Gaussian vs non-Gaussian turbulence: impact on wind turbine loads

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ABSTRACT

From large-eddy simulations of atmospheric turbulence, a representation of Gaussian turbulence is constructed by randomizing the phases of the individual modes of variability. Time series of Gaussian turbulence are constructed and compared with its non-Gaussian counterpart. Time series from the two types of turbulence are then used as input to wind turbine load simulations under normal operations with the HAWC2 software package. A slight increase in the extreme loads of the tower base fore-aft moment is observed for high wind speeds when using non-Gaussian turbulence but is insignificant when taking into account the safety factor for extreme moments. Other extreme load moments as well as the fatigue loads are not affected because of the use of non-Gaussian turbulent inflow. It is suggested that the turbine thus acts like a low-pass filter that averages out the non-Gaussian behaviour, which is mainly associated with the fastest and smallest scales. Copyright © 2016 John Wiley & Sons, Ltd.

KEYWORDS

loads; large-eddy simulation; atmospheric turbulence; proper orthogonal decomposition; aeroelastic simulation

1. INTRODUCTION

In homogeneous isotropic turbulence, the probability density functions (pdfs) of the velocity components are Gaussian. This has been shown to a good approximation both experimentally1 and with direct numerical simulation.2 Because of these results and numerical convenience, many researchers studying wind loads on turbines from the naturally occurring atmospheric turbulence have used the assumption that the entire turbulent inflow field is Gaussian. Based on the work of Shinozuka,3, 4 Veers introduced an inflow turbulence generator based on spectra, such as the Kaimal spectrum,5 and two-point cross-spectra,6 while Mann proposed a model based on a 3D spectral velocity tensor.7, 8 These models are now extensively used and are included in the International Electrotechnical Commission on wind turbine loads.9

Turbulent fields are, however, not Gaussian, especially the smaller scales, characterized in terms of the statistics of velocity differences between points with some distance apart, that exhibit large departures from a Gaussian distribution. Infinitesimal velocity derivatives such a vorticity and energy dissipation are very far from being Gaussian.2, 10 In the atmosphere, turbulence is also non-Gaussian at larger scales as observed in the positive skewness of the vertical wind component during convective atmospheric conditions over flat terrain in comparison with neutral stratification where it is close to zero.11, 12 These deviations from normality are used routinely in dispersion modelling in the convective boundary layer, where the non-Gaussian pdf is modelled as a sum of several Gaussian functions.13 Large departures from Gaussian velocity fields are also expected in complex terrain. For example, highly positively skewed distributions of the along-wind horizontal velocity component close to a canopy edge were observed.14, 15 Furthermore, we might suspect intermittency in the recirculation zones surrounding complex terrain, although clear indications of this remain to be observed.

In order to clarify the role of non-Gaussianity on wind turbine loads, investigators have deployed various simplified models that modify the statistics of the velocity field. Gong et al16 used a Hermite polynomial transformation of a Gaussian field to produce fields with any given kurtosis; see also Nielsen et al.17 and Nielsen, Larsen and Hansen.18 Gong’s method
requires some iterations to both match the (cross)-spectral densities and prescribed one-point pdf of the velocities. The method provides no guarantee that the pdfs of the velocity differences are realistic. Moreover, some physical properties of the fields, such as incompressibility and fluxes of momentum, may not be realistically obeyed.

Mücke et al.\textsuperscript{19} generated non-Gaussian time series with excess kurtosis by the method of continuous time-random walks. The statistics of the generated velocity increments was Gaussian at large time scales but had large kurtosis at small scales. That was partly in contrast to their measurements, which showed intermediate excess kurtosis at all time scales. The simulation model of Mücke et al. does not produce skewness of the velocity increments, which is a fundamental property of small-scale turbulence.\textsuperscript{20} Nevertheless, they successfully reproduced the excess kurtosis of simulated rotor torque increments calculated from their Growian measurements of wind speeds from an array of anemometers where the corresponding Gaussian simulation had close-to-zero excess kurtosis. However, their rain load cycle counts from the Gaussian and non-Gaussian simulations were more or less identical, so it was not shown that non-Gaussianity, in this case, influenced the loads. Methodologically, the continuous time-random walks do not easily match a prescribed spectrum hampering direct comparison with standard methods. A similar study is reported in Wachter et al.\textsuperscript{21} Here, the findings of strong non-Gaussian signatures of increments in time of the rotor torque are expanded to also include analysis of the torque and the power output itself. No results on fatigue or extreme loads, which as you will learn are central to our work, are however reported.

