch: left "ANN wind-power", right "ANN wind-wind + CFD".

The wind farm has been divided into two layouts both sited on the top of two ridges creating two lines in the north-south direction.
For each of the two layouts the Reynolds Averaged Navier-Stokes (RANS) equations are solved with RNG k-ε turbulence closure for 12 wind directions.
The feeds obtained by the mesoscale model are hourly based, merged in long time series picking the day ahead part of each feed.
SCADA data of concurrent periods are used and filtered on the requirement that the turbine itself is in production. The test cover the period from September 2015 to March 2016. Training and validation time series are separated per week like shown in Fig.2.

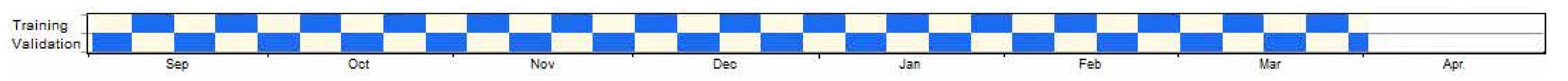

Fig. 2: Training and validation periods.

Results

The training of the ANN is performed on many setups for both approaches, and the more performing one is selected. In Table 1, some results about the validation are reported, in the usual standard error forms employed in wind power forecasting. It is interesting to notice that, in this test case, the errors obtained with both techniques are overall similar: Normalized Mean Absolute Error (NMAE) is about 20% for layout 1 and about 16% for layout 2, with small differences changing technique.
The results are more sensitive to the level of NWP model used: the lower NMAE is obtained using the levels at 100 and 200 meters. This highlights that the NWP level at 10 meter is probably too near the ground to describe the behavior of the wind at the hub heights, while the 300 and 400 meters levels are too far.

NWP Level [m]	Layout	Technique	Bias [kW]	RMSE [kW]	NMAE	NRMSE	Points
10	1	ANN	-336.682	1723.981	0.2087	0.2612	2196
100	1	ANN	-318.798	1694.48	0.2058	0.2567	2196
200	1	ANN	-307.642	1682.663	0.2047	0.2549	2196
300	1	ANN	-346.803	1707.495	0.2073	0.2587	2196
400	1	ANN	-342.965	1769.535	0.2158	0.2681	2196
10	1	ANN+CFD	-416.747	1865.727	0.2058	0.2827	2196
100	1	ANN+CFD	462.121	1803.351	0.1988	0.2732	2196
200	1	ANN+CFD	-417.957	1789.776	0.2003	0.2712	2196
300	1	ANN+CFD	-504.929	1821.04	0.2047	0.2759	2196
400	1	ANN+CFD	-562.539	1902.911	0.2132	0.2883	2196
10	2	ANN	-193.235	1973.729	0.1677	0.2269	1847
100	2	ANN	-166.046	1920.192	0.1618	0.2207	1847
200	2	ANN	-198.062	1909.207	0.1595	0.2194	1847
300	2	ANN	-206.821	1900.868	0.1601	0.2185	1847
400	2	ANN	-237.339	1912.797	0.1616	0.2199	1847
10	2	ANN+CFD	-36.982	2136.938	0.1685	0.2456	1847
100	2	ANN+CFD	7.079	2068.746	0.1605	0.2378	1847
200	2	ANN+CFD	-121.554	2068.857	0.161	0.2378	1847
300	2	ANN+CFD	-78.994	2085.767	0.1617	0.2397	1847
400	2	ANN+CFD	-115.361	2114.197	0.1642	0.243	1847

Table 1: Results (Nominal Power: Layout 1 6600 [kW], Layout 2 8700 [kW]).

The two techniques are compared also on the time series level, and different behavior arises. In Figure 3, a part of the time series of both layouts is sketched: the ANN technique performs better in forecasting the mid-energy levels. The ANN + CFD technique instead performs better in the high-energy levels, especially in the raising phases, and in the low-energy levels. This happens because CFD simulates better the wind flow acceleration in complex terrain and therefore it is capable of dynamically following power output oscillations. The similar performance in terms of error and the different features of the time series suggests that the two techniques could be used as reciprocal approaches and jointly, in an ensemble, improve the overall performance of the forecast.

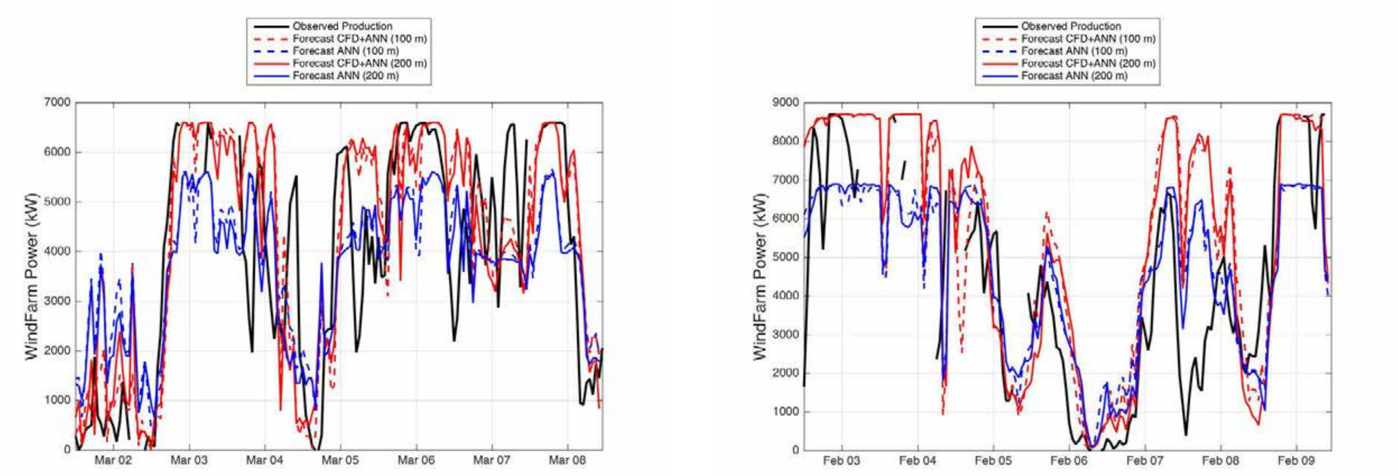

Fig. 3: Plots of the power production and forecasts, left layout 1 and right layout 2.

Conclusions

The main outcome of this work is that the overall performance of the two approaches is very similar, but the hourly performance is not. The analysis of time series actually resembles as expected the pro's and con's of each approach. The performance of the two methods (overall similar, hourly different) suggests that the approaches could be used reciprocally, for improving the overall performance of the forecast.

References

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