Importance of Lidar Measurement Timing Accuracy for Wind Turbine Control*

Fiona Dunne, Lucy Y. Pao, David Schlipf, and Andrew K. Scholbrock

Abstract—A turbine-mounted lidar can measure wind speed ahead of a wind turbine, and this preview measurement can be used to improve turbine control performance by reducing structural loads and/or increasing power capture. Effective lidar-based control requires not only an accurate wind speed measurement, but also knowledge of the expected arrival time of the measured wind. Arrival time is the time it takes for the wind to travel from the measurement focus location to the turbine rotor. Typically, arrival time is assumed to be equal to the distance traveled divided by the average wind speed. Field test data show that this assumption can be improved on average through an induction zone correction. In addition, arrival time can temporarily deviate significantly above or below this average value. If we can anticipate how arrival time will change, we can improve control performance. In this study, we post-process turbine and lidar data to show how arrival time varies and to determine an upper limit on possible improvement as a result of accurately predicting arrival time. Results show that this upper limit is a 26% average increase in coherence bandwidth between the measured wind and the wind that arrives at the rotor. In above-rated wind speeds, for example, this corresponds to a 21% improvement in the performance cost reduction due to incorporating lidar into a blade pitch controller, where the performance cost is a combined measure of generator speed error and blade pitch actuation.

NOMENCLATURE

\( v_u(t) \) Upstream estimate of the approaching rotor-effective wind speed
\( \text{LPF}(v_u(t)) \) Low-pass filtered \( v_u(t) \)
\( v_r(t) \) Estimated rotor-effective wind speed at the turbine rotor
\( t_d(t) \) Time delay between \( \text{LPF}(v_u(t)) \) and \( v_r(t) \), found using time of peak cross-covariance
\( T_v \) Expected \( t_d(t) \) using Taylor’s hypothesis, various expressions replace \( v \), see (3)

I. INTRODUCTION

Wind turbine control can be improved through the use of a turbine-mounted lidar, which measures the wind speed

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pattern because \( v_u(t) \) always depends on the most recent complete scan, which includes measurements taken on half scan pattern ago on average. The most recent complete scan is used to provide a representation of the wind across the full rotor disk.

There are mixed conclusions in the available literature on the importance of accurate timing predictions. One study involving a collective pitch feedforward controller [8] shows (in its Figure 9) that errors of more than 5 s are needed before the combined feedforward/feedback controller performance is worse than that of feedback alone. Another study [6] states that “lead or lag errors in the wind speed measurement, which is fed to the controller, severely reduce the performance of the controller.” The second study uses peak time of cross-covariance between \( v_u(t) \) and \( v_r(t) \) to predict timing, but it does not use real-world data for these signals.

In this study, we analyze timing by using real-world data. We show how quickly timing can vary, and we show how helpful it would be to correctly predict it if that were possible, rather than assuming it stays constant for a constant average wind speed. In Section II, we describe the lidar measurements and how we obtain \( v_u(t) \) and low-pass filter it into \( \text{LPF}(v_u(t)) \). We also describe the wind turbine and the wind speed estimator used to obtain \( v_r(t) \). In Section III, we describe taking windowed cross-covariances between \( \text{LPF}(v_u(t)) \) and \( v_r(t) \) to find \( t_d(t) \), the time delay between them. In Section IV, we pass the signal \( v_u(t) \) through the varying time delay \( t_d(t) \), and show that this provides an improved preview measurement for use in a time-invariant controller. Finally, in Section V, we summarize conclusions.
LAB [11]) is used, which is possible because the filtering is not done in real time. Together these filters minimize the magnitude of \( v_u(t) \) at frequencies at which it may be correlated to \( v_r(t) \) because of tower and lidar motion rather than independent measurements of wind speed. 

The wind speed estimator uses the torque balance method, which assumes

\[
\tau_r - \tau_g = J \dot{\Omega}
\]

where \( \tau_r \) is the torque applied by the wind to the rotor, \( \tau_g \) is the torque generated at the generator (multiplied by the gearbox ratio), \( J \) is the drivetrain moment of inertia (as observed from the rotor side of the gearbox), and \( \Omega \) is the rotor acceleration. Wind speed estimators that neglect rotor acceleration may introduce a time delay because of the inertial response of the rotor.

