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

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Abstract. Due to technology developments, renewable energies are becoming competitive against fossil sources and the number of wind farms is growing, which have to be integrated into power grids. Therefore, 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, and therefore hard to predict. It has a high variability in space and time and wind power forecast is challenging. Statistical methods, as Artificial Neural Networks (ANN), are often employed for power forecasting, but they have some shortcomings: they require data sets over several years and are not able to capture tails of wind power 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 using computational fluid dynamics (CFD). The validation case is a wind farm sited in southern Italy in a very complex terrain, with a wide spread turbine layout.

1. Introduction

Renewable energies are day by day struggling in competitiveness against fossil sources, due to the higher expenses for this kind of energy. For this reason, the financial feasibility of wind farms is often pushed to the limits and wind farms are growing more and more integrated into power grids. The integration is still challenging because wind has a peculiarity with respect to other renewable energy sources: its variability, in time and space.

The quality of the forecast, typically on day ahead basis, is a metric according to which wind farm owners can be charged of penalties, due to the imbalance between what is actually dispatched into the grid and what was declared it would be dispatched. Usually, the farm owner provides a 24 hour forecast in the morning for the day after. Due to the high variability of wind speed during the day, as well as over the year, wind speed records over several years are needed for reasonable statistical forecast methods using numerical weather prediction (NWP) models and ANN.

Furthermore, when a wind farm is sited onshore in a complex terrain, the wind field encounters severe horizontal variations [1] even in few meters and this cannot be represented by NWP models due to their coarse horizontal resolution. To overcome these problems is the motivations of the present study. A challenging validation case is selected: a wind farm sited in southern Italy in a very complex terrain having a vast layout.

Nowadays, wind power forecasting is mostly performed using statistical tools to convert wind speeds calculated by NWP models into power production [2]. Several issues complicate this task. Data mining is one of them: whatever the statistical method is, observed power data need to be cleaned in order to highlight and recognize patterns in the relationship between input and output. Another big issue is that the chain from the NWP wind field to the power output of one or several wind turbines is not straightforward. There is more than one way to downscale the information from NWP and the choice is not irrelevant for the quality of the forecast because wind is a very local phenomenon.

One of the most typical statistical methods to forecast wind power are artificial neural networks (ANN) [3], which connect directly the input from the NWP model to the wind farm power production. Access to a vast amount of supervisory control and data acquisition (SCADA) data is a key for fault diagnosis [4, 5, 6] and performance evaluation [7, 8, 9], but also for improving the quality of the forecast through its validation. ANN provides in average a good forecast but it is sometimes like a black box as it is not easy to understand what is physically happening. In particular, ANNs have difficulties and instabilities [10] in resembling the less populated sectors of statistical distributions and this might affect the wind power forecast, because the wind distribution has considerable tails. For the same reason, the ANN approach might have problems, or at least need to be fed with vast amount of data, when the wind field is challenging like in complex terrain.

There are several possible strategies to overcome these issues. One can point at optimizing the machine learning algorithm, as in [11], where a wavelet neural network is employed and the error measure is optimized too, through the maximum correntropy criterion. Switching from a purely probabilistic approach to a hybrid method, in order to retain a certain degree of determinism, might lead to some advantages. In [12], clustering of weather events is performed and data from three different NWPs are post-processed. Or, physical methods as computational fluid dynamics (CFD) can be used, in conjunction with ANN techniques, for describing the local wind field around a wind farm. This method has a deeper physical basis than a pure ANN forecast and is less demanding by the point of view of input data processing, but it has some shortcomings mostly related to computational challenges in complex geographical contexts. For an up to date review on challenges and methods in wind power forecast, see [13, 3].

In this work, we compare a pure ANN and a hybrid ANN+CFD forecast method [14] on a wind farm operating in southern Italy in a very complex terrain. The objective is to compare the two methods when facing a complex terrain with a highly variable wind field, and scarcity of data, i.e. a poor statistics for a quick forecast. The structure of the paper is as follows: in Section 2, the methods are briefly described. In Section 3, the validation case wind farm and the data sets are introduced. In Section 4, the results are collected. The conclusions are discussed and some further directions of this work are finally proposed in Section 5.

