Turbulent Extreme Event Simulations for Lidar-Assisted Wind Turbine Control

David Schlipf, Steffen Raach
Stuttgart Wind Energy, University of Stuttgart, Germany.
E-mail: david.schlipf@ifb.uni-stuttgart.de

Abstract. This work presents a wind field generator which allows to shape wind fields in the time domain while maintaining the spectral properties. This is done by an iterative generation of wind fields and by minimizing the error between wind characteristics of the generated wind fields and desired values. The method leads towards realistic ultimate load calculations for lidar-assisted control. This is demonstrated by fitting a turbulent wind field to an Extreme Operating Gust. The wind field is then used to compare a baseline feedback controller alone against a combined feedback and feedforward controller using simulated lidar measurements. The comparison confirms that the lidar-assisted controller is still able to significantly reduce the ultimate loads on the tower base under this more realistic conditions.

1. Introduction and Objectives
Lidar-assisted control is considered to be a promising technology to reduce the structural loads of wind turbines. The improvement in control performance needs to be proven in standardized design load cases to exploit the benefits in the design process of wind turbines. The dominant effects such as limitations of the lidar measurements and wind evolution can be already included in fatigue load simulations with interpolation between turbulent wind fields using wind evolution models and a lidar simulator [1]. However, a full set of load cases needs to be considered to assess the benefit for ultimate loads including some with coherent wind fields [2]. These wind fields are unrealistic, but are included in the standards to have a simple and uniform way to assess ultimate loads [3]. Methods of constrained stochastic simulations include extreme events into turbulent wind fields [4, 5, 6] and thus are promising to enable more realistic ultimate load simulations. Previous methods are able to directly provide the wind fields based on very smart and complex calculations.

The paper adds an engineering approach to the methods of constrained stochastic simulations: The wind fields are shaped in the time domain by minimizing the deviation from desired wind fields in an iterative process, while maintaining the spectral properties. In principle, the method can be applied to all types of time constraints and spectral wind models. However, feasibility and convergence need to be further investigated. Here, the rotor effective wind speed of a wind field is fitted to an Extreme Operating Gust (EOG) according to [7]. This allows to have ultimate load simulations with turbulent wind fields: simulations with the DTU 10 MW wind turbine and a lidar simulator in GH Bladed$^1$ are performed, comparing simulations with coherent and turbulent wind fields as well as a baseline and a lidar-assisted controller.

$^1$ For the aero-elastic simulations, GH Bladed v4.5 with the control module including the lidar simulator is used.
2. Shaping of Turbulent Wind Fields

In this section, a short introduction to the generation of random wind fields is given and the new method of generating wind fields fitted to meet certain values in the time domain is presented thereafter.

2.1. Introduction to Random Wind Field Generation

For the generation of turbulent wind fields, the Veers method [8] is a common practice in wind energy [9]. With this method, wind fields are obtained by generating simultaneous time series of the longitudinal, lateral, and vertical wind speed component at defined points on a two-dimensional grid. The time series have spectral properties individually (usually defined by a auto-spectrum) and in relation to each other (usually defined by a coherence function) based on spectral wind models such as the IEC Kaimal model [7] used in this work. The time series are usually generated by an inverse Fast Fourier Transformation (FFT). In order to generate several distinct wind fields, phase angles $\theta_{j,m}$ for each grid point $j$ and for each frequency $f_m$ are chosen randomly, usually by defining a random seed for a random number generator. The generation differs significantly on whether a correlation between the grid points is assumed in the spectral model or not.

