Wind tunnel experimental variability of aerodynamic loads for wind turbine blades

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Abstract. The lift and drag coefficients of airfoils, used in wind turbine blades, are measured by wind tunnel tests. Large uncertainties are possible due to experimental errors and wind tunnel laboratory variability. Uncertainties in the aerodynamic loads have an important effect on the structural reliability of wind turbine blades. In this paper, the aleatory behaviors of the aerodynamic loads for a three-dimensional wind turbine blade are investigated by wind tunnel tests. Different angles of attack and Reynolds numbers are considered to quantify the uncertainties in the lift coefficients.

1. Introduction

The use of offshore wind turbines has rapidly grown in recent years. The size of commercial offshore wind turbines is also becoming larger, resulting in a higher wind power generation and better exploitation of the offshore wind energy potential [1]. However, flow-induced aeroelastic instabilities are more likely to happen with longer and more flexible wind turbine blades [2]. Coupled-mode flutter is one of these aeroelastic instabilities, which can possibly lead to operational failure. Consequently, flutter occurrence can influence the maximum wind power generation and regular operation of offshore wind turbine blades. The prediction of deterministic critical flutter speed has been studied in recent years [3, 4]. Uncertainties associated with the wind turbine blade are always present in the manufacturing process, resulting in the variability of aerodynamic performance of the blade. Complex three-dimension flow condition during the operation of the wind turbine blades can also introduce random variation in the aerodynamic properties. Therefore, flutter influenced by various uncertainty sources must be examined. Previous studies on stochastic flutter of a MW-sized wind turbine blade have shown that the presence of random flow forces in the wind turbine blades can influence the critical flutter speed and may lead to a non-negligible risk of failure [5, 6].

Aerodynamic loads of the sectional airfoils, forming the “backbone” of a wind turbine blade, are always determined through wind tunnel tests. Uncertainties can be present as a result of variability in the wind tunnel measurements and can influence the estimation of the static lift and drag coefficients [7]. Therefore, investigation on the variability of the aerodynamic loads cannot be ignored in the design of wind turbine blades. To study the experimental variability, wind tunnel tests are designed and performed in Northeastern University’s (NEU’s) small-scale wind tunnel. The purpose of this study is to investigate uncertainties in the aerodynamic loads, and use the results for stochastic flutter analysis of MW-sized wind turbine blades. In this
study, the NREL 5MW blade [8] was used as the reference blade. A 3D-printed blade model with appropriate geometric scale ratio was employed under non-rotating conditions. A high frequency force balance (HFFB), which is capable of acquiring the base forces of the blade model, was used in the experimental setup. The blade model was tested under the influence of turbulence and at various angles of attack. Aerodynamic properties such as the lift coefficient and its first derivative with respect to the angle of attack (AoA), were derived to evaluate the random variability during the wind tunnel tests.

This paper is organized as follows. The experimental setup and test procedure are first described in Section 2. The results of the static aerodynamic lift tests are presented and discussed in Section 3.1. Uncertainty analysis (i.e., statistical analysis of the experimental data and fitting of the empirical probability histogram) is subsequently employed to investigate the random experimental errors of the lift coefficients and its first derivative as a function of AoA. Details and further discussion are described in Sections 3.2 and 3.3. Concluding remarks are summarized in Section 4.

2. Experimental setup and test procedure

2.1. Description of experimental setup

The wind tunnel test was carried out in NEU’s small-scale wind tunnel, as shown in figure 1. Dimensions of this test chamber are 560 $\times$ 560 mm. The fan/motor can produce wind speeds up to 20 m/s. For the purpose of evaluating turbulence effects, turbulence was generated by an upstream grid. The grid was assembled by rectangular-section flat bars, which have a 2-cm width, depth of less than 0.5 cm, and a 4-cm center-to-center distance between each bar in both horizontal and vertical directions. The mean wind speed and turbulence intensity were approximately constant along the height of the wind tunnel chamber. The turbulence intensity was measured to be about 14.0 % when the mean wind speed was 10 m/s. Turbulence intensity measurements were obtained at 1.32 m downstream from the grid using Dantex Dynamics dual-sensor gold-plated hot-wire probes (model P9055P0611), which were calibrated to acquire the horizontal wind speed time series in both along-wind (longitudinal) and across-wind directions at a sampling rate of 1kHz. The length scale of the along-wind turbulence component was approximately 5 cm, as determined by previous experiments [9].

