Scanning Doppler Lidar for Input into Short-Term Wind Power Forecasts

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ABSTRACT

Scanning Doppler lidar is a promising technology for improvements in short-term wind power forecasts since it can scan close to the surface and produce wind profiles at a large distance upstream (15–30 km) if the atmosphere has sufficient aerosol loading and there are no sizable blockages from terrain or large structures. However, successful measurements require a large spatial sampling domain and new estimation algorithms that can perform well in the very weak signal regime. The maximum likelihood (ML) algorithm in the spectral domain and a faster version based on the minimum mean-square-error (MSE) are investigated by numerical simulation and with actual scanning Doppler lidar data from the Lockheed Martin Coherent Technologies WindTracer lidar. In addition, the maximum range can be extended by simultaneous estimation of the wind speed and wind direction from a larger azimuth sector scan if the atmosphere is well behaved. Real-time operation is possible using the spectral data from the WindTracer lidar and a dedicated computer to interface with a data assimilation system. Analysis of the Doppler lidar data in the first few kilometers can be used to extract the turbulence conditions for improvements in real-time wind farm operations.

1. Introduction

Improved short-term forecasts of winds from an operational numerical weather prediction (NWP) system would benefit current wind farms (Mueller et al. 2003; Benjamin et al. 2004; Saxen et al. 2008; Hannon et al. 2008; Benjamin et al. 2010; Marquis et al. 2011). The output power of a wind turbine is determined by the wind profile over the altitude range of the turbine blades. The calculation of total power production of a wind farm requires a more sophisticated calculation based on the spatial variations of the hub-height winds as well as power losses from the effects of the wakes produced by upstream turbines. We assume that future predictions of wind power production will be adequate based on reliable forecasts of the wind speed profile incident on the upstream boundary of the wind farm.

Most commercial turbines start producing power at a threshold wind speed $v_{\text{thr}}$ of approximately 4.0 m s$^{-1}$ and quickly ramp up to peak power at a wind speed $v_{\text{peak}}$ of approximately 12.0 m s$^{-1}$. For wind speeds above $v_{\text{peak}}$, the power is constant until a maximum wind speed $v_{\text{max}}$ of approximately 26 m s$^{-1}$ is reached, which automatically curtails the turbine operation. However, before this wind speed is reached, there may be large power fluctuations produced by large-scale turbulent structures. Therefore, the wind speed regime that is most critical for predicting power ramps is between $v_{\text{thr}}$ and $v_{\text{peak}}$.

The shortest forecast time for wind energy integration into the power grid is approximately 30 min, which is required to provide sufficient lead time to adjust the output of natural gas power plants. Longer forecasts times are required for coal-fired plants, resource allocation, and decisions on buying and selling power. There are several techniques to produce reliable short-term forecasts or nowcasts (Mueller et al. 2003; Benjamin et al. 2004; Saxen et al. 2008; Benjamin et al. 2010; Marquis et al. 2011), which require reliable estimates of the current state of the atmosphere (the analysis), and therefore the techniques require accurate measurements of the wind profile over the domain that impacts the 30-min forecast. This domain can be approximately determined by the requirements of an advection forecast to identify the start of a power ramp and the time of...
peak power production. For the start of power production, a 30-min advection forecast would be produced by observing a sudden increase in hub-height wind speed at 4 m s\(^{-1}\) at a distance of 7.2 km upstream. Similarly, for full power production, a 30-min advection forecast would be produced by observing a 12 m s\(^{-1}\) hub-height wind speed at a distance of 21.6 km. Since the wind direction varies from day to day, these measurements need to be made at various locations surrounding the wind farm. However, many wind farms have a few predominant prevailing wind directions, which would reduce the number of fixed measurement systems.

The most comprehensive study of wind power forecasting was undertaken by the Alberta Department of Energy in Canada (Wind Power Forecasting Pilot Project). The working group report [http://www.ukig.org/Work_Group_Paper_Final_3.pdf] included a few key results:

- In the very short term (i.e., up to 6 h out), the forecasting models were comparable to persistence forecasts, where persistence assumes that conditions at the time of the forecast will not change. It should be noted that a persistence forecast by definition will never capture extreme ramps.
- With higher-resolution modeling, better and more weather data are needed to resolve the variability in the weather over the shorter distances.
- The three recommended areas of further research were improved persistence modeling, sources of error, and ramp forecasting.

Similar results were also presented by Marquis et al. (2011).

There are many devices and technologies that can provide reliable wind measurements. The least expensive are surface weather stations that typically measure winds at 10 m altitude with in situ sensors. However, to measure hub-height winds, a tall instrumented tower is needed, which may be very expensive to sample the required upstream locations. Remote sensing measurements of wind profiles using sodar, radar profilers, and lidar at fixed locations are another option. However, this solution may also be logistically difficult because of the availability of suitable locations, data access, availability of reliable power, and overall cost if the number of measurement sites required for an accurate power ramp forecast is large.

The most attractive solution for accurate short-term forecasts is upstream measurements of the wind profiles using scanning coherent Doppler lidar, for example, the WindTracer Doppler lidar manufactured by Lockheed Martin Coherent Technologies, Inc. (Henderson et al. 1991, 1993). This is the only technology that can scan a 3D volume from a range of a few hundred meters to tens of kilometers over the altitude range of wind turbines because the laser beam is very small (less than 10 cm in diameter in the first few kilometers and expanding to an approximately 0.619 m 1/e transverse radius at a range of 30 km) and permits measurements over a large domain that can better match the effective resolution of high-resolution NWP models (Frehlich and Sharman 2004; Frehlich 2006) for improved data assimilation (Frehlich 2006, 2011).