2. The method

Wind power forecast is calculated applying a post-processing on the NWP output. In this study, the weather research forecast Model - WRF is used. Each of the two proposed methods is composed of different steps, leading to the estimate of the power production of the wind farm.

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

- A single ANN processes the output of the NWP model and directly calculates the power production of each single turbine or the whole wind farm. This is the pure ANN approach: the ANN has wind speed and direction of the wind as input variables and power production as output variable.

- An ANN processes the wind conditions, as predicted by the NWP model, targeting the wind conditions on site. These are used as input to the CFD, in order to transfer the forecast

from the reference wind measurement position to the positions of the turbines. The nominal power curve is employed for estimating the power output. This is the hybrid approach: the ANN has NWP wind speed and wind direction as input variables, and observed wind speed and direction as output variable. The CFD flow simulations enable to transfer the wind conditions in the layout area up to the position of each turbine, and to calculate the power production.

The first approach is purely statistical: the ANN stores the correlation information between wind speed and direction from NWP and the measured power production. Such an approach can be seen as a 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) [15], detecting and using the correlation of the wind data between two time series. In this case, the correlation is used between NWP data and observed wind speed and direction at target site. The output of the ANN is used, within the CFD framework, in order to transfer the forecast from the wind measurement position to the positions of the turbines, considering the simulated behavior of the wind depending on the direction of the flow. Also the wake effects between turbines are taken into account using the Jensen model [16] and the nominal turbine thrust coefficient C_t. The calculation is performed using WindSim software [17, 18, 19, 20]. In short, this approach can be defined as ANN wind-wind + CFD method. In both methods, the ANN is fed with the same data in the input layer: time series of wind speed and direction obtained by the NWP model at a defined position in the wind farm layout. Depending on the method, the ANN gives different outputs: the power production of each single turbine (or of the complete wind farm) for the pure ANN approach, or the wind speed and direction at the target reference point for the hybrid method. Therefore, the two ANNs differ in the number and type of the variables set at the output layer. In both cases, the ANNs are single layer perceptrons, trained by feed-forward back-propagation method, unsupervised training. The ANNs can be set with different number of neurons in the inner layer and the performance is sensitive to such a setting. Therefore, many configurations are tested and the best is chosen.

3. The validation case and the data set

The wind farm used for validation is sited in southern Italy. On site, 24 turbines are installed. The terrain is extremely complex: the presence of mountains is important in all the directions and there are severe slopes all around. The highest point in the domain of the wind farm is about 1000 meters above the sea level (ASL), while the lowest one is around 400 meters. The wind farm is divided into two parts, sited on two ridges aligned from North to South. The two ridges are about 5 km far away from each other, so the wind farm can basically be considered as the juxtaposition of two sub-farms of 12 turbines each. For this reason two distinct domains are considered, which have a dimension of about (10×10) km^2 each. 18 turbines out of 24 have 50 meters of hub height, 6 have 55 meters of hub height. The rotor diameters are respectively of 42 and 52 meters. The total power of the wind farm sums up to 15.9 MW.

In the CFD computational domains, the roughness of some forested areas surrounding the wind farm and the complexity of the terrain are taken into account using the information available through the CORINE Land Cover Europe 2006 [21] with 100 meter resolution and the ASTER GDEM v2 worldwide elevation data [1] with 1 arc-second resolution. On the CFD side, the Reynolds-averaged Navier-Stokes (RANS) equations with the RNG k-ϵ turbulence closure are solved. RNG k-ϵ is selected because it is more appropriate in tackling complex terrain effects, as shown also in [22] for the Askervein Hill test case of the IEA-Task 31 Wakebench project.