For wind components without correlation to other points (for example the lateral and vertical component for the IEC Kaimal model), the time series can be considered as a combination of sinusoids only depending on the phase angles associated to the current point. For the IEC Kaimal model, the lateral wind speed $v$ over time $t$ at a grid point $j$ is obtained by a sum of sinusoids over all $n_f$ frequencies with a spacing $\Delta f$. The amplitude for each frequency $f_m$ is defined via the value of the auto spectrum $S_{v,m}$ at the given frequency and the phase of each frequency is defined via $\theta_{j,m}$:

$$v_j(t) = \sum_{m=1}^{n_f} \sqrt{2\Delta f S_{v,m}} \sin(\theta_{j,m} + 2\pi f_m t).$$

(1)

For wind components with correlation to other points (for example the longitudinal component for the IEC Kaimal model), the phase angles of each grid points have an impact on the time series of all grid points. Usually, the impact is decreasing with increasing distance between the grid points. At a grid point $j$, the Fourier coefficient $U_{j,m}$ of the longitudinal wind component at a frequency $f_m$ is given by

$$U_{j,m} = \sum_{k=1}^{j} H_{jk,m} \exp(i \theta_{k,m}),$$

(2)

where $i$ is the imaginary unit, $\theta_{k,m}$ is the phase angle for frequency $f_m$ and for the grid point $k$, and the amplitude $H_{jk,m}$ is obtained by a lower Cholesky factorization of the coherence between point $j$ and $k$. Here, the coefficients at each grid points are also depending on the phase angles from the other grid points, because $k$ is ranging from the first to the current grid point $j$.

See [8] and [9] for more details. In this work, the wind fields are generated with a code inspired by [10].

The important point for the next subsection is that the computational expensive calculation of $H_{jk,m}$ is independent on the phase angles $\theta_{k,m}$. This point is exploited in the fitting of wind fields to meet certain values in the time domain described in the following subsection.

2 The MadHatter code has been implemented in Matlab R2013b 64 bit.
2.2. Wind Field Generation with Time Conditions

In principle, wind fields can be fitted to a wide range of user-defined forms in the time domain with the method presented below. Here, a wind field based on the IEC Kaimal spectral model is shaped in the way that the rotor effective wind speed $v_0$ is as close as possible to an EOG at 25 m/s in $n_t = 8$ defined points in time, see Figure 1a. Parameters such as the total number of grid points $n_p$ are listed in Table 1.

The wind fields are fitted by following process:

(i) All amplitudes $H_{jk,m}$ from the Fourier coefficients are calculated based on the given wind field parameters and the IEC Kaimal spectral model.

(ii) All $3 \times n_f \times n_p$ phase angles are initialized by a random number generator with a chosen seed.

(iii) The turbulent wind field is generated by an inverse FFT using the current phase angles and the previously calculated amplitudes.

(iv) The rotor effective wind speed $v_0$ is calculated from the wind field by averaging the longitudinal wind component in the $n_{cp} = 172$ grid points within the rotor disc excluding points without an airfoil at the hub, see Figure 1b.

(v) The sum of the error between the rotor effective wind speed $\hat{v}_{0,i}$ from the wind field and $v_{0,i}$ from the coherent EOG is calculated in each defined point $i$ in time.

The steps (iii) to (v) are then repeated within an error minimization problem

$$\min_{\theta_1, \ldots, \theta_{n_{cp} \times n_{cfa}}} J \quad \text{with cost function} \quad J = \sum_{i=1}^{n_t} (v_{0,i} - \hat{v}_{0,i})^2,$$  \hspace{1cm} (3)

which can be solved by altering free phase angles of the longitudinal wind component from the considered grid points. Only the first $n_{cfa} = 12$ frequencies of the longitudinal wind component are changed to limit the degrees of freedom. This number is chosen based on following considerations: The defined points in time to meet the EOG are spaced with $\Delta t_c = 1.75 \text{s}$. A time series with this spacing can be defined by the frequencies up to $f_c = \frac{1}{\Delta t_c}$. Since the frequencies are equally spaced with $f_m = m \Delta f$, it is assumed, that the necessary number of free frequencies is $n_{cfa} = \frac{f_c}{\Delta f} = 12$. 
Table 1: Parameters of the generated wind field.