Coherent Doppler lidar is the most sensitive detection method and the eye-safe infrared lidars have been used extensively over the past 15 yr for fundamental atmospheric research (Menzi and Hardesty 1989; Hannon and Henderson 1995; Huffaker and Hardesty 1996), operational measurements of hazards at airports (Hannon and Thomson 1994; Chan 2011), homeland security (Frehlich et al. 2006; Warner et al. 2007), and wind energy research (Banta et al. 2003, 2006; Pichugina et al. 2008; Frehlich and Kelley 2008; Mann et al. 2009; Banakh et al. 2010). Since the Doppler measurement is performed from the scattered laser light from aerosol particles, the maximum range of accurate measurements depends on the atmospheric concentration of aerosols, the laser power, the lidar efficiency, and the signal processing algorithms.

A unique requirement of the wind power forecasting problem is accurate velocity measurements at large ranges upstream, which typically have very weak signal levels and therefore a large spatial average and advanced signal processing algorithms are essential. A Monte Carlo simulation of Doppler lidar data with correlated velocity fields is one method to determine the optimal processing algorithms based on the maximum likelihood (ML) technique. Since the signal levels are very weak, a new estimator based on the minimum mean-square-error (MSE) is derived that requires only two free parameters: the mean velocity and the spectral width. In addition, the performance of the ML and MSE estimators are evaluated for estimation of the wind speed and wind direction using a subsection of the azimuth scan following the work of Smalikho (2003).

Once the optimal processing algorithms and scan patterns have been determined, they can be applied to raw data for typical conditions in Colorado or an area with relatively low aerosol backscatter, and if the opportunity arises, at an operational wind farm in Colorado or other area of interest. As an added advantage, high-quality profiles of the wind speed, wind direction, and turbulence statistics immediately upstream of the wind farm can be produced for better control of the wind turbines to improve efficiency and reduce the maintenance costs associated with high wind shear and high turbulence conditions.
2. Doppler lidar measurements

The development of eye-safe Doppler lidar (Henderson et al. 1991, 1993; Pearson and Collier 1999; Grund et al. 2001; Smith et al. 2006) and new processing algorithms (Rye and Hardesty 1993a,b; Frehlich et al. 1994; Banakh and Smalikho 1997; Frehlich 1997; Frehlich et al. 1997, 1998; Frehlich 2001a; Frehlich and Cormann 2002; Smalikho 2003; Davies et al. 2004; Frehlich et al. 2006; Emeis et al. 2007; Frehlich et al. 2008; Banakh et al. 2010; Kasler et al. 2010; Mann et al. 2010; O’Connor et al. 2010) have produced high-quality measurements of the boundary layer. The High-Resolution Doppler lidar (HRDL) at the National Oceanic and Atmospheric Administration (NOAA; Grund et al. 2001) has a range resolution of 30–50 m with a pulse repetition frequency (PRF) of 200 Hz and data products outputted every 0.5 s. In addition, simulation and analysis of space-based measurements have shown improvements with pulse ac-

of an ideal detector. If the detector noise is dominated by the LO shot noise, for example, Frehlich and Kavaya (1991), Eq. (89), then

\[ \text{SNR} = \frac{\eta_Q}{\hbar v B} \int_0^\infty P_L(t - 2R/c)\beta(R)K(R)^2C(R, t)\, dR \]  

(2)

where \( \eta_Q \) is the detector quantum efficiency, \( \beta(R) \) is the aerosol backscatter coefficient, \( K(R) \) is the one-way irradiance extinction, \( P_L(t) \) is the laser pulse power, \( t \) denotes time, \( C(R, t) \) is the coherent responsivity, \( h \) is Planck’s constant, \( \nu \) is the frequency of the laser, \( c \) is the speed of light, \( B = T_s^{-1} \) is the detector noise bandwidth, and \( T_s \) is the sampling interval of complex data. The signal spectrum is the power spectrum of the detector voltage.

In general, the average coherent Doppler lidar signal spectrum or average periodogram is given by

\[ P(f) = P_S(f) + P_n(f) \]

(3)

where \( P_S(f) \) and \( P_n(f) \) are the average signal and noise spectra, respectively. For ideal coherent Doppler lidar signals, that is, mutually uncorrelated detector noise (the average signal spectrum is normalized by the average noise spectrum) and uniform atmospheric conditions over the processing interval, the ideal spectrum is given by

\[ P(f) = P_S(f) + 1 \]

(4)

where the average periodogram of the Doppler lidar signal \( P_s(kF) \) is given by Eq. (55) in Frehlich and Cormann (1999) with \( G(z) = \sigma^2_{\text{urb}} \) and \( w_{\text{eff}} \) in Eq. (59) is modified to include the effects of the scan geometry. However, a simple approximation is given by Eq. (61) in Frehlich and Cormann (1999), that is,

\[ P_S(jF) = \frac{\text{SNR}}{\sqrt{2\pi wT_S}} \exp\left[-F^2(j - j_m - \delta)^2/(2w^2)\right] \]

(5)

where

\[ F = \frac{1}{T} = \frac{1}{MT_S} \]

(6)

is the spectral resolution; \( T \) is the total observation time per range gate; \( M \) is the number of complex data points; \( j_m \) is the index nearest to the spectral peak; \( \delta \) is the spectral bin offset;

\[ \Delta p = MT_Sc/2 \]

(7)
is the range-gate length; and \( w \) is the effective spectral width, which can be written as

\[ w_v = \frac{\lambda}{2H} \]  

(8)

and \( w_v \) is the effective spectral width in velocity space. Equation (4) can also be written as

\[ P(jF, A, f, w) = Ad(jF, f, w) + 1 \]  

(9)

and

\[ d(h, f, w) = \exp[-(h-f)^2/(2w)^2] \]  

(10)

where \( f = F(j_m + \delta) \).