In contrast, in this paper, we devise a method where non-Gaussian fields generated by large-eddy simulation (LES) are transformed so they maintain the exact same second-order statistics including variations of the statistics with height, both regarding shear and veer, but are otherwise Gaussian. In that way, we can investigate in isolation the question whether it is important to include non-Gaussian properties of atmospheric turbulence when estimating for wind turbine loads.

Extreme loads are driven by a combination of instantaneous increase in wind velocities at discrete spatial regions over the wind turbine rotor coupled with the response of the wind turbine control system in modifying the blade pitch and rotor speed. Therefore, the presence of sudden and large excursions in wind velocity, which is typically reflected in high third-order or fourth-order moments of wind turbulence as can be found in a non-Gaussian process, may lead to higher extreme loads on the turbine. Proper orthogonal decomposition (POD) methods, as for example the principal component analysis, have been used to understand these driving mechanisms for extreme loads on wind turbines,\textsuperscript{22} but such methods only reveal the effects of Gaussian processes. Therefore, a comparison of load simulations using non-Gaussian and Gaussian inflow turbulence will help in answering the question as to whether the turbulence peaks giving larger higher-order moments contribute to a significant increase in the extreme loads. With regard to fatigue loads (the load response to turbulent fluctuations on all scales), the presence of large higher-order moments in the turbulent signal has not been investigated to our knowledge.

In this paper, we will study the influence of a Gaussian versus a non-Gaussian turbulent inflow on the wind turbine loads, both fatigue and extremes, from the perspective of high-resolution LES of the atmospheric boundary layer.\textsuperscript{23} By solving a Karhunen–Loève integral,\textsuperscript{24} we can create Gaussian representations with exactly the same second-order statistics as the non-Gaussian LES data. These representations together with the original LES data serve as the foundation for a load study conducted with the HAWC2\textsuperscript{25} load simulation software package. In the diagram in Figure 1, we summarize the analysis performed in this paper.

The paper is organized as follows: Theory, and the foundation of our work, the LES, are presented in Section 2. In Section 3, we verify that our constructed Gaussian fields have indeed the same second-order statistics as the LES data. Finally in Section 4, we use the two types as inflow to HAWC2, and study the impact on fatigue and extreme loads. In the end, a Discussion and a Conclusion summarize our findings.

## 2. THE CONSTRUCTION OF GAUSSIAN DATA FIELDS

The basis of the analysis is high-resolution data generated with the pseudo-spectral LES code by Sullivan and Patton.\textsuperscript{23} The code simulates the Atmospheric Boundary Layer (ABL) over a flat, homogeneous terrain with high temporal and spatial resolution, and three simulations have been created covering different atmospheric stabilities.

In Figure 1, two paths are laid out: a Gaussian and a non-Gaussian. While the LES fields themselves are non-Gaussian, the Gaussian demands some extra work: a POD.

### 2.1. Large-eddy simulation

We use 20 three-dimensional snapshots of the full velocity field, $u_0(x)$, spanning heights between 50 and 150 m (approximately the rotor size of a medium-sized wind turbine), and with horizontal dimensions (2.4 $\times$ 2.4 km). The number of points in the snapshot is given by $n_x = 600, n_y = 600$ and $n_z = 41$, while the spatial resolution is $\Delta x = 4$ m, $\Delta y = 4$ m and $\Delta z = 2.5$ m. The utilized snapshots are separated by approximately 10 min, while the temporal resolution follows from the Courant-Friedrichs-Lewy (CFL) condition.\textsuperscript{26} The flow is forced by a mean pressure gradient corresponding to a height-independent geostrophic velocity of 5 m s\(^{-1}\). The surface roughness is 0.3 m, while the surface heat flux, $\langle \theta^i w'^i \rangle_0$, is...
Figure 1. The road ahead: (top) the starting point is the LES of the atmospheric boundary layer. From this simulation, two paths are followed: Gaussian: a POD analysis is performed, and non-Gaussian. (middle) Both Gaussian and non-Gaussian 3D fields are transformed into boxes of inflow turbulence by going through a number of steps. (bottom) Both Gaussian and non-Gaussian data sets are used as input for wind turbine load simulations with HAWC2.

