Author's response to the referee comments regarding the paper

Observer-based power forecast of individual and aggregated offshore wind turbines

Frauke Theuer, Andreas Rott, Jörge Schneemann, Lueder von Bremen, and Martin Kühn

We thank the two referees for taking the time to read and review our manuscript and appreciate their feedback and comments. We address each of the remarks below. Please also find a pdf file with changes to the manuscript marked using latexdiff attached.

Anonymous Referee 1:

The main comment is that it is not always clear which contributions are the authors' and which predated the manuscript. [referring to Section 2]

Thanks for this comment. We added additionally references throughout the whole Section 2 to better distinguish between the new contributions of this manuscript, our own but predating contributions and other researchers work.

In the paragraph beginning at line 208, further justification could be given regarding the selection of these parameters.

We have adjusted the paragraph to make our choice of parameters more clear.

Each forecasted time step of the LF considered the six most recent scans, thus can contain wind data measured during the last 15 minutes. This ensures that also turbines positioned far away from the lidar scans can be reached by low wind speeds and their forecasts will not be biased. Wind vectors contributing to the SF were weighted using a tuning parameter of $p = 4$. The choice of this parameter is further discussed in Section 4.1. The SF's bias correction was performed considering a number of $N_\mathrm{t} = 5$ time steps prior to forecast initialization. This ensures that there is enough data for bias estimation while keeping the correlation high. The step length was chosen as $\Delta\tau = 156\,\mathrm{s}$ in accordance with that of the lidar scans. LF and SF were generated with an area of influence of $2D$ and a minimum of 20 required wind vectors (Theuer et al., 2021) and were resampled to contain 500 members. Forecast calibration was performed with a 5 h training interval before forecast initialization. The time window was optimized in a sensitivity analysis. A calibration was only performed for situations with at least 60 % valid data within that training period.

Section number is missing in reference on line 78.

We slightly changed the sentence to make the reference more clear.

In this work this approach is significantly extended further as described in the following: Using SCADA (Supervisory Control and Data Acquisition) data, it is first extended to an observer-based forecast (OF) to increase forecast availability and skill (cf. Section 2.2). In a next step, observer-based forecasts are calibrated by means of Ensemble Model Output Statistics (EMOS) (cf. Section 2.3). Finally, probabilistic power forecasts of individual wind turbines are aggregated using different copula approaches (cf. Section 2.4.)

Paragraph not indented at line 208.

We have corrected this.

In figure 3, keep all subplots the same size; it would be helpful to indicate on a subplot illustrating the entire farm (a-c) the region highlighted in the subset (d).

We have adjusted the size of Figure 3 (d). It now shows all turbines, with those not considered for further analysis in grey. The figure caption was adjusted accordingly.

Anonymous Referee 2:

1. Line 92: Please describe briefly what is meant by "synchronized in time", such that the reader may follow your argument without having to study the paper referenced.

We added a more detailed explanation of the time synchronization in Line 92f..

After wind field reconstruction, the individual lidar scans are interpolated to a cartesian grid and synchronized in time (Beck and Kühn, 2019). Time synchronization refers to the propagation of individual parts of the lidar scans measured at different times to the same time step using semi-Lagrangian advection. It aims at accounting for the large time shift within each scan.

2. Figure 1: The Windpark "Hohe See", next to Global Tech I has been in operation since mid August 2019; your measurement campaign ended in June 2019. Have you seen any influence of Hohe See in your data? In any case, it would be appropriate to indicate Hohe See in Figure 1a as well (e.g. using grey dots) and clarify the impact (or the lack thereof).

We added the layouts of the wind farms Albatros (+) and Hohe See ($\times$) in Figure 1 and adjusted the caption accordingly. Before those wind farms started to operate we were occasionally able to observe the turbines' transition piece as hard targets in the lidar scans. Those hard targets were omitted during data filtering and thus did not impact the forecast. We added a corresponding statement in Line 206f.:

Figure 1 (a) additionally depicts the layout of the wind farms Albatros and Hohe See, which were under construction during the time of the analysis. Those turbines were visible as hard targets in the lidar scans occasionally, which were omitted during data filtering an thus did not impact the forecast.

3. Chapter 3.1 (199ff): This information is clearly important, but it should be presented in the Methods section, not as Results.

We thought about including the information related to the specific campaign and data set in the Methods section, however, decided against it. In Section 2 we are aiming to introduce the methodology in a generic way, independently from the case study analysed in the manuscript. In our opinion it is therefore more suited to include the description of the case study in Section 3, as we also did in our previous study Theuer et al. (2020). Other examples of journal papers using a similar structure are Bessa (2016), Pinson et al. (2009), Schuhen et al. (2012) and Gneiting et al. (2005).

4. Line 245: I believe you want to refer to Figure 3, not 2.

You're right, we changed the reference to Figure 3 (a).

5. Table 12: "normalized power" means P/P_r, I assume? Please clarify.

Thanks for pointing this out. This is a mistake and is meant to read *rated power*. We corrected it in the manuscript.

6. Discussion: I was wondering if you could comment on the expected skill of the presented method for e.g. a 10 minute forecast. Is the range of the lidar the limiting factor, or the simple propagation technique?

The skill of observer-based forecasts in general is expected to decrease with increasing forecast horizon as discussed in line 492ff. and numerous other studies (Würth et al., 2018; Rott et al., 2020; Theuer et al., 2020). Hereby, the range of the lidar (respectively the position of the turbines for the SCADA-based approach) will determine the maximal lead time for which it is possible to generate a forecast. At this stage not yet considering the skill of the forecast, here it is of concern if wind vectors are reaching the turbine of interest at the time of interest. This is also dependent on the wind farm layout, wind speed and direction and the position and scanning trajectory of the lidar (Theuer et al., 2020).

In addition to the availability of the forecast the lidar range will also impact the skill of a lidar-based forecast. Wind speed measurements from far ranges of the lidar scans are associated with larger uncertainty. Further, if wind vectors are primarily selected from the maximal measurement distance of the lidar, the forecast will more likely be biased. In our specific campaign these considerations restricted us to the evaluation of 5-minute ahead forecasts.

Apart from the lidar range, also the wind vector propagation has a large impact on forecast skill. The uncertainty associated with Lagrangian advection is expected to increase for larger propagation distances and duration, thus also with increasing forecast horizon. A first evaluation of lidar-based forecasts with forecast horizons up to 30 minutes based on a currently ongoing campaign confirms this. Further analysis will investigate, among other things, how the forecast skill for larger horizons compares to that of persistence. We expect that the lidar-based forecast is able to outperform persistence for horizons larger than 5 minutes, in particularly during very unstable atmospheric conditions and during ramp events.

As we already discuss the impact of forecast horizon on skill in Section 4.3, Line 492-504, in Theuer et al. (2020) and Theuer et al. (2021) in some detail we did not add further discussion in the manuscript.

References

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