For parameter estimation, the most critical variable for signal strength is the coherent photoelectrons per range gate, which is also called photocounts (Rye and Hardesty 1993a) and can be written as (Frehlich and Yadlowsky 1994)

\[ \Phi_1 = SNR \times M = \sqrt{2\pi w} TA = \sqrt{8\pi w} TA/\lambda \]  

(11)

and the average noise power \( N \) is calculated over a bandwidth of \( T_s^{-1} \).

The most crucial design constraint for coherent Doppler lidar is the alignment of the backscattered field and the LO field on the detector surface (Frehlich 1993, 1994; Siegman 1996; Frehlich 1999). This is equivalent to aligning the transmitter optical axis with the receiver optical axis. In Fig. 5 of Frehlich (1994), the heterodyne efficiency \( \eta_H \) for an optimal monostatic lidar with a circular aperture of diameter \( D \) and a target at a large distance is plotted as a function of the misalignment angle \( \Delta \theta \). A 3 dB loss in \( \eta_H \) and SNR is given by \( \Delta \theta = 0.75\lambda/D \). This determines a maximum angular scan rate for measurements at a large distance \( R \), i.e., for \( R = 30 \) km, a telescope diameter \( D = 0.1 \) m, a wavelength \( \lambda = 1.6-\mu m \), a misalignment angle of \( \Delta \theta = 12 \mu \) radians would result in a 3 dB loss in signal. Since the roundtrip time for the laser light is \( \Delta t = 2R/c = 200 \mu s \), the maximum angular scan rate would be approximately \( \Delta \theta/\Delta t = 0.06 \) rad s\(^{-1} \) or 3.4° s\(^{-1} \), which would provide adequate sampling of the wind field upstream. In addition, the 1/e transverse radius of the lidar beam at 30 km is 0.619 m for a wavelength of \( \lambda = 1.6 \mu m \) (see Fig. 5 of Frehlich 1994), which permits low elevation angle measurements to sample the full plane of the wind turbine and up to the top of the boundary layer depending on the aerosol loading.

Accurate measurements of the radial velocity \( v_r \) at large ranges \( R \) from the lidar requires careful lidar design and signal processing in the weak signal regime (Frehlich 1996; Frehlich et al. 1997; Banakh et al. 2001; Frehlich 2004). An important issue in the weak signal regime is the behavior of the detector noise \( n(t) \), which is described by its average noise spectrum \( P_n(f) \). The shape of the noise spectrum is determined by the low- and high-pass filters and the frequency response of the photodetector and preamplifier. The ideal noise sequence is a mutually uncorrelated Gaussian process called white noise, which has a constant noise spectrum. Then the estimation and detection algorithms are theoretically and numerically tractable and optimal algorithms can be determined (Frehlich 1993; Rye and Hardesty 1993a,b; Frehlich 1996, 1999). Simple noise correction algorithms can be produced based on a measurement of the noise spectrum, assuming the noise statistics change slowly with time (Frehlich et al. 1997).

The performance of the best estimators of the radial velocity in the weak signal regime has been determined by computer simulations (Frehlich and Yadlowsky 1994; Frehlich 1996, 1997, 1999, 2000, 2001a,b; Banakh et al. 2001) and from actual Doppler lidar data (Frehlich et al. 1994, 1997, 1998). The key parameters are the amount of lidar signal from aerosols [SNR or \( \Phi_1 \), Eq. (11)], the number of shots \( n \) of lidar data that can be processed, and the spread of the signal in the frequency domain, that is, the spectral width \( w \) of the signal. Accurate measurements at large distances require a large measurement domain with a large number of lidar shots, where the spectral width is determined by the spatial variations of the wind field over the measurement volume, which requires knowledge of the spatial correlation of the turbulent wind field. Fortunately, accurate coherent Doppler lidar algorithms have been developed to determine the spatial statistics of the turbulent field by employing corrections for the spatial filtering of the lidar pulse and processing range gate (Banakh and Smalikho 1997; Frehlich 1997; Davies et al. 2004; Smalikho et al. 2005; Frehlich et al. 2006, 2008; Banakh et al. 2010; Chan 2011).

A solid-state lidar pulse is well approximated by a Gaussian temporal profile, and the effects of the spatial filtering of the radial velocity by the pulse can then be corrected (Frehlich et al. 1994; Banakh and Smalikho 1997; Frehlich 1997; Frehlich et al. 1997, 1998; Banakh et al. 2001; Davies et al. 2004; Smalikho et al. 2005; Frehlich et al. 2006, 2008) to produce reliable estimates of turbulent statistics. This correction is possible when the lidar pulse parameters are stable and when the mean Doppler radial velocity estimates are given by a one-dimensional convolution of the instantaneous radial velocity with an effective pulse range weighting function (Banakh and Smalikho 1997; Frehlich 1997). Recently, improved profiles of turbulence have been produced based on the variations of the radial velocity as a function...
of the arc distance along an azimuth scan (Frehlich et al. 2006, 2008; Frehlich and Kelley 2008).

One of the most pressing atmospheric problems is understanding the boundary layer processes that adversely affect wind energy production. The American Wind Energy Association has reported that more than 5 GW of new wind power capacity were installed in the United States in 2010. The industry is under producing by an average of 10%–12%, and operation and maintenance costs are higher than predicted. It is suspected that poor knowledge of the full wind and turbulence profiles over the turbine swath height of 40–150 m is one of the main sources, especially at night—when instabilities are generated in the low-level nocturnal jet (Fritts 2005; Banta et al. 2006; Kelley et al. 2006). These highly turbulent conditions in the boundary layer are also important for aviation safety at airports, and careful processing of the lidar data has been shown to be superior to traditional radar measurements at the Hong Kong International Airport (Chan 2011).