0. Above the boundary layer, the lapse rate is slightly stable, $d\theta/dz = 0.003 \text{ K m}^{-1}$, allowing for entrainment of potential temperature into the boundary layer, i.e. $\langle \theta' w' \rangle < 0$ for $z > 0$, thus rendering the stratification conditionally neutral.

The height of the boundary layer is estimated to 616 m. Other studies using the same data are presented in Chougule et al.27 and Berg, Mann and Patton.28

2.2. Proper orthogonal decomposition

The goal is to create a Gaussian incompressible velocity field, $u_0^g(x, y, z)$, from the original LES velocity field, $u_i(x, y, z)$, with identical second-order statistics. To do this, we create a representation through a decomposition of proper orthogonal functions.

The starting point is the spectral tensor, $\hat{\Phi}_{ij}(k_x, k_y, z, z')$, where $k_x$ and $k_y$ are the horizontal wave numbers and $z$ and $z'$ are heights. In horizontally homogeneous turbulence, the second-order statistics is described completely by the spectral tensor alone and is given by

$$\Phi_{ij}(k_x, k_y, z, z') = \frac{1}{(2\pi)^2} \iint R_{ij}(\Delta x, \Delta y, z, z') e^{-i(k_x \Delta x + k_y \Delta y)} d\Delta x d\Delta y, \hspace{1cm} (1)$$

where

$$R_{ij}(\Delta x, \Delta y, z, z') = \langle u_i(x, y, z) u_j(x + \Delta x, y + \Delta y, z') \rangle \hspace{1cm} (2)$$

is the spatial covariance tensor. Because the statistics of a Gaussian field is determined completely by its second-order statistics,24 equation (1) is the obvious starting point for our representation of Gaussian fields.

We generate the Gaussian fields using $3n_z$ basis functions, $\phi^{(n)}$, which are eigenfunctions of the Karhunen–Loève integral24

$$\int_{z_{\text{min}}}^{z_{\text{max}}} \Phi_{ij}(k_x, k_y, z, z') \phi_j(k_x, k_y, z') dz' = \lambda(k_x, k_y) \phi_i(k_x, k_y, z). \hspace{1cm} (3)$$
The integration limits \( z_{\min} \) and \( z_{\max} \) will henceforth be omitted. This procedure is performed for every pair of \( k_x \) and \( k_y \). Using the trapezoidal rule, one can easily expand the left-hand side of equation (3) for a given \( k_x \) and \( k_y \) (which are omitted in the notation for clarity) and obtain the discrete eigenvalue problem

\[
A v = \lambda v
\]

(4)

where \( A \) is a \( 3n_x \times 3n_z \) matrix with complex eigenvectors given by

\[
v = \{ \phi_1(z_{\min}), \ldots, \phi_1(z_{\max}), \phi_2(z_{\min}), \ldots, \phi_2(z_{\max}), \phi_3(z_{\min}), \ldots, \phi_3(z_{\max}) \},
\]

(5)

with normalization

\[
\int \phi_i^{(n)}(z) \phi_j^{(m)}(z) dz = \delta_{nm},
\]

(6)

where \( * \) denotes complex conjugation.

A representation of the velocity field, \( u_i(x, y, z) \), can then be constructed from (here given in Fourier space)

\[
u_i(k_x, k_y, z) = \sum_n a_i^{(n)}(k_x, k_y) \phi_i^{(n)}(k_x, k_y, z),
\]

(7)

where \( a_i^{(n)} \) are uncorrelated coefficients. Solving equation (7), we obtain

\[
a_i^{(n)}(k_x, k_y) = \int u_i(k_x, k_y, z) \phi_i^{(n)}(k_x, k_y, z) dz.
\]

(8)

From the aforementioned equations, it can easily be verified that the coefficients \( a_i^{(n)} \) are

\[
\langle a_i^{(n)}(k_x, k_y) a_j^{(m)}(k_x, k_y) \rangle = \lambda_i^{(n)}(k_x, k_y) \delta_{nm}.
\]

(9)

In addition, the new velocity field is incompressible.

