Forecasting wind ramps: can long-range lidar increase accuracy?

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Abstract. The national funded WindforS project VORKAST investigated the use of a long-range lidar for very short-term power forecasting of a wind turbine in complex terrain. This ability is essential for the grid integration of large amounts of wind energy. This paper describes the process of setting up the lidar, data handling, and wind field reconstruction. A process based on Taylor’s frozen turbulence hypothesis is used to propagate wind speeds to the turbine and to forecast wind ramps. The lidar-based forecast is currently less accurate than persistence in these conditions. It is expected that the use of a more realistic propagation model will improve the forecasts in such complex terrain.

1. Introduction

Germanys goal for the Energiewende is to have a share of renewable energies in total electricity consumption of 35% by 2020, by 2050 even 80% [1]. To achieve these goals, the energy system is being reformed and the process will lead to a decentralized system with many interconnected power generating plants that need to be coordinated. Along with solar and hydro power, wind represents the largest renewable power source within this system. One of the main challenges for the electrical grid operator is to match an electric load profile to the power fluctuations of these weather dependent sources. Electric grid system operators must instantaneously and continuously balance supply and demand to maintain the reliability of the grid. Therefore, predictions of the power from different sources are necessary [2]. Current wind power predictions are based on numerical weather prediction (NWP) models, which use mathematical models of the atmosphere and ocean to predict the weather based on current weather conditions. The horizontal resolution of these models ranges from 1 to 10 kilometers (km) [3]. Short-term forecasts of up to one hour are usually implemented using the persistence method. For this method it is assumed, that there will be no changes in wind speed within the next designated time period, meaning the upcoming wind speed is equal to the present one. While the wind forecast for horizons of more than an hour using NWP models can be regarded as sufficiently precise, the fact that persistence is the state-of-the-art prediction method for horizons of less than an hour can be problematic for locations in which wind conditions frequently change and are therefore not accurately predicted using the conditions at the time of the forecast. This is particularly the case for a phenomenon called wind ramps, also referred to as wind ramping event or wind power ramp, which are defined as a sudden and strong change in wind power output from a wind turbine or wind park [4].
The University of Stuttgart proposes a novel approach for short-term forecasting of the wind power, which is based on wind speed measurements upwind of the wind turbines. Within the national funded WindForS research project VORKAST the use of a long-range wind lidar for wind power forecasting for horizons up to 60 minutes (min) is being investigated. Wind lidar devices measure the wind speed along the line-of-sight (LOS) direction of a laser beam. Modern scanning wind lidars, can measure the LOS wind speed up to a distance of 10 km in a hemisphere centered on the device. The wind speed is measured in multiple range gates along the laser beam and thus measurements with a very high temporal and spatial resolution are possible. In contrast to NWP models and persistence also small fluctuations of the wind speed are captured and the evolution of the wind field over the terrain can be tracked. As a result, short-term wind power forecasts based on lidar measurements offer the possibility to close the spatial and temporal gap to existing methods, especially for wind ramping events. Although a wind ramp is defined as a change in power generation, the cause for the ramp is a change in wind speed. This change can be measured ahead in time using a long-range lidar and thus more accurate predictions could be possible.

2. Measurement Setup

The lidar system used in VORKAST is a HALO Photonics Stream Line XR pulsed scanning lidar as proposed in [5]. The main features, which are crucial to the project objectives, are the 10 km range and the beam steering over the total hemisphere using a two-axis scanner. The footprint which is smaller than a square meter and the power requirement which is below 600 W are beneficial characteristics of the lidar and ideal for elevated, remote measurement sites. The device is depicted in Figure 1 and an overview of its characteristics is given in Table 1. In a first measurement campaign, the lidar is mounted at the top level platform 91 m above ground level of the radio tower “Lauterstein 1” at the Swabian Alps in the south of Germany. The location is chosen due to the undisturbed sight in the prevailing wind direction and the nearly motion free mounting.