The wind turbine blade model represents the NREL 5MW wind turbine blade at a 1 : 200 geometric scale. The blade model was manufactured by 3D printing, using polylactic acid (PLA) material, to accurately represent the geometry of the NREL 5MW blade. Dimensions of the blade model are: blade length (radius) $\ell = 330$ mm, maximum chord length $c_{max} = 23$ mm; the maximum thickness is less than 10 mm. The wind tunnel blockage effect was less than 1 % and was consequently neglected. The vertically-oriented model was connected to an HFFB sensor by a hollow square aluminum bar, located outside the chamber. The HFFB sensor is an ATI Industrial Automation six-axis Gamma-type SI-130-10 force balance, which was placed under the floor of the test chamber (figure 2a).

For the purpose of accurately varying the AoA of the blade, an AoA-control system was designed. The AoA-control system was assembled using a stepper motor that has 200 steps per revolution, and two gears with specifically-designed gear ratio (figure 2b). In addition, the motor was operated by an Arduino MeGA 2560 board in the Arduino software environment. The AoA-control system can rotate the blade model with the resolution of one-degree increments. A “detach system” was designed and assembled with the AoA-control system; consequently, the AoA-control system could be detached and separated from the test model after adjusting the AoA to a desired position.
Blade model
Grid for turbulence
56cm (22in)
Flow direction
HFFB (under the chamber)

Figure 1. NEU’s small-scale wind tunnel.

Stepper motor
Gears
(a) (b)
Aluminum bar
HFFB

Figure 2. (a) Force balance under the chamber; (b) schematic of AoA-control system.

2.2. Wind tunnel test procedure
The base (root) forces of the blade model were measured for eleven AoAs, \( \alpha \in \{-15^\circ, -12^\circ, -9^\circ, -6^\circ, -3^\circ, 0^\circ, 3^\circ, 6^\circ, 9^\circ, 12^\circ, 15^\circ \} \). For each AoA, the blade model was tested at a mean wind speed \( \bar{U} = 10 \text{ m/s} \). The HFFB experiments were repeated 30 times, and the duration of each record was 20 seconds. This duration is equivalent to a 10-minute operation time at full scale for the reference blade by dynamic similarity. Each 20-second interval was treated as an independent realization of the overall time series of the aerodynamic forces. The final objective was the study of turbulence, Reynolds number, AoA and the uncertainty sources. Different AoAs were primarily considered in this paper to investigate the propagation of uncertainties; additional tests considering variations of turbulence intensity and Reynolds number are currently underway.
3. Results and discussion

3.1. Static aerodynamic lift coefficients

The aerodynamic forces (lift) of the blade model, experimentally measured, are calculated by the following equation,

\[ L(\alpha) = \frac{1}{2} C_L(\alpha) \rho \bar{U}^2 S \]  

where \( C_L(\alpha) \) is the lift coefficient as a function of AoA (\( \alpha \)); \( \rho \) is the air density; \( \bar{U} \) is the mean flow velocity; and \( S \) is the reference surface area of the blade. It must be noted that \( C_L(\alpha) \), in this experiment, represents the equivalent lift coefficient of the three-dimension blade model, instead of the lift coefficient for a single airfoil section.

Figure 3 illustrates that there are 6 different airfoil sections used in the design of the NREL 5MW blade. These airfoils provide different aerodynamic properties along the longitudinal blade axis. It is also noticed that the intermediate region between different airfoil sections may not lead to a smooth transition of the lift distribution [10]. Therefore, the aerodynamic performance of the three-dimension blade model can be more complex than the single airfoil section model, and can possibly lead to a larger variation of the lift forces measured in the tests.

Before moving to the main part of this research (i.e., experimental error analysis and aerodynamic performance of the blade model), it is important to examine the static lift coefficients. Figure 4 presents the mean lift coefficients at various AoAs, calculated from the experimental data, compared with published lift coefficients of the six airfoils used for the reference blade (i.e. 2D blade-airfoil section models). The solid, thick black line represents the theoretical values for the equivalent lift coefficients of the 3D blade model used in the wind tunnel experiment. “Theoretical data” (solid thick line) are calculated through the weighted average of the various lift coefficients in the NREL 5MW blade based on variable sectional areas. The experimental data points for each AoA represent the average values of the 30 realizations, as introduced earlier.

