Modeling Uncertainties of Wind Field Reconstruction Using Lidar

David Schlipf\textsuperscript{1}, Martin Koch\textsuperscript{2} and Steffen Raach\textsuperscript{2}

\textsuperscript{1}Flensburg University of Applied Sciences, Flensburg, Germany
\textsuperscript{2}sowento GmbH, Stuttgart, Germany

E-mail: david.schlipf@hs-flensburg.de

Abstract. The use of nacelle-based lidar systems for power performance testing of wind turbines is promising. Here, the knowledge of uncertainties is crucial. Wind field reconstruction is necessary to estimate wind field characteristics such as horizontal wind speed and wind direction from line-of-sight wind speed measurements using a wind flow model. In this work, two types of uncertainties in this process are investigated and confirmed in simulation: the uncertainty caused by measurement errors and by modeling errors. Based on this first investigation, the modeling uncertainty is exceeding the measurement uncertainty.

1. Introduction

Nacelle-based lidar systems are cost effective alternatives to conventional wind measurements with meteorological masts, especially offshore [1]. Lidar systems obtain only the line-of-sight wind speed using the optical Doppler effect. Thus, a lidar system used for power performance testing needs to estimate the horizontal wind speed from the measured line-of-sight wind speeds using a wind flow model and applying wind field reconstruction (WFR) methods.

The unknown uncertainty in this process is one of the main barriers for the adoption of the lidar technology in wind energy [4]. The uncertainty in the line-of-sight wind speed due to several effects has been investigated in [5] and quantified in [2]. In the latter, also a model of the effect to WFR for a nacelle-based lidar with two beams is presented. In several publications, the reconstructed lidar signals are compared to conventional measurements with meteorological masts and methods to improve the accordance to the conventional measurements are proposed, e.g. for lidar measurements in wakes [6] or in complex terrain [3].

In this work, we focus on the modeling of the uncertainties in WFR for a nacelle-based lidar system. The uncertainties are grouped into two main impacts: The uncertainty caused by measurement errors of the line-of-sight wind speeds is investigated in Section 2 and the uncertainty caused by model errors assuming stationary wind instead of turbulent wind is examined in Section 3. Both sources of errors are confirmed in simulations. Section 4 concludes the work and provides a short outlook. The main contribution of this work are:

- The uncertainty caused by measurement errors is modeled for a nacelle-based lidar system with four beams and the impact of different WFR methods (linear and nonlinear) is shown.
- The uncertainty caused by model errors is introduced, modeled and quantified. Here, we compare the lidar signals instead of conventional signals to rotor averaged signals, which are more relevant to power performance testing.
2. Uncertainty caused by measurement errors

In this first investigation it is assumed that the wind field is homogeneous: longitudinal, lateral, and vertical wind speed components are constant over space, i.e. equal in all measurement points at a certain time. However, it is assumed that the line-of-sight measurements are erroneous. The propagation of the error in the line-of-sight measurement to the derived signals is modeled for the linear case in Section 2.2 and for a simple nonlinear case in Section 2.3. For both cases, the error is confirmed by simulations. The used scenario is presented in Section 2.1. Considerations for more complex nonlinear cases are given in Section 2.4.

2.1. Simulation scenario

A pulsed lidar system measuring from a wind turbine with a rotor diameter of \( D = 101 \text{ m} \) is considered, see Figure 1. Here, four measurements are taken at 2.5 \( D \) from the rotor on a circle with a diameter of \( D \). This results in an angle to center-line of \( \theta = \arctan(\frac{0.5D}{2.5D}) \approx 11.2 \text{ deg} \) and angles around center-line \( \phi_i \) of 45, 135, 225, and 315 deg in each measurement point \( i \).

Neglecting the motion of a lidar system and the measurement volume, the line-of-sight wind speed in each measurement point \( i \) can be calculated by

\[
v_{\text{los},i} = x_{n,i}u + y_{n,i}v + z_{n,i}w, \tag{1}
\]

where \( x_{n,i} = \cos(\theta), \ y_{n,i} = \sin(\theta)\cos(\phi_i), \) and \( z_{n,i} = \sin(\theta)\sin(\phi_i) \) are the components of the normalized laser vector for each measurement point \( i \).