![Figure 1: Stream Line XR on the radio tower.](image)

| Table 1: Technical specifications of the Stream Line XR [6]. |
|-------------------------------------------------------------|
| Wavelength | 1.5 µm |
| Max. range | 10,000 m |
| Bandwidth | ±19.4 m s⁻¹ |
| Doppler resolution | 0.0384 m s⁻¹ |
| Length of range gate | 60 m |
| Max. no. of range gates (without overlapping) | 167 |

In Figure 2 the terrain profile of the site in prevailing wind direction (west-northwest) is shown. As can be seen, in 1.3 km distance of the lidar a 100 m met mast is located which is operated by SWE and fully equipped with meteorological sensors with the top height 78.5 m below the lidar. The terrain is complex and in 3 km to 4 km distance of the lidar an escarpment cuts through the topography. Previous measurement campaigns and the analysis of the met tower data have shown that the complex topography of the site leads to complex flow and effects such as reverse flow conditions have been detected. This must be considered in the
further development of the project. In the sector from southwest to north of the lidar there are 9 adjacent wind turbines located. From one of the turbines the nacelle anemometer and power data was made available in ten-minutes mean resolution. Simultaneous measurements from lidar and turbine were carried out for a period from July 2016 to August 2017.

3. Device alignment
Determining the device alignment as well as possible is crucial to the operation of long range lidar measurement campaigns. An accurate knowledge of the exact orientation of the laser beam in every degree-of-freedom is essential for the success of the project as a deviation of a fraction of a degree leads to a substantial error of several dozens of meters in measurements in long distances. Methods for device alignment are not well established yet, therefore a process needs to be investigated. The following steps, which are further explained in the following, are conducted:

- Determination of free sectors with a 360 degree azimuth scan
- Azimuth alignment of the beam with a hard target detection of surrounding wind turbines
- Elevation alignment by using a digital terrain model
- Testing of the repeatability of the alignment correction by scanning a single wind turbine

After the deployment of the device, a determination of free sectors is carried out. Therefore multiple high resolution full azimuth scans are executed. The analysis of the Signal-to-noise ratio (SNR) of the first five range gates gives an overview of undisturbed sectors with 1° resolution. Disturbed sectors will be avoided throughout the measurement campaign. The analysis for the site on the radio tower is shown in Figure 3. Important is the undisturbed sector from 90° to 270° which includes the prevalent wind directions from the west to northwest sector.

For the azimuth alignment of the laser beam the strong direct reflection of the beam on solid objects in the nearer field of view is used. In the analysis a hard-target is assumed when the wideband SNR in a range gate and its surrounding range gates is above 5 dB and the determined line-of-sight velocity is close to 0 m s\(^{-1}\) as seen in Figure 4. Here, the wind turbines scattered around the lidar are used as hard-targets for alignment. With their known position the calculation of the devices misalignment is possible and can be corrected during the data analysis.
Furthermore, with the use of a digital topographic model from Shuttle Radar Topography Mission (SRTM) [7] the elevation misalignment is detected. Therefore and azimuth scan pointing towards the ground is executed and the heights above ground from the SRTM model are compared to the measured heights of the lidar.

To gain the last bit of awareness about uncertainties in beam steering, a horizontal raster scan pattern is performed over the structure of a wind turbine in 1.1 km distance. As seen in Figure 5 the structures of the turbine and also of the met mast to the left behind it are clearly visible in the lidar data. The repeated crossing of the tower shows some inaccuracies in the position repeatability of the lidar. But the maximum misalignment detected with this campaign was 0.03° which can be the result of several not explicit determined factors such as minimal displacements of the radio tower structure, an inaccuracy of the laser beam steering or beam broadening and scattering.
4. Filtering

Filtering of the radial velocity measurements is necessary to prepare the data for the wind field reconstruction by removing corrupted data, which could be the result of too low or too high aerosol, dust or particle concentration in the area. Different filter methods are implemented and tested, with the aim to meet the following filter requirements:

- conservative filtering with least possible data loss
- adaptability to varying environmental conditions
- high velocity for real time capability

To evaluate different filters, several data sets with varying environmental conditions are tested and the quality of the filtering is compared with regard to the requirements. In Figure 6a and 6b the timeline of the unfiltered radial velocity $v_{\text{radial}}$ and the Carrier-to-noise-ratio (CNR) distribution for an exemplary data set are shown respectively. The data set which is shown is used to compare different filter methods and is chosen due to its variability in measurement range.