In order to create Gaussian data fields, we want to leave all second-order statistics unchanged. This is fulfilled by the following expression:

\[
v_i^{\text{G}}(k_x, k_y, z) = \sum_n \gamma(n) \sqrt{\lambda_i^{(n)}(k_x, k_y)} \phi_i^{(n)}(k_x, k_y, z),
\]

(10)

where \( \gamma(n) \) are independent complex Gaussian stochastic variables with zero mean and unit variance (equally distributed on the real and imaginary part). Inserting equation (10) into equation (8), we recover equation (9).

The discrete version of the spectral tensor given in equation (1) is a very large numerical object. In single precision, it amounts to \( 9 \times 41 \times 41 \times 600 \times 600 \) four-byte reals equivalent to 22 GB. We can, however, take advantage of the following symmetry (for a given set of wave numbers, \( k_x \) and \( k_y \))

\[
\Phi_{ij}(z, z') = \Phi_{ji}^*(z', z).
\]

(11)

This means that we only need to calculate \( \Phi_{ij}(z, z') \) for \( z \geq z' \).

The complex eigenvalue problem in equation (4) needs to be solved for each combination of \( k_x \) and \( k_y \). The explicit spatial filtering in Fourier space of the LES, where the upper one-third wave numbers in each horizontal direction are eliminated in order to avoid dealiasing,\(^{23}\) means that only four-ninth of the individual wave numbers are actually non-zero. We use the FFTW version 3.3.3 (www.fftw3.org) for the two-dimensional Fourier transforms.

A horizontal plane of the constructed Gaussian velocity field, \( u_i^{\text{G}} \) at \( z = 100 \) m is presented in Figure 2. The top panels show the \( x \)-component, which is aligned with the geostrophic wind, not the local mean wind direction. It looks like the maximum and minimum values are slightly reduced (most dark and most bright). The spatial structures in the Gaussian field are smaller and look more erratic compared with more fluid-like structures, viz a Michelangelo sketch, in the original LES.

The bottom panels show the vertical component. The picture is now even more pronounced: the swirling fluid structures in the original LES (left) are completely gone in the Gaussian field.

3. TIME SERIES OF TURBULENCE

The HAWC2 wind input consists of time series of 10 min of spatially varying turbulence covering the rotor area. In the present study, we use a turbine with a rotor diameter of 126 m and a similar hub height at 126 m (more on the particular choice of turbine in Section 4). In order to meet these dimensions and taking into consideration the fact that a full load simulation needs many different inputs with varying mean wind speed at hub height, we transform our 3D fields of Gaussian and non-Gaussian turbulence into boxes of inflow turbulence time series.
3.1. Transformation

The following transformations of the flow fields (as presented in Figure 2) have been performed:

1. All physical dimensions are stretched a factor of 1.26 in order to meet the rotor dimensions of the wind turbine in question (D=126 m).
2. All wind speeds are rescaled to match the desired hub height wind speed.
3. The coordinate system is rotated so that the mean wind vector is along the x-axis at hub height.
4. The final time series are created by advecting y-z planes past a virtual rotor plane-sensor. We thus rely on Taylor’s frozen turbulence hypothesis.
5. Different realizations of each flow configuration (with a specific mean wind speed at hub height) are generated by using different seeding of the Gaussian random numbers in equation (10). In this way, we can enlarge the ensemble of Gaussian inflow turbulence time series. The non-Gaussian realizations each stems from a different snapshot in time of the original LES fields. We use 20 realizations for both the Gaussian and the non-Gaussian time series.
The inset presents the normalized fourth-order structure function, the kurtosis, kurtosis value of 3 are evident. This is a consequence of the scaling of velocities performed: let us think of two points

\[
\frac{\langle \delta w(t) \rangle}{\sigma} \quad \text{and} \quad \frac{\langle \delta w(t + \tau) \rangle}{\sigma}
\]

for \( U = 6 \text{ m s}^{-1} \), \( U = 14 \text{ m s}^{-1} \) and \( U = 22 \text{ m s}^{-1} \).

The final dimensions of the turbulence boxes are \( 32 \times 32 \times 4096 \) corresponding to \( 126 \times 126 \text{ m} \times 10 \text{ min} \). This corresponds to a spatial resolution of approximately 4 m and a temporal resolution of approximately 0.15 s. We have created 24 realizations of each hub height mean wind speed ranging from 6 to 24 m s\(^{-1}\) in steps of 2 m s\(^{-1}\).

