Uncertainty in loads for different constraint patterns in constrained-turbulence generation

Jennifer M. Rinker
DTU Wind Energy, Frederiksbergvej 399, Building 114, 4000 Roskilde Denmark
E-mail: rink@dtu.dk

Abstract. This paper investigates the effect that adding constraints to turbulence simulations has on the uncertainty of resulting aeroelastic loads. The constrained turbulence is generated using the open-source constrained turbulence generator PyConTurb (“Python Constrained Turbulence”). A selection of constraint patterns were used to mimic the design of a met mast layout; i.e., the number of sonic anemometers and their locations throughout the rotor. A case study is presented to demonstrate in detail the effects of adding constraints before a larger numerical experiment is presented. The results of the numerical experiment indicate that adding constraints is extremely beneficial in reducing the mean absolute error of both operational parameters and loads. The reduction in mean absolute error ranged from 13% to 98%. The error in the extreme values and damage-equivalent loads were not impacted by the added constraints due to lack of gusts in the original signals and the similarity of the power spectra of the constrained and non-constrained signals, respectively.

1. Introduction

When performing one-to-one loads validation, one of the greatest sources of uncertainty is in the inflow being fed into the rotor. An analyst may have a set of wind speed measurements at discrete points upwind from the rotor, and these measurements must somehow be converted into turbulent inflow in an aeroelastic simulation. The easiest method is to fit a set of input parameters for a turbulence model of choice to the measurements and then use those parameters to simulate turbulence boxes. This can be an issue, however, if the measurements are not well-described by the turbulence model of choice (e.g., different power spectra or non-stationarity). Thus, more advanced turbulence reconstruction methods are needed.

One category of tools that can be applied to this problem are so-called “constrained turbulence generators”. In constrained turbulence generation, the measurements are viewed as a set of constraints to which the generated turbulence box must adhere once it is simulated. There are a variety of techniques that have been applied in wind energy applications, including constrained Gaussian fields based on the Mann turbulence [1], Gaussian fields constrained to lidar measurements [2], the internal model principle [3] and the utilisation of spatial correlation in the Veers method [4].

When using these constrained-turbulence generators with real data, it is essential that the behaviour of the constraining methodology is well understood. For example, if the method is being used with four-point lidar measurements, what is the expected uncertainty? What are some of the weaknesses when using that scanning pattern? It is important that the answers to questions like these are known a priori in order to have a better understanding of the
performance of the technique \textit{in situ}. In practice, this requires a series of sensitivity studies in which turbulence boxes are generated, “measured” with different constraint patterns and then regenerated. Because the original turbulence box is known, it is then easy to determine what the “true” response should be. A selection of papers exist on this topic [5, 6], but they focus primarily on lidar scanning patterns.

This paper uses the open-source constrained turbulence generator PyConTurb (“Python Constrained Turbulence”) [4] to investigate the uncertainty in loads when turbulence is constrained using different constraint patterns. The patterns are chosen to mimic possible designs of a met mast; i.e., its maximum height and the location of the sonic anemometers. The work presented herein is the first step to understanding the applicability of PyConTurb to one-to-one loads validation.

The remainder of the paper is as follows. Specifications of the turbulence simulation methodology and constraint patterns of interest are presented in Sec. 2. A case study to demonstrate in detail the effects of adding constraints on turbulence boxes is presented in Sec. 3. Section 4 presents a numerical investigation into loads uncertainty using multiple random seeds for the different constraint patterns. The final discussion and the conclusions are presented in Secs. 5 and 6, respectively. The code used to generate the results and figures in this paper is available online: https://gitlab.windenergy.dtu.dk/pyconturb/pyconturb-torque2020.

2. Methodology

The technique used in this paper is the constrained-turbulence methodology presented in [4], which is implemented in the open-source software PyConTurb [7]. The design choices common to both the case study and numerical experiment are presented in the following subsections. Further details on the case study and numerical experiment are provided in Secs. 3 and 4, respectively.

2.1. Constraint patterns

To generate constrained turbulence in PyConTurb, an analyst must provide a time series of a turbulence component ($u$, $v$ and/or $w$) corresponding to a specific location of interest. The time series must have the same sampling time as the desired turbulence box. During generation, the created turbulence box is spatially cohered to the provided constraints. The spatial locations of the constraining time series and the turbulence components to be constrained are design choices by the analyst.