After \( \tau_r \) is solved for using the above equation, a lookup table is used to determine the rotor-effective wind speed for the given \( \tau_r \), blade pitch angle \( \beta \), and rotor speed \( \Omega \), with an adjustment for air density \( \rho \). These variables are related as follows:

\[
\tau_r = \frac{\rho \pi R^2 C_P(\lambda, \beta) v_r^3(t)}{2\Omega}
\]

where \( R \) is the rotor radius, \( C_P \) is the power coefficient (fraction of wind power captured), and \( \lambda \) is the tip speed ratio \( (\Omega R/v_r(t)) \). Pitch, torque, and rotor speed signals are low-pass filtered and notch filtered (at 1P, 2P, and the drivetrain torsion frequency) using zero-phase filtering before being used in the estimator. The result of the lookup table is the rotor-effective wind speed \( v_r(t) \) shown in Fig. 4.

### III. Windowed Cross-Covariances

The time delay \( t_d(t) \) between \( \text{LPF}(v_u(t)) \) and \( v_r(t) \) can be estimated from the times of peak windowed cross-covariances between \( \text{LPF}(v_u(t)) \) and \( v_r(t) \). However, simply shifting a window across the data and recording each time of peak cross-covariance results in a \( t_d(t) \) that contains sudden jumps to unrealistic values. Three main steps can reduce these occurrences. First, we choose a Gaussian window with a large enough window size. Second, we detrend (subtract the best-fit line from) the data within each window before applying the cross-covariance function. Third, we enforce a rate limit on \( t_d(t) \), along with a lower limit of 0 s. These steps yield the blue \( t_d(t) \) curves shown in Fig. 5. We show results for three window sizes for comparison, with standard deviations of \( \sigma = 30 \) s, 15 s, and 60 s, and total window sizes of 180 s, 90 s, and 360 s, respectively. Throughout the remainder of this paper, we use only the \( t_d(t) \) resulting from the \( \sigma = 30 \) s window. This choice of window size is a trade-off because smaller sizes give better time resolution and tend to lead to the greatest increases in coherence bandwidth (when \( t_d(t) \) is used as described in Section IV); however, smaller sizes are also more likely to produce non-physical results (which can be impossible to predict) and contain instances of near-zero preview times. A minimum of 1 s to 2 s of preview would be preferable if it were available in real time for control.

Based on Taylor’s frozen turbulence hypothesis [12], [13], \( t_u(t) \) is typically assumed to be equal to \( D/v \), where \( D \) is the distance traveled from the measurement location to the rotor and \( v \) is the average wind speed. Fig. 5, in addition to showing \( t_d(t) \), also shows the expected \( t_d(t) \) computed as

\[
T_v = D/v - d_s
\]

where \( D = 41 \) m, \( d_s = 0.67 \) s, \( T \) stands for Taylor, and the subscript \( v \) varies depending on what choice of \( v \) we use in the equation. We use either \( \text{LPF}(v_u(t)) \) or \( v_r(t) \) for \( v \) in Fig. 5.

At approximately 2,000 s, there is a large spike in \( t_d(t) \). This corresponds to a data set portion when the lidar measurements are relatively inaccurate because of low wind speeds. In this portion, the wind speed as determined by the turbine-based estimator is below 6 m/s; whereas the lower limit of a possible lidar measurement is 6 m/s as a result of the technique used to eliminate data due to accidental lidar sensing of hard targets.
In the remaining data in Fig. 5, $t_d(t)$ on average matches its expected value $T_v$ relatively well, as shown in Table II. It is likely that induction zone effects (slowing of wind as it approaches the rotor) are responsible for $t_d(t)$ being longer than expected on average. Theoretically, the induction zone velocity $U$ is characterized by

$$U_\infty = \left(1 - \alpha (1 + \xi (1 + \xi^2)^{-1/2})\right)^{-1}$$

where $U_\infty$ is the undisturbed velocity and $\xi = x/R$, where $x$ is the distance from the rotor (negative upwind) and $R$ is the rotor radius [14]. The axial induction factor $\alpha$ is approximately the optimal 1/3 in below-rated wind speeds because the turbine is extracting as much power as possible from the wind. This is when we expect the induction-zone slowdown effect to be strongest. As wind speeds increase above rated, the axial induction factor decreases, and the slowdown effect diminishes. The CART2 has a rated wind speed of approximately 13 m/s, and we have little data above this speed.

