Method for the generation of stochastic wind fields fitted to measurement data in real-time

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Abstract. The excitation of the wind turbine by the wind represents one of the main sources of excitation for the components of the wind turbine. The resulting structural loads can be measured relatively easily. The measurement of wind excitation, however, is much more complex. Even with the latest measuring equipment, such as LiDAR, the spatially and temporally high-resolution wind measurement required for the validation of the load measurement in the time domain can only be realized with a disproportionately high financial outlay and is thus unsuitable for large-scale application in the field. The method presented here shall be able to generate a realistic spatial wind excitation by means of the measured wind information present at each wind turbine, thus enabling model and load validation in the time domain. Furthermore, the method is fast enough to calculate the wind excitation in real time, allowing for application in Hardware-in-Loop or as part of a digital twin of the wind turbine.

Keywords: wind generation, load validation, real-time simulation, stochastic process, CTRW, Ornstein-Uhlenbeck process

1. Introduction
The primary purpose of a wind turbine is the generation of electricity from wind. The excitation of the wind turbine by the wind represents one of the main sources of excitation for the components of the wind turbine. The resulting structural loads can be measured relatively easily with high accuracy and resolution. The measurement of wind excitation, however, is much more complex. Even with the latest measuring equipment, such as high-resolution scanning LiDAR (Light Detection And Ranging technology), the spatially and temporally high-resolution wind measurement required for the validation of the load measurement in the time domain can only be realized with a disproportionately high financial outlay and is thus unsuitable for large-scale application in the field.

The measurement of the wind velocity is usually only punctual and as direction and magnitude of the speed. This information is averaged and used as input to generate stochastic wind fields. Their average and standard deviation again correspond to that of the measured values, but the temporal wind fluctuations between wind measurement data and stochastic wind field vary. That makes it impossible to use the measured wind data directly for the validation of simulation models for wind turbine load analysis in time domain or for any real-time application of these models.
The wind fields have to be pre-simulated for a defined period using standard methods as suggested in IEC 61400-1. They are generated via spectral properties and correlations with the frequency range. The transformation back into the time domain already requires the complete wind field. This precludes the use of such methods in the real-time range, since here the wind information has to be calculated continuously.

This paper is structured as follows: after this introduction, the objectives for the method to be implemented are defined. The theoretical principles of the method and the adaptations carried out by the authors are presented in methodology. After presenting the results, they are critically examined and future work is outlined.

2. Objectives
The method presented here is to be used to reproduce the wind excitation of a wind turbine sufficiently realistically so that it enables a comparison of measured quantities that characterize the performance of the wind turbine, such as loads or produced electrical power, with the same, simulated values in the time domain and in real-time. This results in the following requirements for the method: 1) the method must be able to be solved efficiently and sufficiently quickly so that common integration methods can carry out the necessary calculations in real time while observing the requirements of a real-time model; 2) the method should use wind data measured at the location of the wind turbine in order to be able to take into account the wind conditions prevailing there; 3) the method must provide the wind excitation in such a way that the requirements of the real-time model of the wind turbine are met; and 4) the wind excitation must be sufficiently detailed so that the resulting, simulated behavior of the wind turbine matches real measured variables with sufficient accuracy to enable at least a comparison, ideally a validation, of the behavior of the wind turbine in the time domain.

The requirement for real-time capability comes from the envisaged application scenario. The method is to be applied together with a real-time model of the wind turbine in the field in order to reproduce the behavior of the wind turbine. Possible scenarios are a parallel operation of the real-time model and wind turbine with the model in the role of an observer or for the realistic simulation of the behavior of all wind turbines in a wind farm. In addition, the real-time model can be used for a realistic test of alternative control strategies without the need to intervene in the wind turbine, to name just a few possible applications.

In order to meet the requirements for real-time capability of a model, technologies that have been tried and tested at Fraunhofer IWES should be used. For over 10 years now, Fraunhofer IWES has been developing a real-time load simulation model for wind turbines in the Modelica modeling language, which has been in productive operation as a virtual rotor [1] in the Dynamic Nacelle Laboratory (DyNaLab) [2] [3] for several years. Since Modelica is an object-oriented modeling language, submodels such as the method presented here can be easily encapsulated and executed on separate CPUs. The utilization of the CPUs can be set individually using the discrete integration step size, which prevents buffer overflows of the CPU, which ultimately ensures real-time capability. The integration step size should be adjustable in the range from 0.05 s to 0.001 s, which corresponds to a sampling rate of 20 Hz to 1 kHz. Furthermore, the model complexity should be arbitrarily adjustable via the number of grid points in the simulated wind field.