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[1] https://asterweb.jpl.nasa.gov/gdem.asp

The CFD simulations are used in the hybrid method to downscale dynamically the NWP simulations, after the correction of the forecast according to the ANN. In principle, two methods can be adopted to downscale NWP simulations with CFD. The NWP forecast can be interpolated into the CFD computational domain and used as initial condition to the CFD calculation. This approach is very computationally demanding and time consuming. Therefore, it is not suitable for forecasts. Moreover, it does not allow to correct the whole NWP forecast with the ANN technique. Alternatively, a set of CFD simulations under idealized conditions can be performed. Logarithmic wind profiles are given at the inlet of the CFD domain for different wind directions and developed to realistic profiles inside the computational domain during the simulation. A reference point inside the domain is chosen, where the NWP forecast is extracted and used as external forcing to the CFD simulations. According to the forecast at the reference point, the whole three-dimensional wind field calculated by the CFD can be scaled from the idealized CFD simulations through appropriate transfer coefficients that are usually defined as the ratio between the wind speed at the reference point and the wind speed at another whatsoever grid point [23]. This approach is very efficient, as a limited number of simulations is required, the transfer coefficients are calculated only once and then applied in every forecast. The wind forecast is transferred to the positions of the wind turbines only. Moreover, this approach allows to correct the NWP forecast by means of the ANN before the transfer coefficients are applied. In the present case, two computational domains have been created in order to represent the two parts of the wind farm. Each domain has a refined computational grid in the middle, with a maximum horizontal grid resolution up to 40 meters along x and y directions. The resolution decreases from 40 m in the middle to 380 m at the boundaries. The grid resolution is variable along the vertical direction as well, with the highest resolution close to the ground, where the first 5 cells have 20 meters of equal spacing, while the upper cells expand geometrically up to the top of the domain. The computational domains are respectively made of $119 \times 124 \times 20$ and $120 \times 130 \times 20$ cells. The top of the computational domains are respectively 2266 and 2961, while the height of the boundary layer is 1000 meters in both cases. Simulations have been performed with a wind speed equal to 15 m/s at the top of the boundary layer, and 12 wind directions equally spaced of 30 degrees. A sector interpolation is performed to define the transfer coefficients at intermediate directions. The lateral boundary conditions of the simulations for the inlet boundary are logarithmic profiles of the wind speed up to the boundary layer height; the profile is defined using the roughness of each point of the border. In the orthogonal sectors, the two boundaries parallel to the flow are set as fixed wall, while for the diagonal sectors there are two inlet and two outlet boundaries. The outlet boundary is set as free to flow surface. At the terrain surface, the wind speed is set to zero and the roughness is taken into account in the momentum equations. One position inside each domain is selected as reference point to extract the NWP wind forecast: the position of the met-mast is selected for domain 1, while the position of one turbine is selected for domain 2.

Wind forecasts have been performed for the period from September 2015 to March 2016 by means with the NWP model WRF [24]. WRF is a next-generation mesoscale NWP model, designed for operational forecasting as well as atmospheric research. It is developed through a collaborative effort among the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (NOAA), the Department of Defence, the University of Oklahoma, and the Federal Aviation Administration (FAA) of the USA. The WRF system has two dynamics solvers, many packages concerning different schemes for microphysics, PBL parameterization, etc. that interface with the solvers, and programs for the initialization, as well as pre-processing and post-processing phases. The WRF solver used in the present research is the Advanced Research WRF (ARW) solver. This solver integrates the compressible, nonhydrostatic moist Euler equations in flux form, which are conservative for scalar variables [25], formulated using a terrain-following hydrostatic-pressure vertical coordinate. The prognostic variables
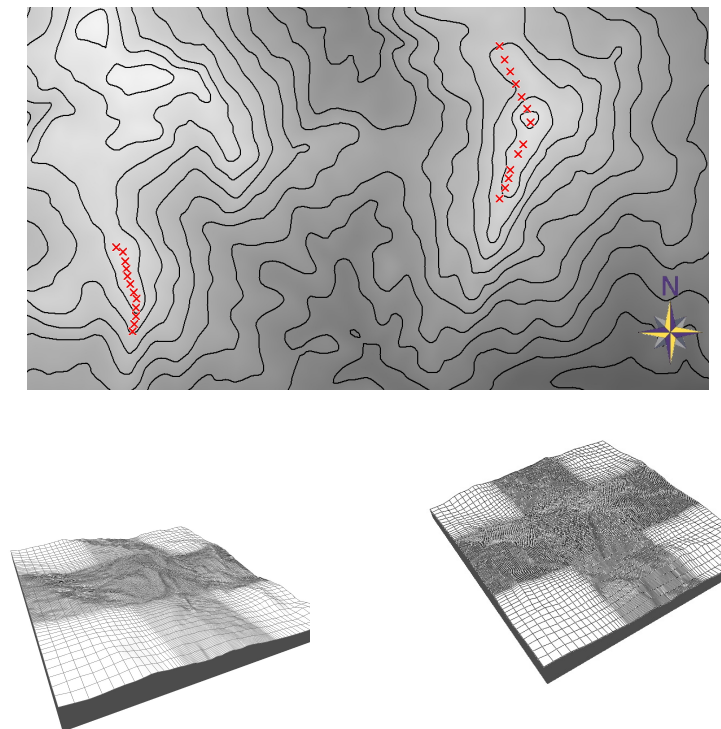
Figure 1. Turbine positions (up); the calculation domain for layout 1 (down left) and layout 2 (down right).