The equivalent lift coefficients, calculated from the test data, do not match the published values well. One possible reason is that the 3D blade model can generate more complex flow conditions (i.e., tip vortex and consequent lift losses) than the 2D airfoil section. Effects of complex flow conditions around the blade model can significantly change the aerodynamic characteristics of the airfoils. It is also possible that the condition of low Reynolds number has an effect on the aerodynamic performance. The maximum value of the Reynolds number in the tests is about 15000. At this low Reynolds number, the boundary layer is more “resistant” to flow transition and reattaches on the airfoil surface as a turbulent boundary layer, resulting in a decreased lift and increased drag [11]. Both explanations of lift deficit in the tests suggest that more studies are still needed to investigate the above-described differences, for example by exploiting CFD simulations with a computational domain that is identical to the wind tunnel setup. These studies are beyond the scope of this paper and have not been considered herein since the primary purpose of this work was the analysis of the random experimental error associated with aerodynamic lift forces, not the determination of the “true values” of the aerodynamic lift coefficient.

3.2. Uncertainty analysis of the lift coefficients, \( C_L \)

The sources of uncertainty associated with aerodynamic forces of the three-dimensional blade model can be related to the variabilities in: digital measurement and equipment, manufacturing of the blade model and laboratory environment. There are 30 realizations of the base forces acquired for each AoA. The mean wind speed \( \bar{U} \) was constant during the wind tunnel experiment. Statistical analysis was first employed to examine the random variability in the lift coefficient \( C_L \), based on the experimental data sets. Next, several probability distribution models were employed to describe the empirical probability histograms. Furthermore, statistical hypothesis
Figure 3. Airfoil sections of the NREL 5MW blade (at full scale).

Figure 4. Mean equivalent lift coefficients of the blade model, compared with the lift coefficients for the airfoils of the NREL 5MW blade.

testing was used to evaluate the goodness of fit. Details of uncertainty analysis are presented in the following paragraphs.

Table 1 provides the sample mean (\( \bar{C}_L \)), standard deviation (\( \sigma \)), skewness (\( \gamma_3 \)), and kurtosis (\( \gamma_4 \)) for 30 realizations at different AoAs. Table 1 also records the coefficient of variation (\( cov \)), defined as the ratio \( 100 \frac{\sigma}{\bar{C}_L} \), and the standard error of the mean (\( SEM \)), defined as the ratio \( \frac{\sigma}{\sqrt{n}} \), where \( n \) is the sample size (\( n = 30 \) in this study). The values of \( cov \) for most cases are under 5 % except for low AoAs (i.e., ±3° and 0°). The latter cases have the \( cov \) ranging from about 10 % to 50 %, resulting from the very low lift forces measured at these angles. Therefore, the random errors of the measurement may have a significant effect on the variation of the experimental HFFB data. Additional wind tunnel tests with 50 repetitions were completed at one AoA only (−15°) to preliminarily examine the effect of the sample size. It was found that the values of the \( cov \) and statistical moments from 50 realizations were essentially similar to those from 30 realizations.

The tolerance interval (\( TI \)) and confidence interval (\( CI \)) were both determined to provide a
Table 1. Statistical analysis of experimental lift coefficients $C_L$.

| $\alpha(\degree)$ | $\bar{C}_L$ | $\sigma$ | $\gamma_3$ | $\gamma_4$ | $\text{cov}$(%) | $SEM$ | $TI$ | $CI$ |
|-------------------|-------------|----------|------------|------------|----------------|-------|------|------|
| -15               | -0.492      | 0.012    | 0.461      | 2.80       | 2.36           | 0.004 | -0.525 | -0.459 | -0.496 | -0.488 |
| -12               | -0.492      | 0.013    | 0.362      | 2.30       | 2.71           | 0.004 | -0.530 | -0.454 | -0.497 | -0.487 |
| -9                | -0.385      | 0.010    | -0.042     | 2.17       | 2.53           | 0.003 | -0.412 | -0.357 | -0.389 | -0.381 |
| -6                | -0.231      | 0.008    | -0.009     | 1.95       | 3.27           | 0.002 | -0.253 | -0.210 | -0.234 | -0.229 |
| -3                | -0.122      | 0.013    | -0.260     | 1.98       | 10.6           | 0.004 | -0.159 | -0.085 | -0.127 | -0.117 |
| 0                 | 0.023       | 0.018    | 0.341      | 2.46       | 53.1           | 0.005 | -0.083 | 0.017  | -0.040 | -0.027 |
| 3                 | 0.116       | 0.006    | 0.787      | 3.13       | 22.8           | 0.002 | 0.008  | 0.038  | 0.021  | 0.025  |
| 6                 | 0.168       | 0.007    | 0.439      | 3.52       | 3.95           | 0.002 | 0.149  | 0.186  | 0.165  | 0.170  |
| 9                 | 0.235       | 0.009    | 0.121      | 2.60       | 3.71           | 0.003 | 0.210  | 0.259  | 0.231  | 0.238  |
| 12                | 0.359       | 0.009    | 0.067      | 2.98       | 2.43           | 0.003 | 0.335  | 0.384  | 0.356  | 0.363  |