One of the fundamental limits to the accuracy of atmospheric estimates of mean velocity and turbulent quantities is the number of independent samples of the relevant processes (Lenschow et al. 1994; Kaimal and Finnigan 1994). Traditional measurements from towers, sodars, radar profilers, and instrumented aircraft essentially produce a spatial sample of the atmosphere along a line defined by the mean wind (or aircraft trajectory). The scanning lidar is the only instrument able to provide high-spatial-resolution observations in a three-dimensional volume, which provides superior statistical accuracy because of the larger number of independent samples of the atmospheric processes. This is very important for atmospheric research of those phenomena that can change quickly, such as frontal passages, drainage flows, and the growth of the convective boundary layer. The 3D scanning patterns with Doppler lidar permit analysis of the turbulent velocity statistics based on spatial variations of the velocity field instead of the traditional reference to a time average (Frehlich et al. 2006, 2008).

Coherent Doppler lidars produce a direct measurement of the Doppler shift induced by the radial velocity of all the aerosol particles illuminated by the laser pulse. These lidars transmit a Gaussian pulse profile with a pulse width $\Delta t$ that varies from 20 to 70 ms full width at half maximum (FWHM). The lidar scanner typically operates at an azimuth scan rate of $2.5^\circ$ per second, a PRF of 500 Hz, a measurement time of $T_{\text{meas}} = 0.2$ s per radial velocity profile or line of sight (LOS), $n = 100$ lidar pulses per LOS, and an azimuth spacing $\Delta \phi = 0.5^\circ$.

The lidar pulse range-weighting function for a range gate centered at distance $R$ is given by

$$I_n(r) = \frac{1}{\sqrt{\pi}r_p} \exp \left[ -\frac{(R-r)^2}{r_p^2} \right]$$  \hspace{1cm} (12)

where

$$r_p = \Delta t (2 \sqrt{\ln 2})$$  \hspace{1cm} (13)

is the $1/e$ radius; $I_n(r)$ defines the spatial extent of the illuminated aerosol targets at a fixed instant of time. For a measurement using a single laser pulse, the average radial velocity of the Doppler lidar estimates for a range gate of length $\Delta \phi$ at a distance $R$ is well approximated by the pulse-weighted velocity, which can be written as (Banakh and Smalikho 1997; Frehlich 1997)

$$m_{\text{wgt}}(R, \phi, \theta) = \int_{-\infty}^{\infty} v_r(s, \phi, \theta)W(R-s) \, ds$$  \hspace{1cm} (14)

where

$$W(r) = \frac{1}{\Delta \phi} \int_{-\Delta \phi/2}^{\Delta \phi/2} I_n(r+s) \, ds$$  \hspace{1cm} (15)

is the effective spatial filter for a radial velocity measurement and $v_r(r, \phi, \theta)$ is the instantaneous radial velocity as a function of range $r$ along the lidar beam axis. The pulse-weighted velocity $m_{\text{wgt}}(R, \phi, \theta)$ is a spatial convolution of the radial velocity with an effective spatial filter $W(r)$ given in terms of the lidar pulse-weighting function $I_n(r)$ and the range-gate length $\Delta \phi$. Therefore, spatial statistics of the wind field can be recovered by careful deconvolution methods and signal processing algorithms (Banakh and Smalikho 1997; Frehlich 1997; Frehlich et al. 1998; Banakh et al. 2001).

For a lidar that transmits a Gaussian pulse [see Eq. (12)],

$$W(r) = \frac{1}{2 \Delta \phi} \left\{ \text{Erf}(r + \Delta \phi/2)/r_p - \text{Erf}(r - \Delta \phi/2)/r_p \right\}$$  \hspace{1cm} (16)

where

$$\text{Erf}(z) = \frac{2}{\sqrt{\pi}} \int_0^z \exp(-t^2) \, dt$$  \hspace{1cm} (17)

is the standard error function. The range-weighting function is shown in Fig. 1 for the 2-µm WindTracer lidar. Note that the FWHM of $W(r)$ is $\Delta R = 85.8$ m, which defines the effective resolution of the lidar radial velocity measurements.

The most attractive 3D lidar scanning geometry is the raster scan, that is, a variable azimuth angle $\phi$ [plan position indicator (PPI) scans] for various fixed elevation angles $\theta$ [see Fig. 2 of Frehlich et al. (2006), which
will require modifications, such as a small elevation angle change near the surface, e.g., 0.2°. An example of the radial velocity \( v_r(R, \phi, \theta) \) as a function of \( \phi \) and \( R \) for a fixed elevation angle \( \theta \) is shown in Fig. 3 of Frehlich et al. (2006) for early morning convection and in Fig. 2 of Frehlich and Kelley (2008) for a high wind case at night collected at the National Wind Technology Center (NWTC) of the National Renewable Energy Laboratory (NREL). The lidar-derived profiles of the turbulence statistics, mean wind speed, and wind direction provide the required statistical description of the atmospheric wind fields for the proposed objective of extending the maximum range of Doppler lidar measurements to improve forecasts of wind power production for optimal energy integration. The three-dimensional sampling of scanning Doppler lidar provides the most accurate information of the wind fields for wind energy research and operations.

The most cost-effective solution to determine the performance of coherent Doppler lidar velocity measurements is computer simulations of known atmospheric wind fields with sufficient resolution to simulate raw Doppler lidar data. This has been successfully employed for both boundary layer measurements (Frehlich 1997, 2001b; Banakh et al. 2001; Frehlich and Cornman 2002) and space-based measurements (Frehlich 2000, 2001a). Since the true spatial statistics of the wind field is known a priori from the simulated turbulent field, both the bias and estimation error of lidar estimates can be determined. New processing algorithms are required to estimate the average radial velocity for the large distances upstream of a wind farm, especially in the weak signal regime, which determines the maximum possible measurement range. The most promising estimation algorithm is a modification of the maximum likelihood estimator to include the effect of the spectral broadening by turbulence (Zrnić 1979; Rye 2000) for a large number of lidar shots in the weak signal regime (Frehlich 1996; Frehlich et al. 1997; Banakh et al. 2001).