With a constant longitudinal wind speed of \( u = 16 \text{ m/s} \) and zero lateral and vertical wind speeds \( v = w = 0 \text{ m/s} \), the line-of-sight wind speed in each measurement point is thus \( v_{\text{los}} = u \cos(\theta) \approx 15.7 \text{ m/s} \).

In [7], an uncertainty \( U_{\text{los}} = 0.32 \text{ m/s} \) at a mean wind speed of 16 m/s is reported, where the uncertainty is calculated as twice the standard deviation of the values averaged over 10 minutes. Therefore, the simulated line-of-sight wind speed \( v_{\text{los},i} \) at each measurement point \( i \) is generated by adding a Gaussian distributed error signal with \( 10^6 \) data points, zero mean, and a standard deviation of \( \sigma = \frac{U_{\text{los}}}{2} = 0.16 \text{ m/s} \) to \( v_{\text{los}} \), respectively. The result of this simplified lidar simulation are four \( v_{\text{los},i} \) data sets, each containing \( 10^6 \) data points representing 10-minute-averages of the line-of-sight wind speed signal in one measurement point. The wind speed components are not only hold constant over space (homogeneous flow assumption), but also over time for the sake of reducing complexity.

Figure 1. Considered trajectory of a pulsed lidar system: location of lidar system (black dot), rotor (black line), measurements (blue dots).
2.2. Linear case
Using the WFR approach proposed in [8], a wind field can be reconstructed by:

(i) setting up the measurement equations by combining a lidar measurement model and a wind
model and
(ii) obtaining the free wind field characteristics either by model fitting or in a simple case by
solving the measurement equations.

For the first step of the WFR, the lidar measurement model from Equation (1) and the following
wind model is used: \( \hat{u} \) and \( \hat{v} \) are assumed to be homogeneous, \( \hat{w} \) is assumed to be zero. Therefore,
the measurement equations are with the measurement matrix \( A \):

\[
\begin{bmatrix}
  v_{\text{los},1} \\
  v_{\text{los},2} \\
  v_{\text{los},3} \\
  v_{\text{los},4}
\end{bmatrix}
= 
\begin{bmatrix}
  x_{n,1} & y_{n,1} \\
  x_{n,2} & y_{n,2} \\
  x_{n,3} & y_{n,3} \\
  x_{n,4} & y_{n,4}
\end{bmatrix}
\begin{bmatrix}
  \hat{u} \\
  \hat{v}
\end{bmatrix}.
\]

For the second step of the WFR, the wind field characteristics are obtained by solving the
equations using the Moore-Penrose pseudo-inverse \( A^+ \):

\[
\begin{bmatrix}
  \hat{u} \\
  \hat{v}
\end{bmatrix}
= 
A^+
\begin{bmatrix}
  v_{\text{los},1} \\
  v_{\text{los},2} \\
  v_{\text{los},3} \\
  v_{\text{los},4}
\end{bmatrix}.
\]

Expressing the free wind field characteristics as functions \( f_u() \) and \( f_v() \) by

\[
\hat{u} = f_u(v_{\text{los},1}, v_{\text{los},2}, v_{\text{los},3}, v_{\text{los},4})
\]
\[
\hat{v} = f_v(v_{\text{los},1}, v_{\text{los},2}, v_{\text{los},3}, v_{\text{los},4}),
\]
the propagation of the error is obtained following [9] by

\[
U_{u,\text{meas}} = \sqrt{\sum_{i=1}^{4} \left( \frac{\partial f_u}{\partial v_{\text{los},i}} \right)^2 U_{\text{los}}^2} = \sqrt{\sum_{i=1}^{4} a_{1,i}^2 U_{\text{los}}} = a_u U_{\text{los}}
\]
\[
U_{v,\text{meas}} = \sqrt{\sum_{i=1}^{4} \left( \frac{\partial f_v}{\partial v_{\text{los},i}} \right)^2 U_{\text{los}}^2} = \sqrt{\sum_{i=1}^{4} a_{2,i}^2 U_{\text{los}}} = a_v U_{\text{los}}.
\]