are the two horizontal components of the velocity, the vertical velocity, the perturbation potential temperature, the perturbation geopotential, and the perturbation surface pressure. The current ARW solver uses the time-split integration scheme described in [26], and the equations are spatially discretized through the Arakawa C-grid staggering method. Every day, the global forecast system (GFS) provides the initial and boundary conditions used to perform the simulations with WRF. The GFS is a numerical weather prediction system, developed and maintained at the National Weather Service of the National Oceanic and Atmospheric Administration in the USA, which performs every day at 00, 06, 12, and 18 UTC a weather forecast up to +16 days ahead valid for the entire globe. The time resolution of the simulations is three hours and the horizontal resolution is 0.25 degrees in longitude and latitude up to +8 days and 0.75 degrees from +8 to +16 days. In the operational chain, WRF uses the GFS conditions available at 12 UTC the day before to calculate the wind forecast from 00 UTC to +48 hours ahead with a time-step of 1 hour, through three nested domains centered over the wind farms with increasing horizontal resolution of 9, 3, and 1 kilometer.

Time series of the wind speed and direction at the two reference points mentioned above have been extracted from the WRF simulations at 10, 100, 200, 300, and 400 meters above ground level. Those data have been used at the input layer for both types of neural networks: the one defined ANN wind-wind and ANN wind-power.

SCADA data are stored on 10-minute time basis and they are post-processed for this study as follows: the data set of each turbine is filtered on the requirement that the turbine itself is in production. As for NWP data, half of the set is employed for training, half for validation. A similar post-processing is performed to the wind speed and direction data sets at the two reference positions, filtering out periods of malfunction.

The total period used is seven months. In order to avoid bias due to seasonal effects, the data

Figure 2. Training and validation periods

are split in weeks, which are alternatively employed for training and validation (Figure 2). In this way, the training and validation data sets are expected to display a reasonably homogeneous behavior, the one with respect to the other. To simulate the run of a real day ahead, as the forecast has to be done in the morning for the day after, 18 hours of each forecast run are cut out and the following 24 hour are used.

4. 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 [13]: bias, root-mean-square error (RMSE), normalized-mean-absolute error (NMAE) and normalized-root-mean-square error (NRMSE), where the normalization factor is the nominal and maximum power production of the layout. In [14] it was shown, on the same validation case as in this work, that availability of plenty of appropriately post-processed data leads to better forecast using the pure ANN approach. Here, the opposite validation ground is investigated: the issue is if there is added value provided by CFD when using (for a quicker forecast) less data. It is interesting to notice that, in this validation case, the errors obtained with both techniques are overall similar: 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 NWP wind field data used as input: the lowest NMAE is obtained using the wind field corresponding to the height of 100 and 200 meters above ground level (AGL). This highlights that the NWP wind fields at 10 meter AGL are probably too close to the surface to describe the behavior of the wind at the hub heights, while the wind fields at 300 and 400 meters AGL are too far from the ground. The two techniques are also compared in terms of power output time series. In Figure 3, part of the time series of power production for the two layouts is reported. The ANN technique performs better in forecasting the mid-energy levels. The ANN+CFD technique performs better both in the high-energy levels, especially in the ascending ramps, and the low-energy levels. This happens because the CFD simulates properly the wind flow accelerations, i.e. speed-up, in complex terrain and is therefore more suitable to follow the dynamics of power output oscillations. The similar performance in terms of error values and the different features of the time series seems to suggest that the two techniques could be used as complementary approaches, and used jointly as an ensemble method for improving the overall performance of the forecast.