Figure 5. Analysis of experimental datasets, tolerance ($TI$) and confidence ($CI$) intervals of the lift coefficient $C_L$ vs. AoA ($\alpha$).

more quantitative illustration of the data variability. The tolerance interval ($TI$) defines the data range that contains a specified proportion of the sample population with a specified confidence level. The two endpoints of the tolerance interval are called tolerance limits, which are calculated as $\bar{C}_L \pm k\sigma$ (if data is symmetric about $\bar{C}_L$), where $k$ is the tolerance factor. The $k$ factor was calculated under the assumption that the variation of the experimental data was approximately normally distributed [12]. In this paper, the $k$ value corresponds to the $99\%$ confidence level that at least $95\%$ of the population will fall within the interval limits. Therefore, $k = 2.84$ was used.

The confidence interval ($CI$), computed from the observed data, may contain the true value of the mean of an unknown random variable. Confidence intervals can also be used as the sample mean estimator. In this study, it was approximately calculated as $CI_{95\%} \approx \bar{C}_L \pm 1.96 \frac{\sigma}{\sqrt{n}}$, where
1.96 corresponds to the 97.5 percentile point of the normal distribution. The confidence interval, used in this paper, will be exact if the experimental data points follow a normal distribution. Furthermore, since the population standard deviation ($\sigma$) is unknown, it was replaced by the sample standard deviation to estimate the CI$_{95\%}$. Both assumptions indicate that CI$_{95\%}$ is an approximation of the confidence interval. Figure 5 illustrates the tolerance and confidence intervals of the lift coefficients, examined from the 30 realizations for each AoA. The average values of $C_L$ as a function of AoA were also plotted in figure 5; each dot marker represents one realization. From visual inspection, it can be concluded that the number of experimental points located outside TI is equal to zero for all the AoAs.

Next, some probability distribution models (including normal, log-normal, and gamma distributions) were selected and investigated. Figure 6 illustrates the empirical histogram of the lift coefficients with 30 realizations and the three probability distribution models at various AoAs. Results suggest that the sample size (30 realizations) is possibly limited and cannot provide an adequate resolution for the probability distribution models. It was also found that all the three continuous distribution models are quite close to each other except one case (i.e., $\alpha = 3^\circ$). This is because the parameters computed through fitting of the Gamma distribution lead to a Gamma distribution very similar to the other two distributions. Subsequently, the Kolmogorov-Smirnov test was employed to evaluate the goodness of fit [13] (null hypothesis). It was concluded that all the models could not be rejected for all the AoAs at the 5 % significance level, indicating that any of the models could not be excluded by hypothesis testing. It is noted that, since the probability distribution models must be physically consistent and the lift coefficients at $\alpha = 0^\circ$ may result in a potential change of sign, a normal distribution is more appropriate for this specific scenario.

In conclusion, the uncertainty analysis suggests that experimental variability should be considered in quantifying the aerodynamic forces (lift) of the blade, and a larger sample population may be used in the future experiments to improve estimation of the probability distributions.

### 3.3. Uncertainty analysis of lift coefficient derivative, $C_{L\alpha}$

As explained in Section 1, the primary purpose of this paper is to quantify the uncertainty in the aerodynamic properties in the wind turbine blades. The lift coefficient derivative as a function of the angle of attack $C_{L\alpha}$ is important since this parameter has a direct effect on the prediction of the flutter onset [5, 6]. Consequently, the lift coefficient derivative ($C_{L\alpha}$) was estimated from the experimental lift coefficients ($C_L$). One realization of $C_{L\alpha}$ is defined as one sweep of $C_L$ over all the AoAs ($\alpha$) so that there are, totally, 30 realizations for $C_{L\alpha}$ at each AoA. Each realization of $C_{L\alpha}$ is considered to be independent. The $C_{L\alpha}$ was estimated through finite differences. Specifically, the $2^{nd}$-order central difference and $1^{st}$-order forward/backward difference were used to calculate the approximations of $C_{L\alpha}$. Details of the mathematical expressions are respectively presented in the following equations,

\[
C_{L\alpha}(\alpha_i) \approx \frac{C_L(\alpha_{i+1}) - C_L(\alpha_{i-1})}{2h}
\]  
\[
C_{L\alpha}(\alpha_i) \approx \frac{C_L(\alpha_{i+1}) - C_L(\alpha_{i})}{h}
\]
Figure 6. Empirical histogram of lift coefficients $C_L$ with 30 realizations at each AoA ($\alpha$), compared with fitting of distribution models.