Due to the symmetry of the used scan geometry, the pseudo-inverse is

\[
A^+ = \frac{1}{4} A^T.
\]

Thus, the amplification factors of the measurement errors can be calculated as:

\[
a_u = \frac{1}{2 \cos \theta}
\]
\[
a_v = \frac{1}{2 \sin \theta \cos \phi_1}.
\]

For the given geometry, the amplification factors are \( a_u \approx 0.510 \) and \( a_v \approx 3.606 \).
The findings are compared to results from the simulation. With the data sets from Section 2.1 and commercial tool\(^1\) for WFR, the reconstructed longitudinal wind speed component \(\hat{u}\) and reconstructed lateral wind speed component \(\hat{v}\) are obtained using Equation (3). Then, the errors in longitudinal and lateral wind speed component are calculated from the correct values \(u = 16\ \text{m/s}\) and \(v = 0\ \text{m/s}\) and displayed in Figure 2. From the standard deviation of these errors, the uncertainties are calculated and as predicted are \(U_{\hat{u},\text{meas}} \approx 0.163\ \text{m/s}\) and \(U_{\hat{v},\text{meas}} \approx 1.154\ \text{m/s}\). The relative errors in the uncertainties, i.e. the values from the simulations compared to \(U_{\hat{u},\text{meas}}\) from Equation (5), have been found to be below 0.1\%.

Following conclusions can be drawn from this study:

- Smaller opening angles / angles to center-line reduce the uncertainty in the longitudinal wind speed component and increase the uncertainty in the lateral wind speed component. In this case, the uncertainty in the longitudinal wind speed component is even smaller than the uncertainty in the line-of-sight wind speed \((a_u < 1)\).
- The amplification factors are independent of the current wind conditions (i.e. the values of \(u, v,\) and \(w\)).
- From Equation (6) follows that the estimation of the longitudinal wind speed component is independent on whether the lateral component is assumed to be zero or not for scans symmetric to the \(y\)-axis. Similarly, the longitudinal wind speed component is independent on whether the vertical component is assumed to be zero or not for scans symmetric to the \(z\)-axis. This is important for example when an odd number of measurement points is used.
- The calculation according to [9] provide very accurate estimates of the uncertainties. This is not surprising in the linear case due to the definition of the standard deviation etc.
- Due to the simplicity, the approach can be also used to evaluate commercial tools for WFR.

\(^1\) Software pewit from sowento GmbH developed to reconstruct wind fields from real lidar data for commercial lidar systems and scenarios, e.g. nacelle-based measurements outside or inside of induction zone. Free test version available soon at www.sowento.com.
2.3. Simple nonlinear case

In the previous study, the longitudinal and lateral wind speed component are reconstructed. However, for applications such as power performance testing, the horizontal wind speed \( v_H \) and the horizontal inflow angle \( \alpha_H \) are usually considered. The wind direction can be obtained from \( \alpha_H \) and the current turbine yaw angle.

The horizontal wind speed and horizontal inflow angle can be reconstructed simply from the reconstructed longitudinal and lateral wind speed component from Section 2.2 by

\[
\hat{v}_H = \sqrt{\hat{u}^2 + \hat{v}^2},
\]

\[
\hat{\alpha}_H = \arctan\left(\frac{\hat{v}}{\hat{u}}\right).
\] (8)

Similar to Equation (4), the wind field characteristics can be expressed by functions

\[
\hat{v}_H = f_{vH}(v_{los,1}, v_{los,2}, v_{los,3}, v_{los,4}) = \sqrt{f_u^2 + f_v^2},
\]

\[
\hat{\alpha}_H = f_{\alpha H}(v_{los,1}, v_{los,2}, v_{los,3}, v_{los,4}) = \arctan\left(\frac{f_v}{f_u}\right).
\] (9)

