Real-time three dimensional wind field reconstruction from nacelle LiDAR measurements

F. GUILLEMIN, H.-N. NGUYEN, G. SABIRON, D. DI DOMENICO
IFPEN, 1 avenue de Bois-Préau, 92500 Rueil-Malmaison, France

M.BOQUET
Leosphere, 16 Rue Jean Rostand, 91400 Orsay, France

E-mail: fabrice.guillemin@ifpen.fr

Abstract. In recent years, Light Detection and Ranging (LiDAR) has emerged as a feasible, reliable and accurate remote sensing technology for wind speed measurements. For a fine and performant use of the LiDAR data in turbine control and monitoring applications, adapted and sophisticated real-time processing is needed. With the objective to retrieve accurate enhanced information from the sensor raw data, this paper aims to present solution to estimate, in three dimensions and in real time, incoming wind characteristics, such as wind speed, wind direction and instantaneous shears. An innovative reconstruction is proposed based on recursive weighted least squares method. The approach is validated for pulsed nacelle LiDAR systems with simulated data, obtained with a specifically developed wind generator tool, including a representative LiDAR Wind Iris TC model.

1. Introduction

A typical wind turbine has a lifetime of twenty to twenty five years. Due to the uncertain environment in which it operates and to its flexible structure, an important amount of effort in the design process is dedicated to ensure that it is able to withstand the various loads that it will experience. Compared with upgrading the mechanical system to extend the lifetime of turbines, modern control systems are more attractive and cheaper cost reducing strategies. Especially, control strategies that take benefit from incoming wind information show promising results, depending on the accuracy of the wind information [1].

LiDAR is now becoming a mature technology for remote wind speed and/or wind direction measurements and rotor effective wind speed predictions. The accuracy of these predictions depends on the quality of the LiDAR measurements, but also on the performance of the reconstruction algorithms used to estimate the wind in region or time intervals that are not directly measured.

This paper presents an innovative, optimization based, wind field reconstruction strategy to retrieve significant wind information from the nacelle LiDAR real-time raw data. The global objective is to obtain accurate high frequency wind estimates in the perspective of a use into LiDAR based turbine control laws.

The evaluation framework of the developed algorithm is explained, followed by a results presentation.
2. State of the art
Standard used algorithms provide useful wind data, but the full representativeness of wind conditions requires additional processing. Some wind field reconstruction methods are based on an assumption of uniform and steady flow across the rotor plane [2]. However, the wind speed has a complex dynamic [3], and it varies considerably with height within the atmospheric boundary layer. In [4], [5], to reconstruct the wind field, by taking into account the horizontal and vertical shears, the uniform assumption is relaxed. At each time instant, a solution of a nonlinear equation is required. However, the approach relies heavily on the Taylor frozen hypothesis, which is in general not the case due to the induction zone as well as the complex dynamic of the wind field. In [6], another method is proposed. The basic idea is to employ a simplified Navier-Stockes equation to model the wind field in conjunction with an unscented Kalman filter. However, this is a 2D wind field reconstruction for a fixed altitude. In addition, it is assumed that all measurements along all beams are available at the same time, which is not the case in practice. Another wind field estimation method is considered in [7]. The main idea to fit a wind model with the LiDAR measurements using an iterative procedure. The approach provides only an estimation of 10 minutes statistics of wind characteristic, which cannot be used for control purpose.

3. Approach: online optimization based wind field reconstruction
The objective is to estimate the wind speed and the wind direction of the incoming wind field in real-time and use it as an input for innovative control strategies, such as LiDAR based individual/collective pitch control [6]. The detection and quantification of incoming wind field characteristics such as shears, gusts and direction changes can be seen as a great asset for turbine production optimization and loads prevention.

Consider a nacelle mounted four beams pulsed LiDAR. More specifically, this is a Leosphere Wind Iris TC (Turbine Control) which is referred to. This sensor measures on each beam the projection of the wind vector on the corresponding line of sight. It measures the wind speed projection at several spaced ranges along each beam from 50m to 200m, at a sampling rate of 4Hz for turbine control applications.

In order to estimate the properties of the wind field scanned by the LiDAR, a cost function to be minimized is considered, taking into account LiDAR measurement uncertainty, temporal and spatial correlations of the estimates. Optimization variables correspond to wind components at specified space locations.