For this paper, five different constraint patterns were selected for investigation (Fig. 1). The constraint patterns were chosen to mimic possible met-mast configurations for loads and/or power validations. Each constraint pattern consists of a collection of points in three possible locations: the bottom of the rotor (“B”), hub height (“H”) or the top of the rotor (“T”). The constraints are named according to the points included in the pattern; for example, the constraint with two points, one at the bottom of the rotor and one at the top, is indicated by “BT”. The constraint patterns are visualized in Fig. 1. Constraining time series were prescribed for all three turbulence components for all patterns; e.g., pattern BHT featured 9 turbulent time series that were given as constraints to PyConTurb.

2.2. Simulation procedure

For both the case study and numerical experiment, the general simulation procedure was as follows. First, the original turbulence boxes were simulated according to the specifications described below. Then, for each constraint pattern of interest, each original turbulence box was sampled using VTMeas (“Virtual Measurements”), an open-source Python package designed to virtually measure turbulence boxes and produce PyConTurb-friendly constraint files [8]. Constrained turbulence boxes were then generated for each constraint file. In the numerical
Figure 1. Constraint patterns under investigation. “B”, “H” and “T” respectively indicate constraints at the bottom of the rotor, hub height and the top of the rotor.

Figure 2. Locations of simulated turbulence points. Light grey indicates points that were simulated but not used. The red points indicate the three possible constraint locations.

experiment, multiple constrained turbulence boxes were simulated from each constraint pattern using different random seeds. In addition to the constrained turbulence, unconstrained turbulence boxes were simulated with the same parameters as the original turbulence, mimicking the standard method of resimulating turbulence during loads/power validations. This scope of this paper does not include the effects of unknown original turbulence parameters on the resulting loads uncertainties; that must be addressed in later work. The last step in the simulation procedure is to use the turbulence boxes as inflow to the DTU 10 MW reference wind turbine [9] modelled in the aeroelastic software HAWC2 [10]. The wind speeds, number of random seeds for the original turbulence boxes and the number of random seeds for the constrained turbulence boxes used in the numerical experiment and the case study are presented in Secs. 3 and 4, respectively.

2.3. Turbulence box dimensions
The turbulence boxes simulated in both the case study and the numerical experiment were 600 s in duration and had 1024 samples, corresponding to a sampling time $\Delta t \approx 0.59$ s. For numerical efficiency, all box dimensions were prescribed to be powers of 2. However, to ensure
Table 1. Dimensional parameters of turbulence boxes.

| Parameter         | Value    | Parameter         | Value       |
|-------------------|----------|-------------------|-------------|
| No. longitudinal points | 1024     | Box width, height | 192.86 m    |
| No. lateral points   | 16       | Lateral, vertical offset | 6.43 m    |
| No. vertical points  | 16       | Vertical center of box | 125.43 m  |
| Total simulation time | 600 s    | Time step         | 0.59 s      |

that constraint and simulation points were collocated, the grid was slightly offset laterally and vertically. This resulted in a single row and column of the box that was generated but not used in the aeroelastic simulation, as indicated in Fig. 2. The box width and height were chosen such that the first 15 columns/rows spanned 180 m, slightly larger than the rotor diameter of the DTU 10 MW. A summary of the dimensions of the simulated boxes is presented in Table 1.

2.4. Profile functions and spatial coherence

When simulating turbulence in PyConTurb, one of the design choices that an analyst must make is the functions used to specify the variation of the mean wind speed, turbulence standard deviation and power spectra as a function of lateral (y) and vertical (z) location. These functions are referred to as “profile functions”.

To ensure perfect reproduction of constraining time series, it is necessary that the profile functions chosen for the turbulence standard deviation \(\sigma_k(y, z)\)—where \(k\) indicates a specific turbulence component—and power spectra \(S_k(f)\) reproduce the values from the constraints when \((y, z)\) is equal to the constraint location. However, it is the analyst’s choice as to what these profile functions should return at a non-collocated point. This paper utilized the default setting in PyConTurb, which is to linearly interpolate \(\sigma_k\) and \(S_k(f)\) from the provided constraints when the simulation point is located between the constraints. Spatial points outside of the constraints take the value from the nearest point. The accuracy of this method is an open research question and is discussed in Sec. 5.