The partial derivatives now depend on the wind field states:

\[
\frac{\partial f_{vH}}{\partial v_{los,i}} = \frac{1}{\sqrt{\hat{u}^2 + \hat{v}^2}} (\hat{u}a_{1,i} + \hat{v}a_{2,i}),
\]

\[
\frac{\partial f_{\alpha H}}{\partial v_{los,i}} = \frac{1}{1 + \frac{\hat{v}}{\hat{u}}} \left(\frac{a_{2,i}}{\hat{u}} - \frac{\hat{v}a_{1,i}}{\hat{u}^2}\right).
\] (10)

With the correct values for \( \hat{u} = u = 16 \text{ m/s} \) and \( \hat{v} = v = 0 \text{ m/s} \), the uncertainties can be calculated by

\[
U_{\hat{v}_H,\text{meas}} = \sqrt{\sum_{i=1}^{4} a_{1,i}^2 U_{los} = a_u U_{los}},
\]

\[
U_{\hat{\alpha}_H,\text{meas}} = \sqrt{\sum_{i=1}^{4} a_{2,i}^2 u^2 U_{los} = a_v \frac{u}{u} U_{los}}.
\] (11)

Thus, the amplification factors of the measurement errors can be calculated as:

\[
a_{vH} = a_u = \frac{1}{2 \cos \theta},
\]

\[
a_{\alpha H} = a_v = \frac{1}{2 \sin \theta \cos \phi_1 u}.
\] (12)

Again, the findings are compared to results from the simulation. With the data sets from Section 2.1, the reconstructed horizontal wind speed \( \hat{v}_H \) and reconstructed horizontal wind inflow angle \( \hat{\alpha}_H \) are obtained using Equation (8). Again, the errors are calculated from the correct values \( v_H = 16 \text{ m/s} \) and \( \alpha_H = 0 \text{ deg} \) and displayed in Figure 3. From the standard deviation of these errors, the uncertainties are calculated and as predicted are close to \( U_{\hat{v}_H,\text{meas}} \approx 0.163 \text{ m/s} \) and \( U_{\hat{\alpha}_H,\text{meas}} \approx 4.132 \text{ deg} \). The relative error in the uncertainty for the horizontal inflow angle is similar to the previous section (below 0.1%). For the horizontal wind speed however, the error is 1.6%.
error [deg] p(\alpha_H) [%] 
error [m/s] p(v_H) [%] p(v_{los,1}) [%]
$-8$ $-6$ $-4$ $-2$ $0$ $2$ $4$ $6$ $8$
$-2$ $-1.5$ $-1$ $-0.5$ $0$ $0.5$ $1$ $1.5$ $2$
$0$ $1$ $0$ $5$ $0$ $5$

Figure 3. Error propagation in simple nonlinear case: Relative distribution of input error: exemplary line-of-sight wind speed of first measurement point $v_{los,1}$ (top). Relative distribution of output error: horizontal wind speed $v_H$ (center) and horizontal inflow angle $\alpha_H$ (bottom).

Following conclusions can be drawn from this study:

- For nonlinear equations for the WFR, the propagation of the measurement error depend on the measurements themselves and thus on the current wind conditions.
- If the wind turbine is aligned with the mean wind direction, the amplification factor for the horizontal wind speed is equal to the longitudinal wind speed component and the amplification factor of the horizontal wind inflow angle is equal to the amplification factor of the lateral wind speed component divided by the mean wind speed. Thus, the uncertainty in the wind direction estimate is getting smaller with higher wind speeds.
- The calculation according to [9] using only the first partial derivative provides less accurate estimates for the uncertainty of the horizontal wind speed. Adding a second order term in the Taylor series expansion as proposed in [9] might reduce the error between the modeled uncertainty and the one obtained from the simulation.