Details of the implemented method are given in section 3. At this point, the requirements of the real-time load simulation model for the method presented here are to be defined. The real-time load simulation model MoWiT [4] [5] couples physical models for aerodynamics, structural dynamics, hydrodynamics and control and computes them in the time domain. This computational model is developed by Fraunhofer IWES and primarily used for load analysis of (offshore floating [6]) wind turbines as well as for automated simulation [7] and optimization [8].
MoWiT is programmed with the object-oriented modelling language Modelica. Each major component of the wind turbine such as the rotor, the nacelle, the tower, the environmental conditions, and the wind turbine control is implemented as a single object. In essence, MoWiT uses a multi-body approach to model the interaction between the individual structural components. The major structural components like the rotor blades and the tower are modelled as flexible bodies using modal reduced, anisotropic beam elements where the superposed eigenmodes represent the elastic degrees of freedom [9].

The aerodynamics are computed at several points along each rotor blade using an unsteady implementation of the so-called Blade-Element-Momentum Theory (BEM). In each time step of the time-domain simulation, an equilibrium between aerodynamic loads and structural motion is calculated. On the one hand, the aerodynamic loads depend on the relative wind speed as the difference between wind speed and structural motion, and on the other hand, the elastic deformations, and thus the structural motion, depend on the aerodynamic loads. The wind speed used in the aerodynamics can be deterministic or stochastic and accounts for horizontal and vertical inclination, shear, and tower shadow [5]. This strong coupling, called aero elasticity, ensures a realistic computation of the rotor dynamics. The modelling approach of MoWiT is state-of-the-art in wind turbine load analysis.

MoWiT expects a sequence of 2-dimensional wind grids, with the wind speeds in all 3 spatial directions at each grid point. This also includes turbulence. The distance between two neighboring grid points should be less than 10 m. The method presented here should also at least provide this information.

3. Methodology

An alternative method for generating stochastic wind fields, taking into account the intermittent distribution of wind speed increments, was developed by Kleinhans [10]. The method uses the so-called continuous time random walk (CTRW) approach and is therefore able to describe the intermittent and non-Gaussian properties of turbulent 3D flows. The main advantage of this method is that the probability of extreme wind speed increments on small time scales is taken into account much more realistically than with standard methods. The increment of the wind speed \( \delta u \) is defined as the change in the wind speed \( u \) over a period \( \tau \):

\[
\delta u(t) = u(t + \tau) - u(t).
\]

The CTRW method essentially uses a system of coupled Ornstein-Uhlenbeck drift and diffusion processes [12] \( u(s) \), which are solved in a non-physical time domain \( s \) and transformed into physical time \( t \) by Lévy-distributed random numbers. The coupled system of individual stochastic processes is driven by the reference process and the resulting reference wind speed \( u_r(s) \). The reference wind speed is calculated based on the mean wind speed \( u_0 \) over 10 minutes at hub height:

\[
\frac{d}{ds}u_r(s) = - \gamma_r(u_r(s) - u_0) + \Gamma_r(s)\sqrt{D_r},
\]

here \( \gamma_r \) is the damping of the reference process, \( D_r \) is the diffusion constant that influences the effect of the random signal \( \Gamma_r(s) \) on the process, and \( \Gamma_r(s) \) is Gaussian white noise with variance 2, i.e. normally distributed, uncorrelated random number for each \( s \). The first summand contains the drift process which is randomly disrupted by the second summand. The fact that the process is continuously calculated in a time domain eliminates the need for a Fourier transformation as with standard wind-field simulation methods used in the wind turbine context (like Veers [13] or Mann [14]), which makes this approach suitable for calculating the wind speed in real time.