| Parameter                                             | Value       |
|-------------------------------------------------------|-------------|
| Mean wind speed                                       | 25 m/s      |
| Turbulence class                                      | A           |
| Number of FFT points                                  | n_{FFT} = 256 |
| Number of frequencies for each wind component         | n_f = \frac{n_{FFT}}{2} = 128 |
| Total time of wind field                              | T = 42 s    |
| Frequency resolution                                  | \Delta f = \frac{1}{T} = 0.0238 Hz |
| Time resolution                                       | \Delta t = \frac{T}{n_{FFT}} = 0.164 s |
| Grid width and grid height                            | 192 m       |
| Spatial resolution                                    | 12 m        |
| Total number of grid points                           | n_p = 17 \times 17 = 289 |
| Number of considered grid points                      | n_{cp} = 172 |
| Number of time constraints                            | n_t = 8     |
| Number of free frequencies of longitudinal wind component | n_{cfu} = 12 |

The other $3 \times n_f \times n_p - n_{cp} \times n_{cfu} = 108,912$ phase angles of the other frequencies, components, and points are not modified during the process. Since the amplitudes $H_{jk,m}$ are not changed, the spectral properties from the spectral wind model such as the auto-spectra in each grid point and the coherences between grid points are maintained. Note that the Fourier coefficients for the longitudinal wind speed and thus the time series of each grid point (including the ones outside the rotor disk) also depend on the phase angles associated to other grid points due to the coupling in Equation (2).

Finally, the error minimization problem can be considered as a system of $n_t = 8$ equations with $n_{cp} \times n_{cfu} = 2064$ unknowns. Here, a gradient-based Levenberg-Marquardt algorithm\(^3\) is used. For the given example, the algorithm converged after three iterations or 2 min on a personal computer using a single core with 2.6 GHz after reaching the stopping criteria (gradient $\nabla J < 1 \times 10^{-4}$, omitting units). Due to the large number of unknowns, a generic algorithm might lead to a faster convergence and will be considered in future work.

Note that in this case, a value of the cost function $J$ close to zero can only be reached for feasible solutions. If for example the turbulence intensity of the wind field is chosen too low, the amplitude of the EOG will not be reachable, since the amplitudes of the superposed sinusoids are defined by the spectral model and scaled by the turbulence intensity. The algorithm will then converge to the closest solution. Thus, the implementation in the cost function $J$ can be considered as “soft constraints”. Additional time constraints such as further points of the rotor effective wind speed or a specific vertical shear during the EOG can be implemented by simply extending the cost function $J$. Competing constraints can be weighted.

3. Ultimate Loads Simulations
In this section, the simulations with the coherent EOG and the turbulent EOG are compared using a feedback control. Then, simulations with feedback control are compared to simulations with additional feedforward control for both the coherent and the turbulent case.

3.1. Comparison of Coherent EOG and Turbulent EOG
In a first step, simulations of the DTU 10MW wind turbine are preformed in GH Bladed disturbed by the coherent EOG and the turbulent EOG, see Figure 2. The simulations with the baseline controller [11] depict that the reactions of the turbine during the coherent and the turbulent EOG (between 10 s and 20.5 s) are very similar. This demonstrates that simulations can be obtained close to current standards with the proposed method.

\(^3\) using `fsolve` of The MathWorks Inc., Matlab R2013b 64 bit, Natick, USA (2013).
In a next step, simulations are performed again with the coherent and the turbulent EOG. Here, the focus is on comparing the feedback controller alone with the same feedback controller combined with a baseline lidar-assisted collective pitch feedforward controller (see [12] for more details). For the combined feedback-feedforward case, two different lidar setups are used: The first setup is a simple point measurement in front of the rotor, see Figure 3a. The second setup is a circular scan pattern considering the limitation to line-of-sight wind speeds and the volume measurements of a pulsed lidar system, see Figure 3b. The scan has been optimized to obtain the best measurement coherence for the SWE scanning lidar system in [13].

For the coherent EOG (Figure 4a), the feedforward controller uses the unfiltered perfect wind preview from the simple staring lidar setup. In this case, the combined feedback-feedforward controller minimizes the variation in the rotor speed almost perfectly and subsequently reduces the tower bending, see Table 2a. This simulation however is unrealistic, since a lidar system is only capable to capture the low frequency part of $v_0$ due to several effects and thus needs to be filtered to avoid harmful and unnecessary control actions [14].