2.4. More complex nonlinear cases

For more complex nonlinear wind field models, e.g. the one used in [7] including an induction zone model, the free wind field characteristics cannot be found by explicit equations such as in Equation (8). For example, the function $f_{a_{ind}}()$ of the dependency of the induction factor $a_{ind}$ from the line-of-sight wind speeds $v_{los,i}$ cannot be found due to the complexity of the nonlinear system of equations. Thus, the partial derivative $\partial f_{a_{ind}}/\partial v_{los,i}$ cannot be determined and the calculation according to [9] cannot be applied directly. However, the line-of-sight wind speed in each measurement point $i$ can be expressed by a function $f_{v_{los,i}}()$ from the wind field characteristics, e.g. the induction factor. Thus, $\partial f_{a_{ind}}/\partial v_{los,i}$ can be approximated by $\Delta a_{ind}$ from the current wind field state to determine $\Delta v_{los,i}$ from $f_{v_{los,i}}()$. This approach will be investigated in a follow-up study.
3. Uncertainty caused by model errors
In Section 2 homogeneous flow and erroneous line-of-sight measurements have been assumed. In this section turbulent flow as defined by spectral models and accurate measurements are considered.

For lidar-assisted control it is common practice to use spectral model and Fourier transform of measurement equations to evaluate the measurement quality of lidar systems and to optimize scan trajectories [10, 11, 12]. This approach is here applied to the 10-minute uncertainty calculation.

To determine the lidar uncertainty in the longitudinal wind component caused by model errors, the signal of the error \( e \) between the signal of the reconstructed longitudinal wind component \( \hat{u} \) and the signal of the longitudinal wind component averaged over the rotor \( \bar{u} \) over time \( t \) is defined as

\[
e(t) = \hat{u}(t) - \bar{u}(t).
\]

The 10-minute average of this signal can be approximated by a moving average with average time \( T = 600 \) s, which can be modeled by a convolution of the signal with

\[
\bar{e}(t) = e(t) * \text{rect}\left(\frac{t - T/2}{T}\right),
\]

where \( \text{rect}(t) \) is the rectangular function defined at time \( t \) as

\[
\text{rect}(t) = \begin{cases} 
1, & |t| \leq \frac{T}{2} \\
0, & |t| > \frac{T}{2} 
\end{cases}
\]

and \( * \) denotes convolution. A continuous signal of the 10-minute average values (holding the averaged value constant over \( T \) instead of merely a signal with moving average) can be obtained by using a Dirac delta function as in [11]. This is omitted here for the sake of reducing complexity.

The lidar uncertainty in the longitudinal wind component caused by modeling error is then calculated as twice the standard deviation \( \sigma \) of \( \bar{e} \):

\[
U_{\hat{u},\text{mod}} = 2\sigma(\bar{e}).
\]

Since the variance is the square of the standard deviation and also the integral of the auto-spectrum, \( U_{\hat{u},\text{mod}} \) can be also calculated by

\[
U_{\hat{u},\text{mod}} = 2\sqrt{\int_0^\infty S_{\bar{e}\bar{e}} df}.
\]

The main idea of the proposed approach is that the auto-spectrum \( S_{\bar{e}\bar{e}} \) and thus the lidar uncertainty is obtained by a Fourier-Transform \( \mathcal{F}\{\} \) of Equation (14) and its complex conjugate \( \mathcal{F}^\ast\{\} \) omitting all scaling constants as

\[
S_{\bar{e}\bar{e}} = \mathcal{F}\{\bar{e}\} \mathcal{F}^\ast\{\bar{e}\}.
\]

Since the Fourier-Transform is a linear operator and since convolution is translated by the Fourier transformation to a multiplication, the spectra can be expressed by

\[
S_{\bar{e}\bar{e}} = \mathcal{F}\{e\} \mathcal{F}^\ast\{e\} \text{sinc}^2(fT) = S_{ee} \text{sinc}^2(fT),
\]
Figure 4. Results from modeled and simulated model uncertainty.