3.1 LiDAR measurements
Denote \( m_{j,x}(t) \), \( j = 0,1,2,3 \), respectively, as the LiDAR measurements for the beams \( j = 0,1,2,3 \), at the distance \( x \) meters, and at time instant \( t \). Denote also \( v_{j,x}(t), v_{j,y}(t), v_{j,z}(t) \) as the projection of the wind speed onto a three axes orthogonal reference \((x, y, z)\). The LiDAR measurement is then given by:

\[
m_{j,x}(t) = a_j \cdot v_{j,x}(t) + b_j \cdot v_{j,y}(t) + c_j \cdot v_{j,z}(t)
\]

where \( a_j, b_j, c_j \) are measurement coefficients directly related to the LiDAR beams orientation. The relation (1) can be written for each LiDAR measurement. A compact vector form can regroup all the measurements, relying on geometric considerations.

To take into account the measurement uncertainties, a more realistic model than (1) is introduced as follows:

\[
m(t) = C_m \cdot \omega(t) + \epsilon(t)
\]

where \( C_m \) regroups all the projections description, \( \omega(t) \) all the wind speed components at measurements locations, and \( \epsilon(t) \) the measurement noise at all measurement locations.
3.2 Spatial Correlations

It is well known that the wind speed changes smoothly in space. Thus, wind components between neighbor locations are highly correlated, especially in the wind propagation direction. Consider the grid represented in Figure 1:

![Figure 1: Example of generated wind field grid (blue dots) and corresponding 4-beam LiDAR measurements (red dots) for 3 measurement distances.](image)

The longitudinal correlation of wind component $v_x(t)$ correlation corresponds to its evolution along x axis. Taking into account figure 1 displayed locations, a high longitudinal correlation can be expressed such as:

\[
\begin{align*}
&v_{x_1} - v_{x_{10}} \approx 0 \\
&v_{x_4} - v_{x_{13}} \approx 0 \\
&\quad \vdots \\
&v_{x_{11}} - v_{x_{20}} \approx 0 \\
&\quad \vdots \\
&v_{x_{18}} - v_{x_{27}} \approx 0
\end{align*}
\] (3)

Considering a vector $\omega$ regrouping the wind speed components at the locations of interest, this can be written in a compact vector form such as $C_{x_1} \cdot \omega \approx 0$.

Similar approach can be applied for the expression of transversal correlation such as $C_{xT} \cdot \omega \approx 0$. This relation is useful to estimate the horizontal shear.

For vertical correlation, the vertical profile power law can be introduced, leading to specific difference equations:

\[
\begin{align*}
&\left(\frac{z_1}{z_2}\right)^\alpha v_{x_2} \approx 0 \\
&\left(\frac{z_4}{z_5}\right)^\alpha v_{x_5} \approx 0 \\
&\quad \vdots
\end{align*}
\] (4)
This can be written in a compact vector form such as $C_{xy}, \omega \approx 0$. This relation is useful to estimate the vertical shear.

This formulation leads to a spatial correlation matrix that gathers longitudinal, transversal and vertical correlations: $C_x = [C_{x1} \ C_{xt} \ C_{xy}]^T$
The same approach is applied, with adapted criteria, to the other wind components, leading to a global spatial correlation matrix: $C_z = [C_x \ C_y \ C_z]^T$.

3.3 Temporal correlations
The temporal correlation quantifies how the wind speed components in a certain location at time $t$ are related to those at time $(t-1)$. Following the same path as for spatial considerations, a relation can be expresses for all the measurements in a specific matrix:

$$C_c(v_x(t), v_y(t), v_z(t), v_x(t-1), v_y(t-1), v_z(t-1))$$

Note that the temporal correlation is strongly related to the wind turbulence, i.e., how fast the wind speed changes with time.

3.4 Cost function minimization implementation
Merging measurements, spatial and temporal relations exposed above, the following optimization problem is obtained:

$$\min_{v_x(t), v_y(t), v_z(t)} \left( C_m(v_x(t), v_y(t), v_z(t))^2 + C_c(v_x(t), v_y(t), v_z(t), v_x(t-1), v_y(t-1), v_z(t-1))^2 + C_s(v_x(t), v_y(t), v_z(t))^2 \right)$$

To obtain a solution, a discrete-time Kalman filter is implemented, according to [10], which leads to the following update equation:

$$\omega(t) = \omega(t-1) + K(t)(m(t) - C. \omega(t-1))$$

with $C = [C_s \ C_c \ C_m]^T$, $K = Kalman \ gain$

The main advantage is that the implementation is in a recursive form, hence it is suitable to real-time implementation and computational constraints. The covariance matrices of the process noise and the measurement noise are optimized through Monte-Carlo simulation.

Once wind components at specified locations of interest obtained, meaningful wind properties are derived based on their definition.