The aforementioned multiplication of all velocities with a constant factor has some consequences, cf. the second aforementioned item: In physical terms, it means that all terms in the governing equations are scaled (the LES equations i.e. the spatially filtered Navier–Stokes equations). Because the LES is filtered at scales much larger than the dissipative scales, there is no viscous dissipation in the LES governing equations, and the only terms that do not scale accordingly are the Coriolis force and the buoyancy term. Because the buoyancy term is very small at the heights of interest (50–150 m), only the Coriolis term is important: multiplying all velocities with a constant factor larger than one thus has the consequence that the Earth spins faster or the latitude is increased. That is, the turbine is in practice positioned further towards the north. We have conducted LES with different values of the Coriolis parameter, and no change in the higher-order statistical moments of velocity increments, characterizing the non-Gaussian aspect of the flow, was observed (see next paragraph): we do therefore not expect this effect to impact the difference between the loads obtained from that of the HAWC2 simulations of the original LES time series and the Gaussian counterpart, presented in Section 4.

The focus in Mucke, Kleinhaus and Peinke\(^{19}\) is the velocity increments. In Figure 3, we therefore present the pdf of the vertical velocity increments, \( \delta w(t) = w(t) - w(t + \tau) \), for different time lags, \( \tau = 1, 7 \) and 30 s for \( U = 6 \text{ m s}^{-1} \). At \( \tau = 1 \text{ s} \), i.e. at the smallest scales, the pdf is clearly non-Gaussian, while it becomes close to Gaussian at \( \tau = 30 \text{ s} \). The inset presents the normalized fourth-order structure function, the kurtosis, \( Kuw = \langle \delta w(t) \rangle^4 / \langle \delta w(t) \rangle^2 \), of the pdfs for \( U = 6, 14 \) and 22 m s\(^{-1}\) as a function of \( U \tau \). The collapse and the expected convergence towards the Gaussian kurtosis value of 3 are evident. This is a consequence of the scaling of velocities performed: let us think of two points at a small distance in the initially 3D turbulence field. In the constructed time series of turbulence, the separation in time will increase with increased mean velocity, \( U \). From this follows that the turbulence in our time series is more non-Gaussian for low mean wind speeds compared with the turbulence for large mean wind speeds. Similar results are obtained for the two horizontal velocity components. In contrast to the turbulence generated and analysed in Mucke, Kleinhaus and Peinke\(^{19}\), the skewness of the distributions of velocity increments in this study is negative, as predicted by the Navier–Stokes equation.\(^{20}\)

The alternative to rescaling the velocity would be to run several LES with different forcing, in practice, a pressure gradient balanced by a geostrophic wind. These runs would develop slightly different boundary layers because of a different amount of turbulent kinetic energy generated by shear production. As a consequence, the capping inversion, defining the height of the boundary layer, would be positioned at different heights, \( z_i \), which in return would change the entrainment of potential temperature into the layers where the wind turbine is positioned, and hence alter the kinetic energy balance. A comparison of loads within the same mean wind speed interval would, however, not be influenced by this change in kinetic energy balance. Because the focus in this paper is on the difference in loads from Gaussian versus non-Gaussian time series, we choose our aforementioned computationally much cheaper rescaling approach and remind the reader that the exact numerical values of the loads are not suitable for quantitative comparisons between different wind speeds.

### 3.2. Verification of time series

In order to verify the statistical moments of the Gaussian fields generated through equation 10, we compare them with similar ones constructed from the original LES velocity field snapshots.
In Figure 4, we show how the pdfs of the velocity increments are now all close to Gaussian for various time separations. The contrast to Figure 3 is striking.

First, we compare statistical moments. These are presented in Figure 5 for $U = 12 \text{ m s}^{-1}$. The original LES and Gaussian profiles for covariances (panel a) and variances (panel b) show very similar values: the vertical structure is reproduced within the width of the error bars, which we have calculated as standard deviations of the mean, $\sigma_{\mu}/\sqrt{N}$, where $N = 20$.

Moving to the skewness, the normalized centralized third-order moment (panel c), and the kurtosis the normalized centralised fourth-order moment (panel d), the Gaussian transformation becomes very clear: Whereas the original LES data display the pronounced positive skewness for the $w$ component (green curve in panel c) and slightly negative values for the horizontal components, $u$ and $v$, all three components approach zero skewness in the Gaussian case as expected. For the kurtosis, the picture is similar: In the Gaussian case, all three components approach the value 3.
Finally, we will inspect the spectral properties of the constructed Gaussian velocity fields. We check that both amplitudes and phases agree with the original LES data because differences would change the forces on the wind turbine and hence the loads.