5. Conclusions and further directions

In this work, the issue of wind power forecasting in complex terrain has been addressed. The validation case is a wind farm, placed in southern Italy in a very challenging site. The layout is very large and steep terrain slopes occur: the highest point in the wind farm layout is at around 1000 meter AGL, while the lowest is at around 400 meters. Wind power forecasts have been calculated for this validation case using two approaches. A pure statistical ANN method takes as input NWP results and reports wind farm power production as output. In the hybrid ANN + CFD approach, an ANN produces as output the wind conditions at a meaningful point from the NWP results. The wind condition is then transferred to the position of every turbine
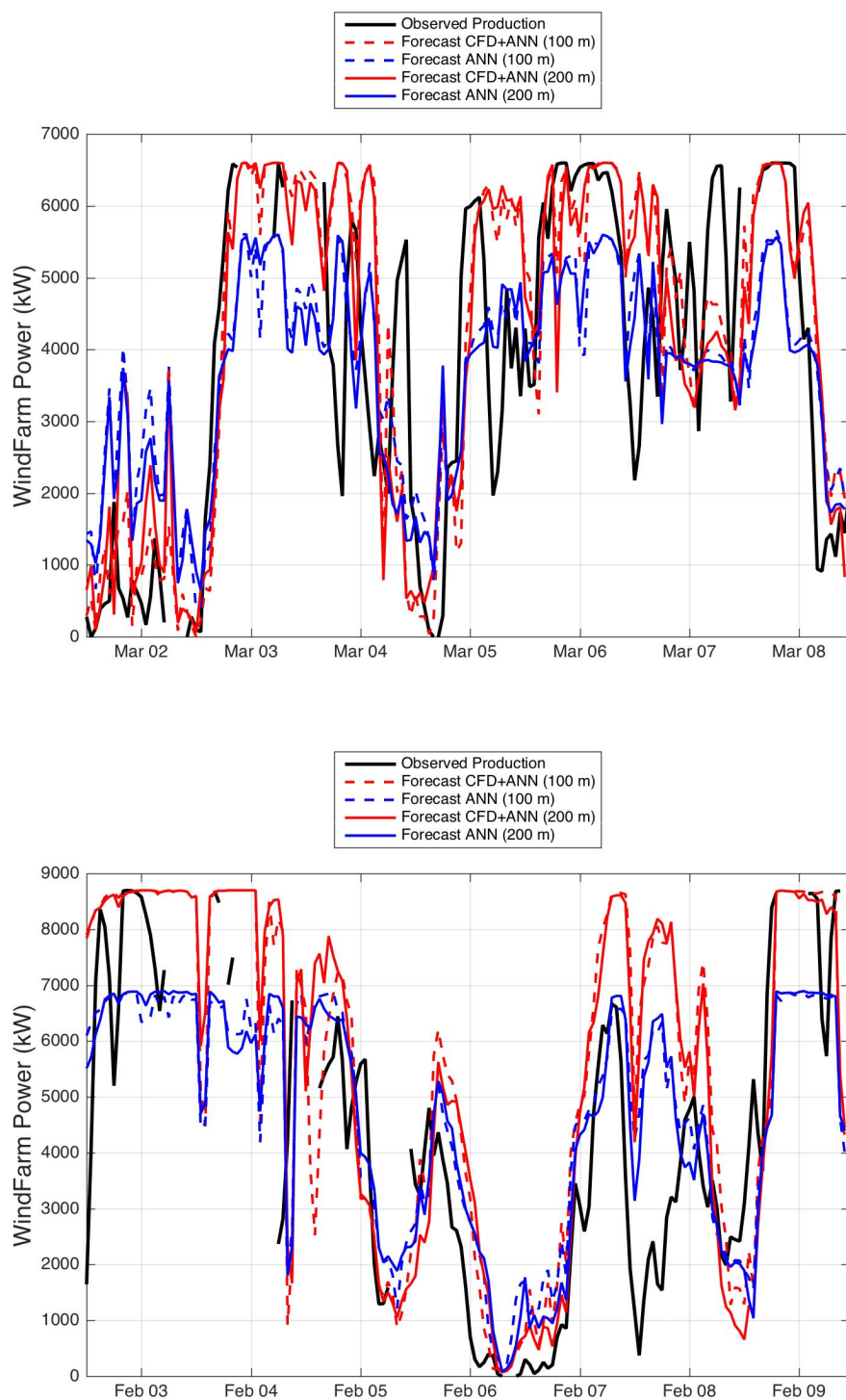
Figure 3. Plots of measured (black line) and simulated power production: ANN (blue lines) and ANN+CFD (red lines), corresponding to using the NWP wind field input at 100 m. AGL (dashed) and at 200 m. AGL (solid), for layout 1 (top) and layout 2 (bottom).