Integrating (4) with respect to $\xi$ and then multiplying by $U/U_\infty/\xi$ gives the arrival time multipliers $M$ shown in Fig. 6. To calculate theoretical arrival time $t_a(t)$ that accounts for the induction zone, use

$$t_a(t)_{\text{Taylor,corrected}} = (D/v) M$$

where $D$ is the measurement distance and $v$ is the wind speed at the measurement location. Our measurement distance results in $x/R = -1.92$, and we assume $\alpha = 1/3$, corresponding to an $M$ of 1.12. This means $t_a(t)$ should be 12% greater than the value we calculated without accounting for the induction zone. Table II shows the uncorrected and corrected versions of $t_{\text{LPF}}(v(t))$, where the corrected version is $(D/v) M - d_a$. It also shows the uncorrected and corrected versions of $T_v(t)$, where the corrected version is $(D/v) M^* - d_a$, where $M^*$ results from integrating (4) with respect to $\xi$ and then multiplying by $1/\xi$. The multiplication factor $U/U_\infty$ is not included in $M^*$ because $v_r(t)$ is assumed to be a delayed estimate of $U_\infty$ instead of $U$. In both cases, the induction zone correction improves the match with $t_d(t)$.

On shorter time scales, $t_d(t)$ often differs from its expected value $T_v$ by several seconds, as shown in Fig. 5. Timing does not stay constant for a constant average wind speed. This may be in part because of the evolution of the wind field, and also the 3D nature of the wind field in which the wind speed at a given location does not always match the speed of travel of the turbulent airflow structure carrying that wind speed. The timing may also be affected by wind shear and wind components in the $y$ and $z$ directions, which exist although we assume them to be zero. In this paper, our goal is not to improve the modeling to predict timing, but to use the time lag found in post-processing to estimate how much room for improvement exists in the current model.

### IV. Filtering Lidar Measurements Using a Variable Time Delay

A controller incorporating lidar measurements, for example the controller used in the field testing [4], can be designed for some given preview time and some given correlation or transfer function estimate. The controller may be adapted

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**TABLE II**

<table>
<thead>
<tr>
<th>Set</th>
<th>$t_d(t)$ [s]</th>
<th>$T_{\text{LPF}}(v(t))$ [s]</th>
<th>$T_{\text{LPF}}(v_r(t))$ [s]</th>
<th>Mean</th>
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<td>Corrected</td>
<td>Uncorrected</td>
<td>Corrected</td>
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<td>6.0</td>
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<td>7.4</td>
<td>5.6</td>
<td>6.4</td>
<td>6.6</td>
</tr>
</tbody>
</table>

*Final 110 s excluded*
as arrival time and correlation change, but so far this has been done on a timescale of a few minutes. Fig. 5 shows $t_d(t)$ ($\sigma = 30$ s) jumping from 3 s to 6 s in only 68 s, for example. One way to address varying arrival time is to delay the measured signal $v_u(t)$ by varying amounts before sending it to the controller. This essentially uses interpolation to stretch and shrink various parts of $v_u(t)$ in time. The amount of varying delay that should be used on $v_u(t)$ is equal to the preview time $t_p(t)$ minus the constant amount of preview expected by the controller.

For this method to be successful, two requirements must be met by the preview time $t_p(t)$. First, $t_p(t)$ must always be greater than or equal to the amount of preview required by the controller. This is required for real-time operation because it is impossible to use negative delay. Second, the slope $\Delta t_p(t)/\Delta t$ (and thus $\Delta v_u(t)/\Delta t$ and $\Delta t_d(t)/\Delta t$ as well) must always be greater than $-1$. If $\Delta t_p(t)/\Delta t = -1$, two different wind speeds would be expected to arrive at the same time, and below a slope of $-1$, wind speeds would be expected to arrive in a swapped order than when they were measured. In situations when arrival time has a slope $\leq -1$, a possible solution is to overwrite the older measurement with the more recently measured wind speed, which is arriving at the same time or sooner.