where sinc() is the the normalized cardinal sine function. Further, the Fourier-Transform can be expanded to its parts and combined again into auto-spectrum $S_{\hat{u}\hat{u}}$ of the reconstructed longitudinal wind component, the auto-spectrum $\check{S}_{\hat{u}\hat{u}}$ of the longitudinal wind component averaged over the rotor and the cross-spectrum $\hat{S}_{\hat{u}\check{u}}$ between both signals:

$$S_{\check{e}\check{e}} = (\mathcal{F}\{\check{u}\} - \mathcal{F}\{\hat{u}\}) (\mathcal{F}^*\{\check{u}\} - \mathcal{F}^*\{\hat{u}\}) \operatorname{sinc}^2(fT)$$

$$= (\mathcal{F}\{\check{u}\}\mathcal{F}^*\{\hat{u}\} + \mathcal{F}\{\hat{u}\}\mathcal{F}^*\{\check{u}\} - \mathcal{F}\{\check{u}\}\mathcal{F}^*\{\hat{u}\} - \mathcal{F}\{\hat{u}\}\mathcal{F}^*\{\check{u}\}) \operatorname{sinc}^2(fT)$$

$$= (S_{\hat{u}\hat{u}} + S_{\check{u}\check{u}} - 2\Re(S_{\hat{u}\check{u}})) \operatorname{sinc}^2(fT). (20)$$

The two auto-spectra $S_{\hat{u}\hat{u}}$ and $S_{\check{u}\check{u}}$ as well as the cross-spectrum $S_{\hat{u}\check{u}}$ can be obtained in a similar process of expanding and combining the parts into known spectra from a turbulence model, see [10, 11, 12].

This is confirmed again by simulation. Figure 4 shows the analytic spectrum $S_{\check{e}\check{e}}$ of the error $e$ and the analytic spectrum $S_{\check{e}\check{e}}$ of the averaged error $\check{e}$ as well as its estimates from the time signals. Here, the IEC Kaimal spectral model [13] is used. As predicted, the uncertainty is $U_{\check{u},\text{mod}} = 0.28 \, \text{m/s}$ at $16 \, \text{m/s}$ and Class A turbulence. Wind evolution is not included at this stage of the investigation.

Accordingly, the lidar uncertainty in the lateral wind component $v$ caused by modeling error can be calculated by

$$U_{\check{v},\text{mod}} = 2\sqrt{\int_0^\infty (S_{\hat{v}\hat{v}} + S_{\check{v}\check{v}} - 2\Re(S_{\hat{v}\check{v}})) \operatorname{sinc}^2(fT) df} (21)$$

where again the auto-spectrum $S_{\hat{v}\hat{v}}$ of the reconstructed lateral wind component, the auto-spectrum $S_{\check{v}\check{v}}$ of the lateral wind component averaged over the rotor, and the cross-spectrum $S_{\hat{v}\check{v}}$ between the two signals can be expressed by known spectra from a turbulence model.

The uncertainty of the horizontal wind speed $v_H$ and the horizontal inflow angle $\alpha_H$ can be obtained by linearizing Equation (8) and thus depend on the current wind conditions, similar to Section 2.3.
4. Conclusions and Outlook

In this work, the uncertainties in wind field reconstruction for a nacelle-based lidar system are investigated. Two main sources are identified and modeled: (i) the uncertainty caused by measurement errors of the line-of-sight wind speeds. (ii) the model uncertainty caused by model error when assuming stationary wind instead of turbulent wind. The models for both types of uncertainty are confirmed and quantified in simulations. In the considered example, the uncertainty caused by model errors for the longitudinal wind is larger than the uncertainty caused by measurement errors. However, several assumptions are used and the intention of this work is more to show an approach how to model uncertainties in wind field reconstruction rather than providing a detailed analysis. This work also links the frequency measures for the lidar-assisted control application to the scalar uncertainty measures for the power performance application.

Planned work will address the propagation of measurement error and the determination of amplification factors for more complex nonlinear models for WFR, e.g. using models of the induction zone. Further, we improve the calculation of the averaged values and incorporate wind evolution models to improve the uncertainty quantification caused by model errors. This will also enable us to compare the uncertainty of conventional wind measurements to lidar measurements in determining rotor-effective quantities of wind speed and direction.

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