Selected quantities of interest for evaluation are:
- **R rotor average wind speed (RAWS)** [m/s]: space mean value of the wind speed component in direction of the hub, at each measurement range.
- **Horizontal Hub height wind speed (HHWS)** [m/s]: value of the wind speed, in the direction and at the height of the hub, for each range.
- **Wind direction (WD)** [°]: space mean value of the direction of the wind, at each range.
- **Horizontal shear (HS)** [s^{-1}]: variation of the wind speed in the direction of the hub, over a distance of one meter, between two locations at the same range and height.
- **Vertical shear (VS)** [s^{-1}]: variation of the wind speed in the direction of the hub, over a distance of one meter, between two locations at the same range and vertically aligned.

These quantities are provided at distances corresponding to the grid definition, upstream the rotor plane. They constitute relevant inputs for enhanced rotor and tower loads monitoring, and for advanced LiDAR assisted control strategies, such as in [11].
4. Performance evaluation

To evaluate thoroughly the performance of the reconstruction algorithm, a comparison framework with a reference has been established, summarized in the diagram figure 2 below.

**Figure 2: algorithm performance evaluation framework**

A specific wind field, with its derived properties of interest is generated. LiDAR raw measurements are obtained from a LiDAR model and fed into the reconstruction algorithm. Estimated properties are then compared with corresponding ones from the generated wind field, taken as a reference. This comparison procedure is expected to be proceeded under several conditions, especially:

- Presence of wind turbine induction zone effects
- Gusts
- Realistic artificial transversal and vertical shear variations
- Direction changes
- Impact of the LiDAR sensor specificities

To do so, a simulator capable of representing a 3D non homogenous full-field is needed. Although accurate tools are already available to provide synthetic non-homogeneous wind fields at low computational costs [8], the algorithm evaluation needs additional features to realize the specific conditions listed above. Thus a specific wind generator has been developed, including a realistic frequency based wind field generator as well as a representative LiDAR model. In addition to classical wind modeling characteristics such as Taylor frozen hypothesis, Kaimal spectrum based turbulence model and power law vertical shear [9], specific features are implemented:

- **Horizontal and linear vertical shear**: Homothetic transformation are applied to the wind field in order to allow for horizontal and vertical linear shears without impact on direction.
- **Gusts** as defined by IEC 61400-1 standard (Mexican hat shaped gusts).
- **Wind direction changes** on the horizontal plane.
- **Induction zone effect** that corresponds to the velocity deficit of the wind field approaching the turbine rotor, which is a function of the distance to rotor and mean wind velocity. This deficit map is obtained from SMARTEOLE processed experimental data and corresponds to a producing Senvion MM82 wind turbine.

Regarding LiDAR, the generator features are:

- **Realistic blade blocking effect** to model the data loss for all measurement ranges of a beam, when a blade is obstructing the line of sight during its acquisition time window. This effect has a noticeable impact on measurement availability, that can decrease down to 60% for lower beams.
- **Pulsed LiDAR Gaussian range weighting function (rwf)**.
- **LiDAR measurement noise modeled** as an additive centered Gaussian white noise similar for all beams and measurement ranges.
Figure 3: Generated radial wind speed (rws) measurement with various levels of representativity.

On figure 3, one can see the superimposition of different time series:
- The “ideal acquisition” for the beam #3 (one of the 2 lower beams). This one is obtained with the projection of the wind vector on the beam#3 line of sight.
- The signal obtained with the application of the rwf, a representative measurement Gaussian noise, and the cyclic down-sampling, due to the beam switching acquisition sequence at 4 Hz (which means 1 Hz for each beam).
- The signal obtained taking into account the blade shadowing effect.

The expected alteration of the signal content, caused by the combination of the above listed specificities, is clearly observed. The corresponding availabilities are realistic and similar to those observed on experimental LiDAR acquisitions, i.e., around 65% for lower beams and 75% for higher beams, at rated rotor speed and 12 m/s mean wind speed.

5. Results
The above described wind generator has allowed to establish an appraisal of the performance of the reconstruction algorithm, under different wind conditions. Twenty different scenarios have been generated in order to provide a wide analysis field of the reconstruction algorithm results. The description of these scenarios is synthesized in the first column of the table displayed figure 10. It consists especially in direction changes, various levels of turbulence intensity, and artificial shear offsets insertions.

The impact of these specific wind characteristics on the accuracy of the quantities of interest can be observed and quantified on the figures below. The time series are those generated with the scenario #2: moderate turbulence intensity (TI), direction change of 15°, horizontal shear offset of 0.02 s⁻¹. The table attached to the figures displays, for each measurement range, the root mean square error (RMSE) of the estimated quantity, with respect to the reference, and the coefficient of determination (R²).
Figure 4: estimated RAWS compared with reference RAWS – RMSE and $R^2$

On figure 4 above, the reconstructed RAWS clearly fits the reference RAWS and captures high frequency turbulence content. The RMSE is noticeably low on closer ranges (below 0.4 m/s) and gets altered on far ranges (higher than 120m).