The first filter that was investigated is the CNR filter. For each measured radial velocity at any range gate the intensity of the backscattered signal is stored besides the actual velocity value. Relating the backscattered signal intensity to the sent signal leads to CNR which is used to determine the quality of the measured data. A common approach when working with radial velocity lidar, is to filter the lidar output respectively to their CNR value, removing all values with a lower CNR than a certain threshold. Many tests with various lidar data have shown that this filter works for short distances very well, since the signal is still strong. However, many radial velocity values from farther range gates that seem to be accurate, but with lower CNR are being removed. This can be seen clearly in Figure 6c and 6d where the exemplary data set was filtered with a CNR threshold of $-25$ dB. Therefore this threshold filter does not concur with the requirements of least possible data loss, since an enormous amount of accurate values is being removed. This observation leads to the necessity of developing different filters that are not, or not only based on the CNR values.

The Normal Distribution Grubbs (NDG) filter is based on a statistical test for outlier identification first implemented by Frank E. Grubbs in 1968 [8]. The idea is to sort the possible outliers into two groups. One with the observation of extreme values deviating from the rest of the data, but still representing physically explainable data. In lidar data this could be a velocity drop due to the wake of wind turbines, or a very short but strong gust. The second group of outliers deviates severely from the rest of the data as a result of an error in recording the numerical value [8]. It is the goal of the filter to detect this second group, leaving the first group untouched embedded in the data. The NDG filter does work for normally (Gaussian) distributed values, therefore an initial test for normal distribution of the raw radial velocity data is necessary. For lidar velocity measurements this usually is the case for environmental conditions with very far visibility and only few scattered corrupted values. As for the CNR filter, a threshold $T_h$ for a value that still can be plausible has to be set previously as filter input. For smaller series Grubbs defined various thresholds [8] but for this usage a threshold most suitable for any environmental condition has to be defined. In Figure 6e and 6f, the results of the filter are shown for $T_h = 3 \text{ m s}^{-1}$.

The last filter that was analyzed is the Range filter. Originally used within image processing for edge detection, to detect relatively large areas of different color intensity, this filter has been adapted to suit the needs to filter long-range lidar data. Assuming a maximum range between minimum and maximum of realistic radial velocities in windows of consecutive range gates, it is possible to detect areas of highly scattered radial velocities which are the result of erroneous measurements. The threshold value for the range filter is set in relation to the turbulence intensity of the data set. In Figure 6g and 6h results are shown for a range of
Figure 6: Results of the different filter methods for an exemplary data set. To the left the timeline of the radial velocity is shown and to the right the radial velocity is plotted against the CNR.
3 m s$^{-1}$. Less obviously good radial velocity data is removed from the data set in comparison to the standard CNR and NDG filter, which is mostly noticeable in large distance measurements with weak signal returns. Additional positive aspects of the filter are the independence from the dominant wind speed and the removal of randomly distributed radial velocities due to failure in the measurement.

The comparison of different filter methods that are set up to analyze radial velocity data, that was taken during varying environmental conditions, shows the necessity to use different filters for different conditions. This is because each filter does only perform in its best way during certain environmental conditions, and not always. Therefore key precondition to the filter process is the correct classification of the data (e.g. normal distribution) and the correct selection of the most suitable filter method. Overall, the range filter shows the most promising results since it is very robust and works for different environmental conditions. In addition, less valid radial velocity data is removed compared to the CNR and NDG filter. Therefore it is used for the following analysis.

5. Wind field reconstruction

One of the challenges when working with lidar data is to reconstruct the wind vectors at discrete points of the measured wind field correctly from the line of sight velocity data $v_{\text{los}}$. The basic equation that needs to be solved is given as

$$v_{\text{los},i} = \frac{x_i}{f_i} u_i + \frac{y_i}{f_i} v_i + \frac{z_i}{f_i} w_i$$

where the lidar measures in point $[x_i, y_i, z_i]$ with a measurement distance $f_i$ and the unknown local wind vector is $[u_i, v_i, w_i]$ [9]. To solve this equation, at least three measuring points are necessary and assumptions must be made. Assuming a constant and homogeneous wind field during the measurement, the previous equation can be described in matrix form for all measured radial wind speeds.

$$\begin{bmatrix} v_{\text{los},1} \\ \vdots \\ v_{\text{los},n} \end{bmatrix} = \begin{bmatrix} \frac{x_1}{f_1} & \frac{y_1}{f_1} & \frac{z_1}{f_1} \\ \vdots & \vdots & \vdots \\ \frac{x_n}{f_n} & \frac{y_n}{f_n} & \frac{z_n}{f_n} \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix}$$