Simulation of coherent Doppler lidar signals can be performed for time-domain data as well as spectral data if the spectral coefficients are uncorrelated. However, the spatial correlation of the velocity field is required. We assume a von Kármán turbulence model that consists of a simple functional form (Hinze 1959) suitable for computer algorithms. Profiles of turbulent statistics have been produced from Doppler lidar radial velocity statistics by removing the contribution from the estimation error and by careful correction for the spatial filtering of the velocity field by the lidar pulse. The energy dissipation rate \( \epsilon \), the velocity variance \( \sigma^2 \), and the outer scale \( L_0 \) of turbulence have been estimated by fitting measured velocity structure functions to the von Kármán turbulence model. An example of these profiles is shown in Fig. 2 for an early nighttime case at Lafayette, Colorado (0348–0410 UTC 13 June 2006), using the 2-µm eye-safe WindTracer lidar and the azimuth structure function technique (Frehlich et al. 2006, 2008; Frehlich and Kelley 2008). Note that the wind speed WS at 10 m is less than 5 m s\(^{-1}\) and therefore a surface measurement would not provide a useful estimate of the hub-height wind speed of 12 m s\(^{-1}\). The values of the turbulence parameters are similar to past results, and \( L_0 \) increases with height, which indicates larger eddy sizes aloft.

An example of the azimuth structure function for the 100-m altitude of Fig. 2 (95–105 m) is shown in Fig. 3, which requires the range-weighting function of Fig. 1 for correct interpretation. There is considerable spatial filtering by the lidar pulse, since \( L_0 = 43.4 \) m and the lidar pulse width \( \Delta r = 66 \) m and the effective overall range resolution from the pulse and sampling is 85.8 m—compare above. However, the best-fit model is in good agreement with the data and computer simulations, and they have shown that accurate turbulence estimates are feasible for these conditions. Therefore, the von Kármán turbulence model will be used for evaluation of new velocity estimation algorithms. The benchmark case is defined by the turbulence parameters of Fig. 3, that is, \( \sigma = 0.79 \) m s\(^{-1}\), \( L_0 = 43.4 \) m, and \( \epsilon = 0.0106 \) m\(^2\) s\(^{-3}\). A full evaluation of performance will require a larger set of turbulence parameters to fully sample conditions near a wind farm, especially for the
most challenging conditions, such as sudden large changes in the wind speed that can produce unpredictable power ramps. The turbulence intensity $T_1 = \sigma/\langle WS \rangle = 0.0747$ where $WS$ is the wind speed, is a useful quantity for wind farm operations and can be routinely produced by a scanning Doppler lidar if there are data in the first 2 km.

3. Simulation of Doppler lidar data

An accurate prediction of a wind power ramp requires wind profiles at various ranges upstream of a wind farm. The geometry of the problem is shown in Fig. 4, where the radial velocity $v_r(r, \phi, \theta) = v_t(x, y, z)$ and the atmospheric contribution $P_L (t - 2\tau/c) \beta(r) K(r)^2 C(r, t)$ along the lidar beam axis $r$ must be given [see Eq. (2)]. The velocity components are given in terms of a mean flow $[U_0(x, y, z), V_0(x, y, z), W_0(x, y, z)]$ and a turbulent component $[u(x, y, z), v(x, y, z), w(x, y, z)]$, that is,
\[
U(x, y, z) = U_0(x, y, z) + u(x, y, z)
\]
\[
V(x, y, z) = V_0(x, y, z) + v(x, y, z)
\]
\[
W(x, y, z) = W_0(x, y, z) + w(x, y, z)
\]  
(18)

and the radial velocity \( v_r(\phi, \theta) \) is given by the dot product of the velocity field and the direction angle \( \mathbf{r} \), that is,

\[
v_r(\phi, \theta) = \mathbf{r} \cdot (U, V, W)
\]
\[
= \cos \theta \sin \phi U(x, y, z) + \cos \phi \cos \theta V(x, y, z)
\]
\[
+ \sin \theta W(x, y, z)
\]
(19)

where

\[
x = r \cos \theta \sin \phi
\]
\[
y = r \cos \theta \cos \phi
\]
\[
z = r \sin \theta.
\]  
(20)

For this study, the effects of terrain are ignored, the mean vertical velocity \( W_0(x, y, z) = 0 \), and the mean horizontal velocity are given by

\[
U_0(x, y, z) = -W_\sigma \sin(\text{dir})
\]  
(21)

and

\[
V_0(x, y, z) = -W_\sigma \cos(\text{dir})
\]  
(22)

where \( \text{dir} \) is the wind direction.

A Monte Carlo technique is used to generate the turbulent component based on the von Kármán model, assuming the elevation angle \( \theta = 0 \) (see appendix C of Frehlich 1997). The azimuth angle \( \phi \) varies over a wedge centered on the upstream wind direction for each fixed elevation angle \( \theta \). If conditions suddenly change, then the size and location of the wedge can be adjusted for better performance. Monte Carlo techniques provide the most accurate simulations (Frehlich 1997) if the atmospheric variables are sampled along the lidar beam at a spacing \( \Delta s \) that is sufficiently small for convergence and the atmospheric conditions are statistically uniform.