The assumed turbulence class was IEC class A. One of the aspects of turbulence simulation based on the Veers method is variation in the resulting turbulence standard deviation, which is a product of the spatial correlation procedure [11]. In this paper, the turbulence was not scaled after generation to the correct standard deviation. Thus, there will always be some variation in the produced turbulence standard deviation.

The mean wind speed profile function was prescribed according to a power law with exponent \(\alpha = 0.2\), as defined according to the wind turbine design standard IEC 61400-1 [12]. It was assumed that the reference wind speed was known exactly, which ensures that all turbulence boxes have the same mean wind speed profiles. Although this means that any differences in the aeroelastic simulations directly result from the generated turbulence and not differences in the mean wind speed value, this assumption poses some problems with respect to real-world applicability. Further discussion on this is presented in Sec. 5.

The spatial coherence model used is a modified version of the exponential coherence model in IEC 61400-1 [12]. In particular, coherence is also applied to the lateral and vertical turbulence components, with coherence length scales that correspond to the prescribed length scales for the Kaimal spectrum.

1 This is not necessary when specifying constraints, but it allows for easier comparison and verification in our numerical experiments.
3. Case study

To demonstrate the constraining methodology and gain insight into how adding constraints affects the generated turbulence, a case study is presented in this section. A single original turbulence box with a hub-height wind speed of 12 m/s (rated wind speed) was generated before being sampled by VTMeas to create the five constraint files representing measurements. Then, using the same random seed, five constrained turbulence boxes were generated (one for each constraint pattern) and one unconstrained turbulence box representing a standard turbulence simulation with the right statistics but no constraints. The same random seed was used for the six turbulence boxes in order to highlight the effect of adding a constraint: having the same random seed means that the six turbulence boxes started with the same random phases before spatial correlation. The profile functions and spatial coherence were defined as described in Sec. 2.4. The seven turbulence boxes (1 original, 1 non-constrained and 5 constrained) were then used as inflow for the DTU 10 MW.

The resulting rotor speeds for the different aeroelastic simulations are given in Fig. 3. The top subplot contains the rotor speed values, and the bottom subplot contains the error with response to the response from the original box. The response of the turbine to the original turbulence box is indicated by the dark grey dashed line, the response to the non-constrained box is indicated by the lighter grey dotted line and the responses to the constrained turbulence boxes are indicated by the coloured lines. Interesting time points are indicated by the vertical grey lines and letters; they will be discussed below.

As expected, there are several time points for which the no-constraint simulation differs quite substantially from the original (e.g., from 300 to 500 s). The response for the box with a single point at the bottom of the rotor (“B”) has the largest error of the constrained boxes, which is logical. The next-worse responses are from turbulence boxes H and BT. This is interesting, considering that the BT pattern has points at the top and bottom of the rotor, but it is largely

**Figure 3.** Comparison of rotor speed response to original turbulence box (“Original”), to one with no constraints (“No con.”) and to those from the different constraint patterns. The top row contains the rotor speed values and the bottom row contains the error with respect to the rotor speed from the original turbulence box. The vertical grey lines indicate time slices of interest.
Figure 4. Longitudinal wind speed in y-z plane for time A. Orange circles indicate the locations of constraints.

As a result of the random phases that correspond to this random seed.

To graphically illustrate how adding the constraints affects the turbulence box, the longitudinal turbulence at location \((y, z)\) for the different turbulence boxes at time A is given in Fig. 4 where A is indicated in Fig. 3. As we can see from Fig. 3, the only response at time A that tracked the response from the original turbulence was box BHT; the other constrained boxes and the non-constrained box are still operating near rated rotor speed. The reason for this is quite clear when we consider the turbulence slice in Fig. 4. The random seed chosen for the reconstructions results in phases that would normally feature a high wind speed at this time, indicated by the yellow blocks in the no-constraint subplot. Adding more constraints helps counter this high wind speed, finally resulting in box BHT, which matches the original box quite well.

Not all time steps feature the same clear observation that adding more constraints results in a better turbulence box—and therefore a more accurate aeroelastic response. Time B in Fig. 3 is a good example of this: the most accurate responses are actually B and BT, whereas the turbulence boxes that used a hub-height constraint are less accurate. This is a product of the random seeds used in the original turbulence box and in the non-constrained/constrained turbulence boxes. To draw more concrete conclusions about the effect of constraints on aeroelastic response, it is necessary to run a numerical experiment with multiple random seeds on both the original turbulence box and on the non-constrained/constrained turbulence boxes.