The cross-spectrum is defined by

\[
\chi_{ij}(k_x, \Delta y, z, z') = \frac{1}{\sqrt{2\pi}} \int \Phi_{ij}(k_x, k_y, z, z') e^{i(k_y \Delta y)} dk_y,
\]

where \( \Phi_{ij}(k_x, k_y, z, z') \) is the spectral tensor defined in equation (1) and \( \Delta y \) is a given distance along the \( y \)-axis. From the cross spectrum, we can define the coherence, \( \text{coh} \), and phase, \( \varphi \), respectively:

\[
\text{coh}_{ij}(k_x, \Delta y, z, z') = |\chi_{ij}(k_x, \Delta y, z, z')|^2
\]

\[
\varphi_{ij}(k_x, \Delta y, z, z') = \arg(\chi_{ij}(k_x, \Delta y, z, z'))
\]

with the one-dimensional spectrum, \( F_i(k_x, z) = \chi_{ii}(k_x, 0, z) \). Results are presented in Figure 6 for horizontal separations at hub height and in Figure 7 for vertical separations around hub height.

In Figure 6, the phases are presented for the three components in the top panels. Even though the scatter is rather large, the symmetry, \( \varphi_{ij}(k_x, \Delta y) = -\varphi_{ji}(k_x, -\Delta y) \) is recovered for separation, \( \Delta y = \pm 32 \text{ m} \) and \( \Delta y = \pm 59 \text{ m} \), and components, \( i = 1, 3 \), while it is close to zero for the smallest separations, \( \Delta y = \pm 16 \text{ m} \). Furthermore and more important is the agreement between the original LES and their corresponding Gaussian curves. The coherences are given in the bottom panels. The classical feature of decreasing coherence with wave number at increasing separation and largest observed coherence for the cross-wind component, \( v \) (blue curve), is observed. Again, we see a match between Gaussian and non-Gaussian data.

In Figure 7, we look at separations in the vertical direction. The known physical feature with largest phases observed for the cross-wind component, \( v \), is observed as well as increasing phases for increased vertical separation, \( \Delta z \). For all separations, \( \Delta z \), and all components, \( j \), we observe similar behaviour between the Gaussian and non-Gaussian data. For the coherences, we observe how the largest coherence moves from the vertical to the cross wind component as the separation increases. Again, we observe similar behaviour for the Gaussian and non-Gaussian data.
We have also looked at cross ($i \neq j$) component spectra (not shown) and find a similar agreement between the two data sets. We can therefore conclude that we have succeeded in transforming the non-Gaussian LES data into Gaussian counterparts. We therefore carry on with a direct comparison of the loads from the two data sets using HAWC2 in order to quantify the effect of non-Gaussianity.

**4. LOAD CASES**

The NREL 5 MW reference turbine is used for the simulations. The machine has a rotor diameter of 126 m with a hub height of 90 m. The turbine was assumed to be land-based with a rigid foundation. Because of the extent of the vertical domain of our LES, we assume that changes in the hub height (from 126 to 90 m) do not alter the loads because we assume similar wind shear and veer. This is a fair assumption because all the operational mean wind speeds are simulated using the aeroelastic software HAWC2, and are hence independent on the specific hub height. The test turbine represents a modern turbine, and it is therefore relevant to know the impact of non-Gaussian atmospheric turbulence on the loads.

Following the International Electrotechnical Commission (IEC) 61400-1 Ed.3 standard, the critical load case DLC 1.1 (normal turbulence conditions) is run for extreme and fatigue load predictions. The moments related to the blade, tower and main shaft are simulated. We will run the load case using both the original LES data (non-Gaussian) and the Gaussian data set. If significant differences are observed in the extreme and fatigue loads on the individual components based on the two data sets, it indicates that the higher statistical moments present in the non-Gaussian atmospheric turbulence are relevant to include in simulations.