On figure 5 below, the estimated HHWS is compared with the reference HHWS. It can be observed that, even with only 4 radial measurements at locations noticeably far from hub height and alignment, the wind reconstruction algorithm provides an estimate that contains many of the turbulent events effectively occurring at hub height location. Moreover, it is to note that the direction is changing from 0 to 15° between $t=300s$ and $t=350s$. This has no impact on the accuracy of estimated hub height wind speed. The optimization based wind reconstruction is in fact able to track the wind direction change and take it into account for wind speed estimates computation.

Figure 5: estimated HHWS compared with reference HHWS – RMSE and $R^2$

Figure 6 shows estimated and reference space mean wind direction time series at 50m range. The estimation performance decreases with distance ahead rotor increasing, as seen on attached table of figure 6 (RMSE increases, $R^2$ decreases). This can be explained by the distance between the measurement locations which increases with the range.
On figure 7, estimated and reference horizontal shears are compared. It is to note that an artificial shear offset of 0.02 s\(^{-1}\) has been inserted in the generated wind. The purpose of this is to test the algorithm performance on an artificially “complexified” site. One can see that the algorithm captures properly this offset, even during the direction transient, between 300 and 350 s. This is a noticeable asset as it allows to separate properly shears from direction changes, preventing output quantities from non-realistic biases, even in an inhomogeneous flow, with distant locations and projected measurements. RMSE is low for all distances. \(R^2\) is quite low, due to the fact that the reconstruction doesn’t capture all the turbulences with the exact amplitude of the reference.

On figure 8, estimated and reference vertical shears are compared. One can see that the instantaneous vertical shear is properly tracked. \(R^2\) is relatively low, due to the same reasons as for HS.
Figure 8: estimated VS compared with reference VS – RMSE and $R^2$

Figure 9 below displays the coherence of estimates of HS and VS with the corresponding generated reference signals. This shows the capacity of the reconstruction to retrieve relatively high frequency content of the wind, from realistically altered radial measurements. Considering these results, one can deduce that wind shear properties can be estimated at up to 0.2 Hz.

The figure 10 below exposes the results of the benchmark for all the 20 scenarios. For each scenario, and for each quantity of interest, the table displays the RMSE averaged on all the ranges. This provides a global performance indicator.
Reading of the test scenarios description:

- VS/HS constant: Vertical/Horizontal Shear constant offset, at 0.02 s⁻¹.
- VS/HS varying: Vertical/Horizontal Shear varying offset, between +0.02 s⁻¹ and -0.02 s⁻¹.
- TI high: High level of turbulence intensity, such as TI∠=0.2, TIT=0.14, TiZ=0.07.
- TI mod: Moderate turbulence intensity, such as TIX=0.1, TIX=0.07, TIZ=0.05.
- WDxx: Wind direction change of xx°, operating at 300s, during 50s.

Figure 10: mean RMSE table for all considered quantities of interest, for all test scenarios

This table allows to check the reproducibility and robustness of the algorithm performance, under varying wind conditions. One can summarize the observations with the following items:

- High accuracy of RAWS, HHWS, HS and VS, under all moderate turbulence cases.
- Noticeable RMSE of RAWD and HHWD (hub height wind direction).
- Around 1% of TI (Turbulence intensity) RMSE on all cases of moderate turbulence, and around 2% of TI RMSE for cases with high turbulence. Considered variables are here the rotor average Turbulence intensity (RATI) and the TI at the measurement locations.
- Robustness to direction change amplitudes, whatever the value in [5 10 15 25 50]°.
- Robustness to shear offsets
- Decrease of the performance under high turbulence conditions.

6. Conclusion and perspectives

To further improve the benefits of LiDAR data, an optimization based reconstruction algorithm has been developed to elaborate robust wind information from raw LiDAR measurements. To validate the algorithm performance, an enhanced wind generator including a Wind Iris TC LiDAR model have been implemented in order to realize a wide and relevant evaluation framework.

The exposed results demonstrate the performance of the algorithm under various challenging wind conditions. Further developments are in progress to provide accurate predictions of the wind characteristics at the rotor plane, based on the use of the accurate multi-distance estimates described in this article.

The validation framework will also be extended with the use of a dedicated LiDAR assisted control simulation platform, including a realistic model of the Senvion MM82 wind turbine. This will allow to measure the performance gains of the LiDAR based controller, exposed in [10], in terms of loads.
mitigation and production optimization, with the use of the optimization based wind reconstruction algorithm.

A full experimental validation is also being proceed on the acquired data of SMARTEOLE experimental campaigns.

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