4. Numerical experiment

As noted above, an investigation with multiple random seeds for the original and recreated turbulence boxes is required to draw meaningful conclusions about the effects of constraints on aeroelastic simulations. Such an investigation is presented in this section. The design of the numerical experiment and the different error metrics used to quantify the resulting uncertainty are presented in Sec. 4.1. The remaining subsections analyse the resulting uncertainties in turbulence, operational data and loads.
| Parameter | Value(s) |
|-----------|----------|
| Wind speed | 6 m/s, 12 m/s, 18 m/s |
| No. random seeds, original | 6 per wind speed |
| No. random seeds, constrained | 12 per original box |

4.1. Design of experiment and error metrics

For the numerical experiment, six original turbulence realisations were simulated at three different hub-height mean wind speeds (6, 12 and 18 m/s, respectively corresponding to below, at and above rated). From each original realisation, 12 regenerated turbulence boxes were created for the five constraint patterns as well as for the unconstrained case. The profile functions and spatial coherence were defined as described in Sec. 2.4. Considering the three wind speeds, six original turbulent seeds, five constraint patterns and 12 turbulent seeds per recreation method, a total of 1314 turbulence boxes (18 original, 216 non-constrained and 1080 constrained) were simulated and then used as inflow in HAWC2. The parameters for the experiment are summarised in Table 2.

For each non-constrained and constrained simulation (hereafter referred to as “reconstructed” simulations for brevity) and for each load channel $x_i(t)$, the effects of adding constraints were quantified using a series of error metrics:

- **Signal mean absolute error.** Defined as $\text{MAE}_i = |x_{\text{orig},i} - x_{\text{recon},i}|$ where the overbar is the mean with respect to time.

- **Turbulence mean absolute error.** Similar to MAE, except that the mean of the absolute error in the wind speed is taken over all grid points and all times.

- **Error in extreme value.** Defined as $\text{ErrExt}_i = \text{ext}[x_{\text{orig},i}] - \text{ext}[x_{\text{recon},i}]$, where “ext” is either a max or min function depending on the sign convention of the signal.

- **Error in 10-minute DEL.** Defined as $\text{ErrDEL}_i = \text{DEL}_{\text{orig},i} - \text{DEL}_{\text{recon},i}$, where DEL represents the 10-minute damage equivalent load (DEL).

Once calculated, the error metrics are grouped according to wind speed and constraint pattern. In other words, for a given (1) wind speed, (2) constraint pattern and (3) error metric of interest, there are 72 values of the error metric (12 random seeds for each of the 6 original seeds) that are collected into a single sample. The sample size is large enough to allow us to consider the change in the mean and variance of the error metric as a function of the constraint pattern and wind speed.

4.2. Error in turbulence

The metric used to quantify the error between the reconstructed turbulence and the original turbulence is the mean absolute error (MAE) between the two turbulence boxes, calculated at all points and time steps. The resulting MAE values for the longitudinal turbulence component $u$ for the different wind speeds and constraint patterns are visualised in the box-and-whisker plots in Fig. 5. As noted previously, each box-and-whisker contains the MAE values for the 72 reconstructed seeds from the 6 original seeds. The percentages in the upper right corner indicate the reduction in the mean MAE from the non-constrained case to the BHT case. As would be expected, there is a distinct decrease in both the mean MAE and the variance as more constraint points are added. It is interesting to note that the variation on the H-pattern MAE is quite large, possibly caused by PyConTurb’s interpolator for the profile functions (discussed further in Sec. 5). Additionally, the BT pattern is generally slightly less accurate than the BH pattern, especially for larger wind speeds. The reduction in the mean MAE ranges from 16% to 19%.
4.3. Error in operational parameters
The MAE values for the rotor speed, pitch angle and generator torque are visualised in Fig. 6. There are mixed results in the rotor speed and pitch angle below rated due to the minimum rotor speed and pitch angle values that are inherent in the controller. However, all of the other subplots generally show the same trends as seen in the turbulence MAE. In particular, the MAE for the non-constrained case is the largest, followed by the B, H, BT, BH and BHT patterns. The difference between the BT and BH patterns is much more discernible in the operational data than what was observed in the turbulence MAE in Fig. 5. The reduction in the mean MAE is quite high, ranging from 23% (rotor speed, below rated) to 98% (pitch angle, below rated).