The most fundamental power spectral estimate of variable \( u \) and pulse index \( l \) is the periodogram \( \hat{P}_u(jF, l) \), given by

\[
\hat{P}_u(jF, l) = \frac{1}{M} \sum_{k=0}^{M-1} w_n(kT_s) u(t_{\text{ref}} + kT_s, l) \exp(-2\pi ikj/M)
\]  
(23)

where \( l \) is the lidar shot number; \( t_{\text{ref}} \) defines the start of a range gate; and \( w_n(kT_s) \) is the window function, which we assume is unity. An average periodogram \( \hat{P}(jF) \) or average power spectrum is then given by

\[
\hat{P}(jF) = \frac{1}{n} \sum_{l=1}^{n} \hat{P}_u(jF, l).
\]  
(24)

A much faster simulation algorithm is produced by assuming (Rye and Hardesty 1993a; Banakh et al. 2001) the spectral estimates \( \hat{P}(jF) \) are mutually uncorrelated chi squared (gamma random deviates) with probability density function (PDF)

\[
p_n[\hat{P}(jF)] = \left[ \frac{n}{\hat{P}(jF)} \right]^{n} \frac{\hat{P}(jF)^{n-1}}{\Gamma(n)} \exp\left[ -n\hat{P}(jF) / \hat{P}(jF) \right]
\]  
(25)

that is generated with the routine gamdev in Press et al. (1992). The ensemble average periodogram \( \hat{P}(jF) = \langle \hat{P}(jF) \rangle \) can be calculated using Eq. (55) in Frehlich and Cornman (1999) with \( G(z) = \sigma^2_{\text{turb}} \) and with \( w_{\text{eff}} \) in Eq. (59) modified to include the effects of the scan geometry.

Spectra from these two simulation techniques for the new WindTracer lidar parameters are shown in Fig. 5 as well as the ML estimates of the three unknown parameters \( (A, u, w_o) \), assuming Eq. (5) is valid (Banakh et al. 2001). The turbulence model is from Fig. 3, the wind speed estimates are referenced to 10.6 m s\(^{-1}\), the wind direction is \( \theta^\circ \) (wind blowing from the north), the lidar wavelength \( \lambda = 1.617 \, \mu \text{m} \), the range-gate length is \( \Delta p = 1500 \, \text{m} \) or \( T = 10 \, \mu \text{s} \), the distance to the center of the range gate is \( R_{\text{cen}} = 20.0 \, \text{km} \), the spectral amplitude \( A = 0.035 \, \text{0.054} \), the lidar pulse radius is \( r_p = 28.79 \, \text{m} \), the lidar pulse width is \( 47.9 \, \text{m} \, \text{FWHM} \) or \( 0.319 \, \mu \text{s} \, \text{FWHM} \), the effective spectral width \( w_o = 0.92 \, \text{m s}^{-1} \), the signal strength [Eq. (11)] is \( \Phi_0 = 1 \), the scan rate is \( 2^\circ \, \text{s}^{-1} \), the azimuth angle spanned is \( \Delta \theta = 8^\circ \), the PRF = 750, the raw spectral points is \( M = 50 \) with \( N_{\text{spec}} = 4 \) spectra averaged, which produces a spectral resolution of \( 0.3234 \, \text{m s}^{-1} \), and there are \( n = 3000 \) lidar pulses per spectra. The spectral and Monte Carlo simulations produce similar results.

4. Doppler lidar estimation algorithms

Since the Doppler lidar signal at large ranges upstream is very weak, the most promising estimation algorithms are based on the ML technique and the minimization of the MSE between the spectral data \( \hat{P}(f) \) and a model \( P(jF, A, f, w) \) for \( n \) lidar shots. If the spectral estimates are mutually uncorrelated, then the log-likelihood function (Helstrom 1968; Rye 2000)

\[
\Lambda[\hat{P}, A, f, w] = \sum_{j=1}^{M} \ln p_n[\hat{P}(jF)]
\]  
(26)
which becomes [see Eq. (25)]

\[
\Lambda[\hat{P}, A, f, w] = M[n \ln n - \ln \Gamma(n)] - n \sum_{j=1}^{M} \ln \hat{P}(jF, A, f, w) \\
+ (n-1) \sum_{j=1}^{M} \ln \tilde{P}(jF) - n \sum_{j=1}^{M} \hat{P}(jF) \\
+ (n-1) \sum_{j=1}^{M} d(jF, f, w) \\
- \sum_{j=1}^{M} d^2(jF, f, w) \\
\] (27)

Here, the ensemble average power spectrum Eq. (4) is given by Eq. (5) and \( f = \hat{F}(j_m + \delta) \).

The ML estimates of the three unknown parameters are given by the maximum of \( \Lambda[\hat{P}, A, f, w] \). In addition, the ML estimates of \( v_r \) and \( w_y \) are given by \( v_r = \lambda f/2 \) and \( w_y = \lambda w/2 \), respectively, which are shown in Fig. 4 for the two different simulation algorithms.

The ML estimator is numerically intensive since the maximum of \( \Lambda \) must be determined for the three unknown parameters, that is, over a three-dimensional sampling grid for \( A, f, \) and \( w \) with parabolic interpolation used to increase the numerical accuracy. Another more efficient estimator is produced by minimizing the mean-square-error

\[
\text{MSE} = \sum_{j=1}^{M} [\hat{P}(jF) - 1 - Ad(jF, f, w)]^2 \] (28)

with respect to \( A, f, \) and \( w \). A solution is produced by taking the derivative of Eq. (28) with respect to \( A \), that is,

\[
A(f, w) = \frac{\sum_{j=1}^{M} \hat{P}(jF) - 1 \sum_{j=1}^{M} d(jF, f, w)}{\sum_{j=1}^{M} d^2(jF, f, w)} \] (29)

and a parabolic interpolation is used to improve the numerical accuracy. The results of the MSE estimator for the two spectral simulations of Fig. 5 are shown in Fig. 6 for \( A, v_r, w_y, \) and \( F_1 \). There is little difference between the two estimators.