Without zooming in, $t_d(t)$ in Fig. 5 appears to meet the requirement of $\Delta t_d(t)/\Delta t > -1$. However, upon zooming in, we see that the time of peak cross-covariance is discretized at the sample rate (40 Hz). This results in steep steps, many with slope equal to $-1$. To solve this problem, we filter this data with a boxcar filter of 11 samples in length, which, for this data, provides just enough smoothing to keep $\Delta t_d(t)/\Delta t > -1$. The boxcar filter is centered so that no time delay is introduced. After smoothing the data, Fig. 7 was created by stretching and shrinking $LPF(v_u(t))$ from Fig. 4 according to $t_d(t)$ from Fig. 5. Because of this, it sometimes lags and sometimes leads the original $LPF(v_u(t))$, and this results in a better correlation at low frequencies to $v_r(t)$. We are most interested in improving low-frequency correlation because the low frequencies contain the most power in the wind and have the most effect on the turbine.

Fig. 8 shows coherence (correlation as a function of frequency) using three methods of variable time delay. $T_{LPF_{100}(v_u(t))}$ means that the wind speed $v$ used in (3) is the lidar measurement filtered with a first-order low-pass filter with a cutoff of 0.003 Hz. This is most similar to the method used in the field tests: the time delay is updated slowly, on the order of minutes, based on a filtered version of the measured wind speed. Using $T_{v_u(t)}$, the time delay is updated instantaneously, with no filter on the measured wind speed. Surprisingly, this improves coherence compared to $T_{LPF_{100}(v_u(t))}$, even though by using a time delay with such high frequency variations, we are subjecting the signal to a swapped order of data points due to slopes being below $-1$ as previously described. Fig. 9 shows that there is a general trend toward improved coherence bandwidth as low-pass filtering cutoff frequency is increased. However, some filtering should be employed to ensure availability of a minimum preview time for control. Using $t_d(t)$ for the time delay gives the best coherence bandwidth. Although creating the signal $t_d(t)$ in real time is not possible, this method estimates an upper limit of coherence bandwidth improvement that is possible to achieve through improved knowledge of arrival time. Table III shows the results from these three methods on the four data sets in terms of coherence bandwidth. We define coherence bandwidth as the pole location of the first-order low-pass filter whose magnitude squared best fits the magnitude squared coherence.

On average across all four data sets, our results show a 26% increase in coherence bandwidth when going from using $T_{LPF_{100}(v_u(t))}$ to $t_d(t)$, and a 13% increase in coherence bandwidth when going from using $T_{v_u(t)}$ to $t_d(t)$. These
A method for accurate real-time prediction of these quick variations in arrival time is outside the scope of this paper. Instead, we used post-processing to obtain these variations in arrival time from CART2 field test data. Knowing these variations in advance, compared to a method of predicting arrival time similar to that used in the field tests, would have increased coherence bandwidth between measured and rotor-estimated wind by 26% on average, and therefore could have improved control performance. In above-rated wind speeds, for example, this translates to an approximately 21% improvement in the performance cost reduction due to incorporating lidar into a blade pitch controller. This work sets an upper limit of possible performance improvement because real-time prediction at best will be no more accurate than what can be achieved in post-processing.

**REFERENCES**


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**TABLE III**

<table>
<thead>
<tr>
<th>Set</th>
<th>$T_{L,PF}(\sigma^2(v_{t}(t)))$</th>
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<th>$t_{d}(t)$</th>
<th>$% \Delta$</th>
<th>$% \Delta$</th>
</tr>
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<td>0.0749</td>
<td>0.0846</td>
<td>26</td>
<td>13</td>
</tr>
</tbody>
</table>

Coherence bandwidths [Hz] between turbine estimate $v_{t}(t)$ and lidar measurement $v_{l}(t)$ with three methods of variable time delay.

increases, for example, would allow a pitch controller to provide an improvement in its combined goal of generator speed regulation and minimal pitch actuation: Each 1% improvement in coherence bandwidth allows an approximately 0.8% improvement in the cost reduction due to using lidar [15], when the cost function is defined as minimizing

$$J_c = r \ast \sigma^2(\text{blade pitch}) + q \ast \sigma^2(\text{generator speed})$$

(6)

where [15] describes the ratio between $q$ and $r$.

**V. CONCLUSIONS**

Using data from field tests on NREL’s CART2 wind turbine, we have shown how the arrival time of the lidar measurements varies, we have filtered the measured wind speed signal using a variable time delay, and we have found an upper limit on the improvement that can be obtained through better prediction of arrival time. The data show that we can improve the prediction of average arrival time by using an induction zone correction when using Taylor’s frozen turbulence hypothesis. This allows a good prediction of average arrival time, but arrival time can temporarily deviate significantly above or below this average value.