4.4. Error in loads
Due to space constraints, only two load channels will be considered in this paper: the tower-base fore-aft (TBFA) bending moment and the flapwise blade root (FBR) bending moment of Blade 1. Only the MAE of the TBFA bending moment is presented because its ErrExt and ErrDEL demonstrated similar trends as the corresponding FBR bending moment values. The results for other loads channels displayed similar trends and can be visualised using the code available on the paper’s GitLab repository.[2]

4.4.1. Tower base fore-aft bending moment
The MAE values for the TBFA bending moment are visualized in Fig. 7. Once again, there is a very substantial drop in the MAE when constrained turbulence is used, and more points result in generally lower MAE. Similar to the operational data, there is a clear difference in the MAE values for the BH and BT patterns, indicating the importance of choosing constraint points wisely. The reduction in mean MAE ranges from 13% to 34%.

4.4.2. Flapwise blade root bending moment
The box-and-whisker plots with the MAE, ErrExt and ErrDEL values for the FBR bending moment (Blade 1) are visualised in Fig. 8. As seen in the other analysed values, there is a general decreasing trend in the MAE for the different constraint patterns, with the exception of BT. However, there are more outliers present, especially above rated. This is possibly caused by differences in the rotational speeds of the original and

[2] https://gitlab.windenergy.dtu.dk/pyconturb/pyconturb-torque2020
Figure 6. MAE values of the rotor speed, pitch angle and generator torque. Numbers in corner indicate the percent reduction of the mean MAE from the non-constrained case to the BHT case.

Figure 7. MAE values for the tower base fore-aft bending moment. Numbers in corner indicate the percent reduction of the mean MAE from the non-constrained case to the BHT case.
5. Discussion

A few of the observations made in the previous sections merit more discussion.

Large variation of turbulence MAE for Pattern H. As observed in Sec. 4.2 and Fig. 5, the MAE values for the longitudinal turbulence generated using Pattern H have significantly more outliers than the other patterns, a trend that then manifests in the corresponding MAE values of the resulting aeroelastic signals. This is likely due to the profile interpolation options chosen for this investigation. Because there is only one constraint, the power spectrum and turbulence standard deviation at all simulation points are assigned the same values. However,
the Veers method’s spatial correlation procedure will result in profiles that vary with each new realisation. Thus, some realisations will feature power spectra that differ substantially from the “true” Kaimal values, resulting in increased turbulence MAE values. The same phenomenon occurs for Pattern B, but because the point is closer in space to the bottom left corner, the upper-triangular nature of the Cholesky decomposition produces less variation in its profile functions. Thus, Pattern B does not exhibit as many outliers as Pattern H. Future work is underway to investigate possible improvements into the interpolator logic to reduce this sensitivity to the constraining time series.

Assumption of known shear. This investigation assumed that the mean wind speed profile for all turbulence boxes was known perfectly. It should be noted that this is an unrealistic assumption for the generation of constrained turbulence from real measurements. Further work is needed to quantify the effect that unknown shear profiles will have upon the error metrics.

Insensitivity of extremes/DELs to constraints. As noted in Sec. 4.4.2, ErrExt and ErrDEL were relatively insensitive to constrained turbulence, regardless of constraint pattern. This is a direct consequence of two facts: (1) the turbulence parameters for the reconstructed cases matched the original parameters and (2) there were no gusts/nonstationarities in the original turbulence. Because the turbulence parameters for the original and reconstructed cases were the same (or were interpolated from the constraints), the ensemble-averaged power spectra of the reconstructed turbulence boxes are the same as the original power spectra. Because the frequency content of the turbulence is similar and there is little temporal phase correlation caused by gusts or nonstationarities, the aeroelastic responses for the non-constrained and constrained cases feature similar frequency content and similar DELs. This is demonstrated by Fig. 9, which plots the time series and power spectra of the FBR bending moment for the original case, non-constrained case, and BHT case. The time series show a marked improvement in the signal tracking (resulting in a decreased MAE), but the PSDs for the three signals are almost identical.