The process is stationary, Gaussian, Markovian, and tends to drift toward its long-term mean \( u_0 \) over time. The three-dimensional wind field \( u^{(k)}(s) \) for each grid point in the rotor plane is calculated from
a system of coupled, stochastic processes. Each individual stochastic process follows the vertically sheared reference wind speed \( u_r(s) \).

\[
d\frac{d}{ds} u_i^{(\kappa)}(s) = -\gamma^{(\kappa)} \left( u_i^{(\kappa)}(s) - \xi_i^{(\kappa)} u_r(s) \right) + \sum_j H_{ij}^{(\kappa)} \left( D^{(\kappa)}, r^{(\kappa)} \right) \Gamma_j^{(\kappa)}(s),
\]

where \( \gamma^{(\kappa)} \) is the damping of the process in each direction \( \kappa = (u, v, w) \), \( \xi_i^{(\kappa)} u_r(s) \) the sheared wind speed profile and \( H_{ij}^{(\kappa)} \) the correlation matrix of the wind speed fluctuations, with the parameters contained therein: \( D^{(\kappa)} \) is the diffusion and \( r^{(\kappa)} \) is the radial correlation of the diffusion of wind speed in the rotor plane.

According to [10], the correlation matrix is given by

\[
H_{ij}^{(\kappa)} = \begin{cases} 
  i \geq j : & \xi_i^{(\kappa)} \exp \left(-\sqrt{\frac{(y_i - y_j)^2 + (z_i - z_j)^2}{r^{(\kappa)}}} \right) \\
  i < j : & 0 
\end{cases}
\]

with the coefficients

\[
\xi_i^{(\kappa)} = \frac{\sqrt{D_{ii}^{(\kappa)}}}{\sqrt{\sum_{k=1}^3 \exp \left(-2\sqrt{\frac{(y_i - y_k)^2 + (z_i - z_k)^2}{r^{(\kappa)}}} \right)}}.
\]

To transform the processes from Eq. 2 and 3 from the non-physical time domain \( s \) to the physical time domain \( t \), an \( \alpha \)-stable, completely distorted, truncated Lévy process is used:

\[
d\frac{d}{ds} t(s) = \tau^c_a(s).
\]

The Lévy distributed random numbers \( \tau^c_a(s) \) are influenced by the characteristic exponent \( \alpha \) and the cut-off parameter \( c \).

The Euler algorithm for solving the differential equations was implemented as described in [10]. The implementation of the time transformation causes difficulties in the algorithmic implementation taking into account the real-time requirement and is therefore not considered for the time being. The time transformation does not affect the properties considered here, as already examined in [20]. Since Kleinhans’ initial introduction, the model has been used by several authors to determine the impact of intermittency on the loads of a wind turbine. In [15] [16], the CTRW model was already adapted to measurement data from the GROWIAN measurement campaign. In [17] [18] [19] [20], the model was also used for various applications. In the latter, a dependency between the diffusion parameters and the required standard deviation \( \sigma \) of the simulated wind time series was set, which inspired us to choose our parameters in Table 1. In [11] a comparison of the resulting design loads in accordance with IEC 61400-1 DLC 1.2 was carried out for different wind models.

In this publication, wind measurement data from the wind measuring mast of the Testfeld BHV project from April 13, 2019 are used, which are recorded with a sampling rate of 1 Hz. The parameters of the simulation in table 1 are calibrated using the wind measurement data at a height of 115 m and the wind velocities at the grid points in the entire rotor plane are generated. The upper index \( (\kappa) \) was omitted if
the same parameter was used for the different wind directions. In section 4, the simulated wind time series are compared with wind measurement data at heights of 25 m, 55 m and 85 m in order to assess the quality of the simulation. The mean values and turbulence intensities, as well as the spatial correlation and the power spectral density (PSD) of the simulated time series are compared with the measurement data. The analysis is limited to the $\kappa = u$ direction of the wind velocity.