If sufficient linear independent measuring points are available, the global wind velocity components $u$, $v$ and $w$ can be estimated using the inverse $A^{-1}$ or the Penrose inverse $A^+$ determined by the least-square method.

$$\begin{bmatrix} u \\ v \\ w \end{bmatrix} = A^{-1} \begin{bmatrix} v_{\text{los},1} \\ \vdots \\ v_{\text{los},n} \end{bmatrix}$$

The following procedure was used for the wind field reconstruction in this paper. Assuming that the vertical component $w$ of the wind field can be neglected, a global wind field reconstruction per lidar scan was performed in a first step with Formula 3 to determine the horizontal wind vector over the entire measurement range. From the reconstructed global velocity components $u_{\text{global}}$ and $v_{\text{global}}$ a global wind direction was derived. In a second step, assuming that the wind direction did not change for the duration of a scan, the local horizontal wind speeds were determined by projecting the radial wind speeds $v_{\text{los},n}$ onto the global wind direction. To validate the procedure, the reconstructed global wind direction and local wind speed are compared to met mast data (Figure 7). The data is averaged over 10 minutes and the
Figure 7: Comparison of 10-min averaged wind direction and horizontal wind speed data from met mast (black) and lidar (grey).

wind speed data of the range gate above the met mast is used. The data shows good accordance and wind direction changes are well captured.

6. Wind evolution
Wind evolution is a crucial factor for the success of lidar-based forecasting. Only if the wind conditions at the turbine show similarities with the wind conditions measured in the distance, a forecast can be made and expected to be meaningful. To assess this similarity, multiple pairs of reconstructed horizontal wind speed data sets from the distance and close to the turbine and the lidar unit are compared. As a tool for comparison, the coherence is calculated which quantifies the similarity between two signals in terms of frequency. The coherence is a function which can take values between 0 and 1. If the coherence is 1, two time signals are similar over the whole frequency range, if it is 0, they have no frequency in common. Consequently, measurements which are taken at two spatial separated points should result in a coherence of 1 if the wind field does not change in between and thus also the frequencies remain the same.

The coherence is applied to data sets that contain 60 min of continuous wind speed measurements from 4 km and 0.2 km distance to the lidar. For the intended comparison, the full 60 min of measurements must be from periods when the wind direction matches the lidar units measuring
orientation. If this criterion is fulfilled, the wind conditions passing the 4 km mark can be expected to pass the 0.2 km mark a few minutes later in time. Another criterion that had to be fulfilled in each data set is that at least 90 percent of valid data remained after applying the range filter. With these criterion applied, a total number of 13 data sets are available for the analysis.

Figure 8 shows the averaged coherence of distant measurements and those close to the lidar of all 13 investigated data sets on a logarithmic frequency scale. It is apparent that the coherence is only high for very low frequencies and quickly decreases to a value of 0.4 or less for any frequency higher than 0.003 Hz. A high coherence of at least 0.7 is obtained only for frequencies lower than 0.0021 Hz. This frequency corresponds through the relationship $f = 1/T$ to a period $T$ of 476.2 s or 7 min 56 s. This means that only variations of the wind speed measured in 4 km distance with periods of above roughly 8 min are also captured in a distance close to the lidar. Smaller fluctuations in the wind speed are lost along the way. The reason for this can be found in the complexity of the terrain at the measuring site as seen in Figure 2. It appears that the variations in surface height as well as roughness have a considerable influence on the wind conditions and lead to significant changes in wind speed. Consequently, the forecast horizon is also limited to 8 minutes as changes in the wind speed with shorter periods cannot be expected to be forecast with accuracy. However, it should be noted that the evolution of the wind depends on atmospheric and environmental conditions forecast horizons of less or more than 8 minutes can well be possible.

![Figure 8](image-url)

Figure 8: Averaged coherence of measurements from 4 km distance and 0.2 km in front of the lidar, derived from 13 measurement blocks of 60 min.

### 7. Forecasting of wind ramp events

Wind ramps are defined as a quick and strong increase or decrease of wind power generation of a wind turbine or wind farm. The increase is referred to as an upward ramp and the decrease as a downward ramp. There is no standard mathematical definition of the duration $\Delta T$ or the change in Power $\Delta P$ of a wind ramp event [10][4]. Instead, the definition usually depends on the location as well as the size of the considered wind turbine or wind park.