The load simulations are performed with 20 random seeds (generated following item 5 in Section 3.1) at each mean wind speed ranging from 6 to 24 m s$^{-1}$. In common practice, when the Mann wind turbulence model is applied as per the IEC 61400-1 Ed.3 Annex B, it is often required to scale the standard deviation of the wind velocities in the individual boxes of turbulence to the required IEC turbulence classes. A rescaling of each individual box of turbulence distorts the total turbulence spectra, although it preserves the overall integral of the spectrum, i.e. the variance. Also, in the IEC turbulence model, the turbulence intensity increases for decreasing mean wind speeds in order to reflect non-neutral flow cases occurring for low wind speeds. In our case, the turbulence intensity is constant for all mean wind speeds as a result of the velocity scaling, thus referring to neutral conditions only. In this regard, our study hence differs from the IEC standard. The spread of longitudinal turbulence intensity at hub height is presented in Figure 8.

The error bars, the standard error of the mean, are largest in the case of Gaussian turbulence. For all wind speeds, the two sets are within the error bars, making the data set valid for load comparison.
Figure 8. Longitudinal turbulence intensity, $I_{LU}$, for both Gaussian (red) and non-Gaussian (blue) input data at hub height. A horizontal offset between red and blue data points have been added for increased readability.

Figure 9. Extreme moments as a function of mean wind speed, $U$: non-Gaussian LES (blue) and Gaussian (red) for (a) blade root flap, (b) blade root edge, (c) tower base fore-aft, and (d) tower base side. A horizontal offset between red and blue data points have been added for increased readability.

Because of the aforementioned lack of scaling to IEC turbulence classes, the load case DLC 1.1 run performed in this paper does not conform to an IEC class. This approach does not in any way affect the comparison of extreme loads between the two wind models as any differences in loads due to non-Gaussian behaviour will still be captured.

4.1. Extreme loads

The absolute maximum from each 10 min simulated load sample at each mean wind speed bin is obtained. Figure 9 shows the absolute maxima of the blade root moments and tower base moments for non-Gaussian (blue) and Gaussian (red) inflow turbulence, respectively.

The variation in loads observed (points on a vertical line) within a given mean wind speed bin among the different seeds is significant in all four plots. In order to conclude more, we plot the mean over all seeds of the extreme loads at each mean wind speed with error bars given by standard deviation of the mean.

The means are presented in Figure 10. In panel c, showing the tower base fore-aft moment, we observe large scatter for mean wind speeds higher than $20 \text{ m s}^{-1}$, and there is a tendency that the non-Gaussian-based extreme moments are marginally higher. We also calculated the $p$-values (not shown) based on a $t$-test assuming that the individual extreme moments are Gaussian and that the standard deviations are equal between the two populations. The values came out above
0.1 in most cases, making the difference between the two data sets statistical insignificant, as we can also observe in panels a, b and d. On the other hand, the extreme moments need not be Gaussian. If we furthermore take into account a partial load safety factor of 1.35 (the load factor using an extreme value turbulence model—not performed in this study), the difference between the non-Gaussian data and the Gaussian data is well within the margin of the safety factor, and hence, the difference is insignificant.

In Figure 11, we compare the mean extreme main shaft and the tower top moments between the two populations. In none of the panels do we observe any significant difference between two sets.
4.2. Fatigue loads

The fatigue design loads are usually determined by simulating operational conditions with normal turbulence wind input from cut-in to cut-out mean wind speeds and also for wind turbine start-ups and shut-downs under normal conditions. Herein, the start-up and shut-down conditions are not considered, and further, as mentioned earlier, the turbulence intensity is not as per IEC standard classes. Rain flow counting methods process the simulated load time series over all turbine components to determine the damage equivalent loads (also denoted damage equivalent moments), which are thus...
defined as

$$S_{eq} = \left( \sum \frac{n_i}{N_{eq}} \right)^{1/m} \quad (15)$$

where \( n_i \) is the number of cycles at load/stress of \( S_i \), \( m \) is the S–N curve slope of the component material (herein considered 10 for glass fiber blades and 4 for the drivetrain and tower) and \( N_{eq} \) is the characteristic number of cumulative cycles in 20 years of operation (\( N_{eq} = 8.6 \cdot 10^5 \)) assuming a Rayleigh annual mean wind speed distribution. The damage equivalent moments for the blade, tower top and tower base are computed based on the \( S_{eq} \) and presented in Figures 12 and 13.

In neither Figure 12 and 13 do we observe any significant difference in the Damage Equivalent Moment (DEM) based on the two populations. That is, higher-order statistical moments in the inflow turbulence seem not to be crucial when estimating turbine fatigue.