### Table 1. Parameters of the CTRW model.

| Parameter | Value |
|-----------|-------|
| $u_0$     | 8.58 m/s¹ |
| $\gamma_r$ | 0.0323 s⁻¹ |
| $D_r$     | 0.0083 σ² s⁻¹ |
| $\gamma$  | 0.152 s⁻¹ |
| $D_{ii}(\kappa)$ | $\gamma k(\kappa) \sigma^2 - \left(\xi_i(\kappa)\right)^2 \frac{\gamma^2}{\gamma + \gamma_r} \frac{D_r}{\gamma_r}$ |
| $r$       | 22 m |
| $\Delta s_{ii}$ | 0.05 s |

In contrast to the previous uses of the CTRW model, the parameter $\sigma$ varies during the simulation. At time $t$ it corresponds to the standard deviation of the wind measurement data at a height of 115 m in the period $(t - 100$ s) to $t$. The parameters $D_r$ and $D_{ii}(\kappa)$ therefore vary over time. This has the effect that changing turbulence is reflected in the simulated wind speeds. The parameter $D_{ii}(\kappa)$ results from the moments of the Ornstein-Uhlenbeck processes as already derived in [15]. The factor $k(\kappa)$ is the pre-factor for the turbulence intensity, which has the values $k_u = 1$, $k_v = 0.8^2$, and $k_w = 0.5^2$ according to the IEC 61400-1 standard. The correlation radius $r(\kappa)$ was set constant for all directions as $r(\kappa) = r$. So far, the parameter $u_0$ has been set as a 10-minute average. A varying $u_0$ has caused an excessive spatial correlation. In the future, $u_0$ will also be smoothly adapted. The shear profile $\xi_i$ was fitted to the wind measurement data.

The method uses the same interface for the exchange of wind information as the MoWiT real-time model in order to be able to provide the wind time series for every spatial direction at every grid point (Eq. 3).

### 4. Results

The wind measurement data from a 10-minute measurement time series are compared with the CTRW simulation. A longer time series was simulated because the parameter $\sigma$ denotes the standard deviation of the last 100 s, which requires a pre-simulation time of at least 100 s. The wind speed time series at a height of 115 m is plotted in figure 1. The varying turbulence intensity over time is reflected in the simulation data. In order to adjust the turbulence intensity and the spatial and temporal correlations, the parameters had to be varied. The mean wind speed $\bar{u}$ and the turbulence intensity $TI$, which by

$$TI = \frac{\sigma}{\bar{u}}$$  \hspace{1cm} (7)

is linked to the standard deviation are compared in Table 2. The high agreement of the mean wind speeds is due to the adaptation of the shear profile $\xi_i(\kappa)$ to the measurement data. Furthermore, the deviations in the turbulence intensities would be larger if the standard deviations of the time series varied more with the height. By adapting the diffusion parameter $D_{ii}(\kappa)$, a varying standard deviation could also be taken into account in the model.
Table 2. Comparison of the mean wind speed \( \bar{u} \) and the turbulence intensity TI of 600 s time series of the measurement data and the simulation with the CTRW model.

| height [m] | \( \bar{u} [\text{m/s}] \) measuring data | \( \bar{u} [\text{m/s}] \) CTRW | Relative deviation of \( \bar{u} \) [%] | TI [%] - measuring data | TI [%] - CTRW | Relative deviation of TI [%] |
|-----------|--------------------------------------|----------------------------|----------------------------|-----------------|-----------------|-----------------------------|
| 115       | 8.58                                 | 8.56                       | 0.17                       | 8.85            | 8.49            | 4.02                        |
| 85        | 7.61                                 | 7.60                       | 0.17                       | 9.74            | 9.57            | 1.71                        |
| 55        | 6.45                                 | 6.43                       | 0.20                       | 11.78           | 11.31           | 4.02                        |
| 25        | 5.44                                 | 5.44                       | 0.00                       | 13.00           | 13.37           | 2.88                        |

Figure 1. Comparison of the wind time series at height 115 m. The varying standard deviation of the measurement data is reflected in the simulation.

The power spectral density (PSD) is typically considered in order to compare the time series in their frequency characteristics. The course is approximately described by the Kaimal spectrum

\[
S_{uu}(f) = \frac{4 L_u/L_{hub}}{(1 + 6fL_u/L_{hub})^{5/3}}.
\]  

(8)

In figure 2, the PSD of the 600 s measurement data and simulation data is plotted at a height of 115 m. Since the measuring data has a sampling rate of 1 Hz and the simulation data has a sampling rate of 20 Hz, the spectrum of the simulation data extends further. Apart from that, they show a good agreement. If averaged over many simulated time series, the fluctuations would decrease, and the course would be smoother.
Figure 2. Power Spectral Density (PSD) of the 600 s wind time series at 115 m height. The scale parameter $L = 340.2$ m and the mean wind velocity $\overline{u}_{hub} = \frac{8.58}{s}$ m was taken for the Kaimal spectrum (Eq. 8) according to IEC 61400-1.