For this investigation, the turbine data of the reference turbine in the vicinity of the lidar measurement location is analyzed for a period from July 2016 to August 2017. The only turbine data that was available were 10-minute averaged blocks (referred to herein as 10-min data). By
applying the minimum-maximum method described in [36] to the power data, several dozen upward and downward ramps are detected for a ramp duration of $\Delta t = 60$ min and a change in power of $\Delta P = 40\%$, compare Table 2. Only data from the wind direction sector compliant with the measurement direction is taken into account. An exemplary time line of generated power with marked wind ramps is given in Figure 9.

| $\Delta t$ [min] | $\Delta P$ [%] | Up-Ramps | Down-Ramps |
|------------------|----------------|----------|------------|
| 60               | 40             | 35       | 22         |

Table 2: Ramp findings in wind turbine data for July 2016 - August 2017 after wind direction filtering.

Figure 9: Exemplary time line of generated power with wind ramps marked for a time window of 60 min and a change of power of 40\%.

The process of forecasting wind ramp events using lidar data (Figure 10) starts with wind field reconstruction from the filtered line-of-sight (LOS) wind speed data (Section 5). To predict the wind speed at the turbine, a propagation model then has to be applied to the reconstructed horizontal wind speed measured in the distance. In this analysis, the simple assumption from Taylor’s Hypothesis is applied. It claims that turbulent eddies are transported with the mean flow and do not change their properties but remain unchanged, or frozen [11]. Using this assumption, the time shift $t_{\text{shift},i}$ for each measured range gate $i$ is calculated with the relationship $t_{\text{shift},i} = \frac{x_i}{u_i}$ where $x_i$ is the averaged distance to the range gate and $u_i$ is the averaged horizontal wind speed. The time shift is calculated for every 10-min of measurement data. By applying the time shift of each range gate to the respective time series of horizontal wind speed data and then averaging, the forecast of the wind speed at the turbine location is achieved. It should be noted that for this analysis the forecast is carried out in 10-min blocks due to the fact that the turbine data was only available in these intervals. This means that lidar data of the last 10 minutes is used to forecast the next 10, and 10-20 minutes of wind speed.

In a last step the power curve of the wind turbine is used to forecast its power output. The power curve is derived from 10-min power and nacelle anemometer data and gives the relationship between the wind speed and the generated power. The power is forecast as a time series using the predicted wind speed and is then averaged over 10 minutes to compare it with the actual power data.

To evaluate the forecast, the root-mean-square error (RMSE) of predicted and actual power are calculated (Figure 11) for two forecasting horizons 0-10 min and 10-20 min. The lidar-based
forecast is compared to the persistence method, which uses the present power output value for the forecast. It is also differentiated between periods with and without ramp events. The results show that for the present set-up the lidar-based forecasts results in a higher error than persistence for both forecasting horizons. During ramp events, the error is higher for both methods but it must be noted that only few data is available. The error of the lidar-based forecast is reduced with increasing forecasting horizon (not during ramp events), whereas the persistence error increases as expected.

The reason for the high error of the lidar-based forecast is the complex terrain at the measuring site and the propagation model that was applied. As shown in Section 6, the wind speed measured in the distance evolves due to the terrain and is not very well correlated to the wind speed that reaches the turbine. The simple propagation model of Taylor does not account for those changes. Consequently an error is induced in the forecasting process when predicting the wind speed at the turbine. This error is then magnified by the cubic nature of the power curve. The use of realistic flow models instead of simple propagation could be a solution.

8. Conclusion and outlook
This paper evaluates the use of a scanning lidar for forecasting the power output of a wind turbine on a minute-scale horizon at a complex site. Results from the lidar-based forecast are generally worse than persistence in this complex flow, and contrast with promising results from other investigations in coastal regions [12]. This is most likely due to the difficulty of propagating wind speed over long distances in such conditions. During wind ramps, local roughness and buoyancy effects dominate compared to larger scale phenomena. This reduces correlation distances which in turn reduces the accuracy of the lidar-based forecast.

Short term forecasting remains extremely important for integrating wind farms into the electrical grid. There is scope for improving the results in complex terrain through a more
realistic propagation model, such as meso- to microscale flow models. This will be investigated in future projects.

Acknowledgments
This work was funded by the German Federal Ministry for Economic Affairs and Energy under code number 0325740B. We thank our VORKAST project partner Center for Solar Energy and Hydrogen Research Baden-Württemberg (ZSW) for the excellent cooperation.

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