The ErrExt values are relatively insensitive to the addition of constraints for similar reasons. Because the original turbulence simulations are stationary, they lack gusts and extreme events that drive the extreme loads. Moreover, because the parameters used to simulate the non-constrained cases match the original parameters, the resulting extreme values are already quite similar. Thus, for the numerical experiment presented here, the use of constrained turbulence does not improve ErrExt. However, it is expected that this would not be the case when reconstructing turbulence with nonstationary events.

Where to place instruments on a met mast. Given the results presented in this paper, we should finally draw conclusions regarding the placement of instruments on a met mast. First, it is quite apparent that, of the options analysed in this paper, a full-rotor met mast with measurements at the bottom, hub-height and top of the rotor was the best option, as would
be expected. A full-rotor met mast without a hub-height measurement created generally worse reconstructions than a hub-height met mast with two measurements, despite having constraint points spanning the length of the rotor. Thus, the second-best option was a hub-height met mast with measurements at the bottom of the rotor and at hub height. Lastly, even if a hub-height met mast cannot be obtained, placing a single measurement device at the bottom of the rotor shows a marked improvement in MAE versus having no constraints at all.

6. Conclusions
This paper investigates the addition of constrained turbulence when considering one-to-one loads validation. The constrained points were selected to mimic a met mast instrumented with 3D sonic anemometers at various heights, and their locations were varied along the rotor to determine which configuration would lead to reduced uncertainty in the resulting loads. The constraining methodology is based on the Veers method, as implemented in the open-source constrained-turbulence software PyConTurb.

Two numerical investigations were presented. For both investigations, five constraint patterns were considered in which a varying number of sonic anemometers were placed at three separate locations in the rotor: at the bottom, hub height and top of the rotor. The first numerical investigation was a case study that demonstrated how the addition of constraints modified the generated turbulence and resulted in a more accurate rotor speed with respect to the original turbulence box. In general, adding a single constraint at the bottom of the rotor produced poor results. The most accurate response was the constraint pattern with three points equally spread along the height of the rotor.

The second numerical investigation simulated multiple turbulent realisations at multiple wind speeds. The results show a significant improvement in the mean absolute error for the turbulence itself and for a selection of channels from the aeroelastic simulations. The reduction in the average mean absolute error from the a case with no constraints to a case with three constraint points ranged from 13% (tower-base fore-aft moment, above rated) to 98% (pitch angle, below rated). There was no significant improvement in the error of the max value or the damage-equivalent load, which is an expected result from the design of experiment. To gain improvements on the extreme and fatigue loads, future investigations are necessary that consider nonstationary original turbulence and a mismatch of original/reconstruction turbulence parameters.

References
[1] Nielsen M, Larsen G C, Mann J, Ott S, Hansen K S and Pedersen B J 2004 Wind simulation for extreme and fatigue loads Tech. Rep. Risø-R-1437(EN) Risø National Laboratory Roskilde, Denmark
[2] Bos R, Giyanani A and Bierbooms W 2016 Remote Sensing 8 758
[3] Raach S, Schlipf D, Haizmann F and Cheng P W 2014 Wind Energy 20 79–95
[4] Rinker J M 2018 Journal of Physics: Conference Series vol 1037 (IOP Publishing) p 062032
[5] Dimitrov N and Natarajan A 2016 Wind Energy 20 79–95
[6] Pettas V, Costa García F, Kretschmer M, Rinker J M, Clifton A and Cheng P W 2020 AIAA Scitech 2020 Forum p 0993
[7] Rinker J M 2020 PyConTurb. Version 2.6.dev1 URL https://gitlab.windenergy.dtu.dk/pyconturb/
[8] Rinker J M 2020 VTMeas. Version 0.2.dev0 URL https://gitlab.windenergy.dtu.dk/pyconturb/VTMeas.
[9] Bak C, Zahle F, Bitsche R, Kim T, Yde A, Henriksen L C, Natarajan A and Hansen M H 2013 Description of the DTU 10 MW reference wind turbine Tech. Rep. I-0092 DTU Wind Energy
[10] Larsen T J and Hansen A M 2015 How 2 HAWC2, the user’s manual Tech. Rep. Risø-R-1597 DTU Wind Energy
[11] Jonkman B J and Kilcher L 2012 TurbSim user’s guide: Version 1.06.00 Tech. rep. National Renewable Energy Laboratory
[12] International Electrotechnical Commission 2005 Wind turbines - part 1: design requirements 3rd ed.