The performance of these two estimators is defined by their mean and standard deviation as a function of the signal strength \( F_1 \) for various atmospheric conditions and lidar parameters. The true velocity is defined as the spatial average of \( m_{wgt} \) Eq. (14) over the sector scan. Results are shown in Figs. 7 and 8 for 100 000 realizations for each signal level \( F_1 \). The bias of the estimates is small for all the cases considered here, even for \( g \) when \( \Phi_1 \) is small. Note that there is very little difference between the two algorithms, and that the standard deviation of the spectral width \( w_y \) and amplitude \( A \) become smaller for larger signal strength \( \Phi_1 \). When there are no outliers, the standard deviation of the radial velocity \( v_r \) becomes \( g \), which is very small for these atmospheric conditions. These same algorithms could be
applied to space-based Doppler lidar data in weak signal regimes (Frehlich and Yadlowsky 1994; Frehlich 1996; Frehlich et al. 1997; Frehlich 2000, 2001a, 2004; Koch et al. 2007; Kavaya et al. 2007). The optimal performance of these estimators can be determined for various conditions and scan patterns to extend the range of useful data. However, even more improvement in the maximum range can be produced by estimating both the WS and dir using a large sampling region upstream with a sector scan (Smalikho 2003; Frehlich et al. 2006, 2008; Frehlich and Kelley 2008).

Since the goal of this work is to provide improvements in short-term wind power forecasts, only an angular wedge approximately aligned to the average wind direction will be considered instead of a full 360° azimuth scan (Smalikho 2003). This wedge can be slowly changed after each volume scan to maintain correct sampling of the upstream conditions. The log-likelihood function is produced from $K$ average spectra of $n$ lidar shots per spectrum, that is,

$$L = \left[ \sum_{i=1}^{K} \sum_{j=1}^{M} \ln P(jF, A, [f - 2v_r(i)/\lambda], 2w_v/\lambda) \right] - n K M \ln n - \ln n! - n \sum_{i=1}^{K} \sum_{j=1}^{M} \ln P(jF, A, [f - 2v_r(i)/\lambda], 2w_v/\lambda)$$

where $v_r(i)$ is the average radial velocity for azimuth angle $\phi_i$ and elevation angle $\theta$ [see Eqs. (19), (21), (22)]; $P(jF, i)$ is the average periodogram for $\phi_i$; and the ML estimates of $A$, WS, dir, and $w_v$ are determined by the maximum value of $L$, where a parabolic interpolation is used to improve the numerical accuracy. In a similar manner, the MSE estimates are produced by maximizing
\[ P(\text{WS}, \text{dir}, w_v) \]
\[
= \sum_{i=1}^{K} \sum_{j=1}^{M} \left[ \frac{P(jF, i) - 1}{d[jF, [f - 2w_v(i)/\lambda], 2w_v/\lambda]} \right]
\]
\[
\text{with respect to WS, dir, and } w_v \text{ where}
\]
\[ Q(\text{WS}, \text{dir}, w_v) = \sum_{i=1}^{K} \sum_{j=1}^{M} d[jF, [f - 2w_v(i)/\lambda], 2w_v/\lambda] \]
\[
\text{and an offset for WS is included in the analysis. In addition, an estimate for } A \text{ is given by}
\]
\[ A = \frac{P_{\text{max}}(\text{WS}, \text{dir}, w_v)}{\sqrt{Q_{\text{max}}(\text{WS}, \text{dir}, w_v)}} \]
\[
\text{and a parabolic interpolation is used to improve the numerical accuracy. Note that } P_{\text{max}}(\text{WS}, \text{dir}, w_v) \text{ and } Q_{\text{max}}(\text{WS}, \text{dir}, w_v) \text{ denote the maximum value of } P \text{ and } Q, \text{ respectively.}
\]
Simulations were performed with the parameters of Fig. 7 and WS = 10 m s\(^{-1}\), a wind direction of 0° (from the north), 1875 lidar shots per spectra (2.5 s or 5° per spectra), 10 spectra per estimate (50° azimuth sector), and 10 000 estimates per \( \Phi_1 \). The fraction \( b \) of random outliers is now based on the estimate of WS using the algorithms in Frehlich (1997). Results are shown for the ML estimator in Fig. 9 and for the MSE estimator in Fig. 10. When there are few random outliers (\( b < 0.001 \)), the estimation error in WS is given by \( g \). Only the MSE estimator has an estimate for the standard deviation of \( A \) when no signal is present. The performance of the MSE estimates is very similar to the ML estimates and therefore should be used for this weak signal regime.

5. Analysis of Doppler lidar data

The simulation of coherent Doppler lidar signals for realistic conditions is very useful for optimizing performance. However, actual Doppler lidar data are required for real-world conditions and applications, such as short-term forecasting. A test dataset was provided by Lockheed Martin Coherent Technologies, Inc. at their Louisville, Colorado, facility. To address the needs of the wind power industry, a scan pattern was selected that sampled nonurban conditions away from Denver, Colorado, that is, an azimuth scan from \( \phi = -45° \) to 45° at various fixed elevation angles \( \theta \) for the morning of 22 September 2010.

Each lidar shot consists of a monitor pulse and then aerosol data. A best fit to the monitor pulse provides the frequency for zero velocity, the pulse width, the time offset of the pulse (to assign range), the frequency chirp, and the amplitude following the analysis of Frehlich et al. (1994). Plots of the monitor pulse parameters with time are similar to Fig. 2 of Frehlich et al. (1994). A nearby hill blocks the zero elevation angle scan, which provides an accurate average noise spectrum \( P_n(f) \) as shown in Fig. 11. Also shown is the predicted scaling for the standard deviation (SD) of the raw periodogram, that is, \( \text{SD}[P_n(f)] \), which is very accurate for most of the frequency range.