According to the Wiener-Khinchin theorem, the PSD is the Fourier transform of the autocorrelation, which describes the temporal correlation of a wind time series with itself. In addition to temporal correlations, we also want to ensure spatial correlations of the simulation data. To compare spatial correlations of two time series at the heights $z_1$ and $z_2$, the Pearson correlation coefficient is considered:

$$\rho_{1,2} = \frac{\sum_i (u(z_1, t_i) - \overline{u}(z_1))(u(z_2, t_i) - \overline{u}(z_2))}{\sigma_{z_1}\sigma_{z_2}}.$$  

The expected exponentially decreasing correlation is taken into account in Kleinhans’ correlation matrix (4). In the measurement data, however, this is only apparent in the case of longer time series, which is why a 3600-second time series was used to evaluate the spatial correlation. In figure 3, the correlation coefficient $\rho$ of the measurement data and the simulation data are compared. Up to a distance of 60 m, the CTRW model shows good agreement with the measurement data. The correlation of the simulated time series at a distance of 90 m is higher than that of the measurement data. Even at higher distances, the value of the measurement data is not met because the correlation in the selected parameters does not fall below a certain minimum value due to the dependence on the reference process. A different correlation could perhaps be achieved with a different choice of parameters. It should be noted that the correlation radius $r = 22$ m in the CTRW model does not correspond to the correlation radius $r = 31.61$ m in the spatial correlation. This is because $r$ describes the correlation radius of the diffusion terms $\sum_j H^j_H (D^k, r^k)I^j_H(s)$ in (Eq. 3) and not the correlation of the processes $u^i(s)$. The processes $u^i(s)$ are more correlated due to their dependence on the reference process $u_r(s)$. 

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Figure 3. The spatial correlation coefficient of the measuring data and the simulation is compared for 3600 s time series.

5. Conclusions
This work describes a method for generating stochastic wind fields in real-time using measurement data. The essential properties of the measurement data are reproduced by the simulated wind data such as mean wind speed, turbulence intensity, spatial correlation and frequency spectrum. The standard deviation of the simulation, and thus the turbulence intensity, follows the standard deviation of the measurement data. However, this only works well in the entire wind field if the standard deviation of the measurement data is relatively constant over the height. Depending on the location of the wind turbine, this is not always the case. Contrary to the original theory of the CTRW, no time transformation has been carried out in the method presented here. Although the essential properties of the wind measurement data can nevertheless be reproduced, the time transformation should be added later in order to also be able to map the intermittent properties of measured wind data. In addition to the standard deviation, the method should also follow the mean wind speed of the measurement data in the future, which is not yet used during the verification of the method.

The approach of using the measured wind time series directly and thus replacing the reference process (Eq. 2) has proven difficult. Theoretically, this procedure works, but leads to a much poorer spatial correlation between the measured and the simulated time series. The indirect use of the measurement data now used consequently leads to deviations in the time series. This can impair the validation of simulated and measured loads in the time domain, which is the aim of the method. For this reason, this approach will continue to be investigated in the future, so that the simulated wind field and the measurement data fit together sufficiently precise in the time domain.

Since the method is formulated based on equations and is continuously solved in the time domain, real-time application is basically given. The authors see the first concrete applications in various future research projects. A first step to fulfil the 4th requirement of the method from section 2 is to take place in the project Testfeld BHV and aims to use the method together with the MoWiT real-time model to reproduce the measured time series of loads of a 8 MW wind turbine. In addition, wind measurement data with higher resolution are then available in order to check the suitability of the method even on smaller time scales.
Acknowledgements

This research was realized within the Testfeld BHV project FKZ 0324148, which was funded by the German Federal Ministry for Economic Affairs and Energy. The authors thank Dr. Julia Gottschall (Fraunhofer IWES) for advice on statistical analysis of wind data and for the provision of suitable measurement time series. The authors also thank Dr. Matthias Wächter, and Sebastian Ehrich (ForWind, Institute of Physics, Carl von Ossietzky University Oldenburg, Germany) for support in implementing the stochastic process and selecting suitable parameters.

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