5. DISCUSSION

An effective method to compute Gaussianized 3D turbulent time series over a spatial region has been developed. The time series are constructed in such a way that the spectral characteristics and all other second-order statistics of the original non-Gaussian LES turbulence fields are preserved. Time series from both the original LES and its Gaussian counterpart are used for load simulations. With 20 seeds, we obtained equal mean values of the longitudinal turbulence intensity, one of the main parameters within the IEC standard. The largest variation of the turbulence intensity was observed in the Gaussian fields.

We have used HAWC2 to calculate loads on a 5 MW wind turbine. The simulations showed no significant differences in the estimated fatigue loads when using rain-flow counting based on inflow time series of non-Gaussian turbulence versus Gaussian turbulence. In a similar result is found. They, on the other hand, also calculate time increments of the rotor torque time series and identify non-Gaussian tales on time scales up to 10 s. Based on this, they therefore conclude that non-Gaussian effects are important. In our study, we only focus on mechanical loads internal to the structure, which takes time to build up and hence do not respond instantaneous on a change in torque. We therefore cannot comment further on the findings in Mucke, Kleinheins and Peinke and also in Wachter et al. on this matter.

In order to explain the vanishing effect of non-Gaussian turbulence on the fatigue loads, we turn towards the classical assumption of the turbine as a low-pass filter: the rotational speed range of the rotor in the simulated wind speed range is between 8 and 12.1 rpm, and the turbine thus acts as a low-pass filter, cutting off the high-frequency modes often associated with intermittent turbulent events, gusts, giving rise to non-Gaussian statistics.

For the extreme loads, we observed a small tendency towards higher peak absolute extreme moments for the tower base fore-aft moment when using non-Gaussian turbulent inflow for the highest operating mean wind speeds. Because only the maximum values are used when extrapolating extremes from the inflow data, we would expect some kind of increased loading. The remainder of the extreme moments, however, seems unaltered. We do not, at present, know why only the tower base fore-aft moment was altered. One can argue that the tower base fore-aft moment is mostly prone to fluctuations with length scales the order of the size of the rotor itself or larger. We have, however, seen in Section 3 how the non-Gaussian effects are largest on the smallest scales, much smaller than the size of the rotor, thus indicating that the fore-aft moment should not be affected.

In Section 3, we furthermore discussed how the turbulence for low mean wind speeds is more non-Gaussian compared with the turbulence for large wind speeds. This effect is not reflected in the moments.

Future work will show if the results presented in this paper will also prevail in stable and convective boundary layers where non-Gaussian and Gaussian turbulence may differ more strongly. In extremely stable boundary layers, we expect the deviation from Gaussian to be largest but at smaller scales, while convective boundary layers might deviate at large-scale motion. Furthermore, the roughness length used in this study, \( z_0 = 0.3 \) m, is rather high. We have carried out LES simulations with a lower roughness and compared the pdf of the velocity increments with the one presented in Figure 3. No difference was observed. We believe that the mesh resolution is a more crucial factor for changing the non-Gaussian effects compared with changing the physical parameters, as for example, the roughness length or the Coriolis parameter. As argued in Sullivan and Patton, the SGS model is parameterized at the second-moment level, and hence, SGS models of higher moments are unknown. The non-Gaussian effect, here defined through higher-order moments, are therefore dependent on the mesh resolution.

A direct comparison with the Mann turbulence model is also welcomed in order to establish if other of the assumptions made in the Mann model might have any influence upon the calculated moments, most prominent being the assumption of constant vertical shear and zero wind veer due to the neglect of the Coriolis force. Using a different wind turbine could also alter the results obtained here because the low-pass filter characteristics might be different, for example, by changing rotor speed and size.
6. CONCLUSION

From high-resolution LES data, we have constructed Gaussian turbulence with the exact same second-order structure as the LES data by the use of a POD technique. The fields were transformed into boxes of time-resolved turbulence for various mean wind speeds suitable for aeroelastic load simulations with HAWC2. Results for both extreme and fatigue loads during wind turbine operation did not show any significant difference when using non-Gaussian or Gaussian inflow turbulence. We attribute this to the fact that non-Gaussianity prevails most strongly in eddies smaller than the rotor so that they are thus filtered away.

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