To apply the two estimators (ML and MSE), each raw spectrum or periodogram is normalized by the average noise spectrum and then the frequency of the aerosol data is corrected by the monitor frequency, which defines zero velocity. In addition, the level of the normalized
spectrum is shifted to unity based on the average normalized spectrum away from the signal peak (in this case, from $-24.2$ to $-8.1 \text{ m s}^{-1}$) to correct for small drifts in the average noise spectrum. An example of an average spectrum with the lidar parameters of Figs. 7 and 8 at an elevation angle of $\theta = 3^\circ$ is shown in Fig. 12 as well as the predicted spectrum for the ML estimator and the MSE estimator (see Figs. 5 and 6). The estimated parameters are similar for both estimators in this weak signal regime and about half of the spectral width is due to the random velocity variations over the sampling volume. The wind speed and wind direction can be approximated by the largest radial velocity and the corresponding azimuth angle. Increasing the range-gate length $D_p$ and the azimuth angle domain $\Delta \phi = |\phi_2 - \phi_1|$ would also improve these estimates if the atmosphere is approximately constant. A simultaneous estimate of wind speed and wind direction is difficult because of the complex terrain north of the site and the fact that the direction of the wind is not contained in the azimuth scan domain of the data.

The WindTracer lidar also has an archive of the spectral estimates produced during the scanning pattern. However, because of computational limits, only

![FIG. 10. As in Fig. 9, but for the MSE estimator. A threshold for the estimates of $A$ is given by the mean value of $A$ when no signal is present plus $2\sigma$.](http://journals.ametsoc.org/jtech/article-pdf/30/2/230/3355372/jtech-d-11-00117_1.pdf)

![FIG. 11. (top) The average noise spectrum and (bottom) the ratio of the standard deviation of the periodogram to the average noise spectrum vs frequency.](http://journals.ametsoc.org/jtech/article-pdf/30/2/230/3355372/jtech-d-11-00117_1.pdf)

![FIG. 12. The average noise- and frequency-corrected spectra and the predicted parameters of the spectral model Eqs. (3) and (5) (see Figs. 5 and 6) for a range gate centered at 21.6 km (20.850–22.350 km), an azimuth angle of $10.93^\circ < \phi < 18.94^\circ$, an elevation angle of $\theta = 3^\circ$, and an altitude of 1.130 km, assuming a flat Earth: (top) MSE and (bottom) ML.](http://journals.ametsoc.org/jtech/article-pdf/30/2/230/3355372/jtech-d-11-00117_1.pdf)
120 spectra (range gates) are calculated with $M = 128$ spectral points and $n = 375$ lidar pulses or 0.5 s of data. The spectra are normalized by a stored average noise spectrum, and the frequencies shifted to the central index of $(M/2) + 1$. To improve the spectral noise correction, a new average noise spectrum is calculated from the spectral data for the same azimuth angle region of the zero elevation scan that is blocked by nearby hills. The resulting normalized spectrum (with a shift of the noise floor based on the average spectrum over $-24.2$ to $-8.1$ m s$^{-1}$) and the ML and MSE estimates are shown in Fig. 13 for a similar scan region to Fig. 12. The spectral resolution is $\Delta v = 0.7896$, which is sufficient for the estimation task. There is some spectral leakage because of the small number of spectral points, which can be easily corrected, for example, Frehlich and Cornman (2002). The average spectra clearly show the aerosol signal at the same velocity as the raw data processing of Fig. 12 but with less spectral resolution.

6. Summary and discussion

Scanning Doppler lidar has a well-defined range-weighting function $W(r)$ (see Fig. 1) that can produce accurate profiles of wind speed, wind direction, and the von Kármán turbulence statistics, such as the velocity standard deviation $\sigma$, the outer scale of turbulence $L_o$, and the energy dissipation rate $\epsilon$ (see Fig. 2) using the structure function of radial velocity in the azimuth and a correction for $W(r)$ as shown in Fig. 3. This can be done routinely to improve operations (see Fig. 2) if there are data in the first few kilometers. The von Kármán model of Fig. 3 is chosen as a benchmark case for simulations of signal spectra (Figs. 5 and 6) as well as the performance of the ML and MSE estimators as a function of the signal strength $F_1$ for a single measurement pixel (Figs. 7 and 8), and even better results are produced by simultaneous estimates of wind speed WS and wind direction dir using a large azimuth arc (Figs. 9 and 10).

The performance of the ML and MSE estimators is also determined from raw coherent Doppler lidar data provided by Lockheed Martin Coherent Technologies, Inc. by estimating the lidar pulse parameters (Frehlich et al. 1994) and the average noise spectrum (Fig. 11). Corrections for the fluctuations in the monitor frequency and careful normalization by the average noise spectrum and the spectral level averaged over $24.2$ to $8.1$ m s$^{-1}$ produces acceptable signal at a range of $21.6$ km with a range gate of $1.5$ km and an azimuth interval of $\Delta \phi = 8^\circ$ (see Fig. 12). Similar results are produced by the analysis of the archived WindTracer lidar signal spectra, which have different averaging domains and spectral resolution. A useful estimate of the upstream wind direction and the wind speed is produced by the azimuth angle with the largest radial velocity. The maximum range of useful data for data assimilation can be extended by the simultaneous estimation of both the WS and dir using a larger sampling domain if the atmospheric conditions are well behaved. Clearly, careful processing of scanning Doppler lidar data can extract useful velocity information at large ranges upstream for short-term wind power forecasts. The numerically efficient MSE estimator has similar performance to the ML estimator and is therefore the estimator of choice. The impact of complex terrain is not known and resolving this issue would require a field campaign or a more advanced computer simulation.

Unfortunately, there is no scanning Doppler lidar data near any wind farm and there are many critical unanswered questions, which include the following:

- Are there enough aerosols near wind farms for effective measurements?
- Do the variations in the winds drastically increase the spectral width?
- Do atmospheric processes such as frontal passages permit accurate short-term forecasts?

More research is needed to evaluate this promising new technology.
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