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

NWP height [m] AGL	Layout	Technique	Bias [kW]	RMSE [kW]	NMAE	NRMSE	Points
10	1	ANN	-336.682	1723.981	0.209	0.261	2196
100	1	ANN	-318.798	1694.480	0.206	0.257	2196
200	1	ANN	-307.642	1682.663	0.205	0.255	2196
300	1	ANN	-346.803	1707.495	0.207	0.256	2196
400	1	ANN	-342.965	1769.535	0.216	0.268	2196
10	1	ANN+CFD	-416.747	1865.727	0.206	0.283	2196
100	1	ANN+CFD	462.121	1803.351	0.199	0.273	2196
200	1	ANN+CFD	-417.957	1789.776	0.200	0.271	2196
300	1	ANN+CFD	-504.929	1821.040	0.205	0.276	2196
400	1	ANN+CFD	-562.539	1902.911	0.213	0.288	2196
10	2	ANN	-193.235	1973.729	0.168	0.227	1847
100	2	ANN	-166.046	1920.192	0.162	0.221	1847
200	2	ANN	-198.062	1909.207	0.160	0.219	1847
300	2	ANN	-206.821	1900.868	0.160	0.219	1847
400	2	ANN	-237.339	1912.797	0.162	0.220	1847
10	2	ANN+CFD	-36.982	2136.938	0.169	0.246	1847
100	2	ANN+CFD	7.079	2068.746	0.161	0.238	1847
200	2	ANN+CFD	-121.554	2068.857	0.161	0.238	1847
300	2	ANN+CFD	-78.994	2085.767	0.162	0.240	1847
400	2	ANN+CFD	-115.361	2114.197	0.164	0.243	1847

through CFD modeling, and the turbine power output is calculated using the nominal power curve. The philosophy of this validation is to stretch both approaches to their limits, by using. reasonably short data sets. This allows to have a quicker forecast, but poor statistics challenges the capability of ANN in capturing the dynamics of the power production. On the other hand, the complexity of the terrain creates a possible conflict between the grid resolution of the NWP and the scale of local dynamics in the wind farm. Furthermore, in harsh environments, CFD is challenged by itself in its capability in resembling the features of the wind flow [1]. The main outcome of this work, as summarized in Section 4, is that the global performances of the two approaches are very similar, but local performances are not. The analysis of time series actually resembles as expected the pros and cons of each approach: the purely statistical approach of ANN represents better the mid-energy levels, while ANN + CFD better performs in high energy levels (especially when there are ascending ramps) and low energy levels. Even though on the CFD side the compromise between computational simplicity and precision is stretched to its limits, the hybrid approach provides an interesting added value in capturing the dynamics of the flow. The performances of the two methods (globally similar, locally different) suggest that the approaches could be used reciprocally, for improving the overall performance of the forecast. This is actually the main further direction of the present work, to be pursued on this validation case and possibly also on another wind farm having the same features (vast layout, challenging combination of terrain-driven flow and wakes, big data sets at disposal), which is well known in the literature [27, 1, 28] because it has been a test case of the IEA-Task 31 Wakebench project [29, 30].

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