For the turbulent EOG (Figure 4b), the same setup (unfiltered wind preview from the staring lidar) leads to larger rotor speed variation without reducing the loads significantly, see Table 2b. This shows that using a low correlated signal without the appropriate filtering can have a negative impact to the control performance. Similar results have been reported during field testing [15]. Positive impacts are obtained, if the feedforward controller uses the optimized lidar scan pattern, wind field reconstruction and an appropriate low pass filter to cancel out all uncorrelated frequencies (see [13] for details). With this configuration, the lidar system is able to extract the overall effect of the gust and the combined feedback-feedforward controller is able to reduce the maximum value of the tower fore-aft bending moment by $38.5\%$ compared to the feedback only case.

Table 2: Maximum values of simulations.

|                | FB | FB+FF staring | FB+FF optimized |
|----------------|----|---------------|-----------------|
| $\Delta \Omega$ [rpm] | 2.10 | 0.05 | 2.28 |
| $M_{yT}$ [MNm]   | 215.0 | 86.5 | 143.0 |
(a) Simple staring lidar setup.  (b) Optimized lidar scan pattern.

Figure 3: DTU 10 MW wind turbine with two different lidar scan configurations.

(a) Unrealistic simulations with coherent wind.  (b) More realistic simulations with turbulent wind.

Figure 4: Reaction of the DTU 10 MW wind turbine to an EOG at 25 m/s: Feedback controller only (dark blue), combined feedback-feedforward using the simple staring lidar and no filtering (light blue) and using the optimized lidar scan pattern (red, only for turbulent wind).
4. Conclusions and Outlook

The work presents a new method of constrained stochastic simulations. These methods generate wind fields with certain time and spectral properties and thus are promising to perform more realistic ultimate load calculations for lidar-assisted control. Previous methods provide wind fields directly based on complex calculations. This new method fits wind fields in an iterative process to the desired form. The time constraints can be easily implemented in a cost function. The method is demonstrated by fitting an EOG to a turbulent wind field. The wind field is then used to assess the benefits of a lidar-assisted controller for ultimate load reduction. Using a turbulent wind field, a lidar simulator, an appropriate lidar data processing, and a collective pitch feedforward approach, the lidar-assisted controller is able to reduce the maximum value of the tower-base fore-aft bending moment by $38.5\%$ over a baseline controller.

The proposed method can be applied to different types of time conditions. For example, additional conditions can be used for the lateral wind component and the EOG can be combined with a direction change. Further, the wind field can be shaped such that the EOG is only present in a certain section of the rotor disc, etc.

The long-term research goal behind this work is to find a method which can be included in standards for the certification of wind turbines. From our understanding, the following – partly competing – goals are important:

(i) The method should be realistic.

(ii) The method should be reproducible.

(iii) The method should be compatible with current standards.

(iv) The method should be applicable by the industry.

An important step for (i) will be to include wind evolution into the simulations by the method presented in [1], such that the wind field containing the EOG will be an evolved version of the wind field in which the lidar simulation are performed. By including wind evolution models from Large-Eddy simulations [16] or from field measurements [17], the lidar simulation can be done in a more realistic, but still reproducible manner, addressing (ii). However, a method to include the uncertainty in the timing of the signal as reported in [18] might be also useful.

The following procedure might be helpful in order to have compatibility to current standards (iii): The coherent ultimate load simulations could be performed as before, if no lidar is used. For lidar-assisted control, a standard could request a certain number of turbulent simulations similar to fatigue load case, where usually six 10-minute-simulations per wind bin are done. The ultimate loads could then be the maximum value from a certain number of turbulent simulations incorporating the same wind characteristics as the coherent simulations.

In order to address (iv), the advantages and disadvantages between this method and direct constrained stochastic simulations [4, 5, 6] needs to be investigated and the applicability of the methods for industry needs to be assessed. Further, a workshop to initiate guidelines on how to use lidar in the certification process of wind turbines is planned within the IEA Wind Task 32.

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4 www.ieawindtask32.org/about/objectives/loads-and-control/
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