Figure 7. Results of the $p$ values from the Kolmogorov-Smirnov test for the lift coefficients $C_L$ at each AoA ($\alpha$).

\[ C_{La}(\alpha_i) \approx \frac{C_L(\alpha_i) - C_L(\alpha_{i-1})}{h} \]  

where $h$ is the constant angle increment (i.e., $h = 3 \times \frac{\pi}{180}$ in radians).

The same analysis procedure, used in Section 3.2, was employed herein to estimate the random variability of $C_{La}$. Table 2 reports the statistical moments, tolerance interval ($TI$)
and confidence interval (CI95%), estimated from the 30 realizations of $C_{L\alpha}$. Details on the calculation of the moments are omitted for the sake of conciseness. Furthermore, the factors used for the evaluation of TI and CI95% are the same as the values used in Section 3.2, under the assumption that the empirical distribution of $C_{L\alpha}$ follows the normal distribution. Figure 8 illustrates the variation of $C_{L\alpha}$ at different AoAs. Larger variation of $C_{L\alpha}$ was observed both from visual and numerical examination, compared with the variation of $C_L$. The percentage of experimental data points falling outside the TI varies from 0% ($\alpha = -12^\circ \sim 12^\circ$) to 3.3% ($\alpha = -15^\circ, 15^\circ$)(one point outside).

Table 2. Statistical analysis of experimental lift coefficient derivative $C_{L\alpha}$.

| $\alpha$ (°) | $C_{L\alpha}$ (rad$^{-1}$) | $\sigma$ | $\gamma_3$ | $\gamma_4$ | cov(%) | SEM | TI | CI |
|--------------|----------------------------|---------|-----------|-----------|--------|-----|----|----|
| -15          | 0.00                       | 0.278   | -0.498    | 4.23      | –      | 0.084| -0.79| 0.79| -0.10| 0.10|
| -12          | 1.03                       | 0.131   | -0.438    | 3.05      | 12.8   | 0.040| 0.65| 1.40| 0.98| 1.07|
| -9           | 2.49                       | 0.128   | -0.112    | 2.53      | 5.14   | 0.039| 2.13| 2.85| 2.44| 2.54|
| -6           | 2.50                       | 0.147   | -0.189    | 2.41      | 5.86   | 0.044| 2.09| 2.92| 2.45| 2.56|
| -3           | 1.89                       | 0.188   | 0.238     | 2.40      | 9.93   | 0.057| 1.36| 2.42| 1.82| 1.96|
| 0            | 1.39                       | 0.131   | 0.526     | 2.62      | 9.46   | 0.040| 1.01| 1.76| 1.34| 1.44|
| 3            | 1.42                       | 0.160   | -0.379    | 2.33      | 11.2   | 0.048| 0.97| 1.87| 1.36| 1.48|
| 6            | 1.38                       | 0.083   | 0.390     | 2.79      | 6.04   | 0.025| 1.14| 1.62| 1.35| 1.41|
| 9            | 1.14                       | 0.109   | 0.069     | 3.25      | 9.63   | 0.033| 0.83| 1.45| 1.09| 1.18|
| 12           | 1.83                       | 0.084   | -0.05     | 2.16      | 4.58   | 0.025| 1.59| 2.07| 1.80| 1.86|
| 15           | 2.38                       | 0.210   | -0.228    | 2.76      | 8.83   | 0.063| 1.78| 2.98| 2.30| 2.46|

Note – : cov($\alpha = -15^\circ$) is very large because mean of $C_{L\alpha}(\alpha = -15^\circ)$ $\approx$ 0

Figure 8. Analysis of experimental datasets, tolerance (TI) and confidence (CI) intervals of lift coefficient derivative $C_{L\alpha}$ vs. AoA ($\alpha$).
For the purpose of predicting the failure probability due to flutter through Monte Carlo sampling, a large sample population of $C_{L_{\alpha}}$ is needed. It will be more convenient if a probability distribution model could be used to represent the empirical probability histograms. Therefore, the same distribution models (normal, log-normal, and gamma models), examined in Section 3.2, were considered again to find an adequate probability distribution of $C_{L_{\alpha}}$. Figure 9 illustrates the fitting results and compares the models with the empirical histogram of $C_{L_{\alpha}}$ at each AoA. It is difficult to evaluate the goodness of fit for different models from a visual inspection. Thus, the Kolmogorov-Smirnov test was again employed to determine the goodness of fit.

All the models for all the AoAs could not be rejected at the 5% significance level, as documented in figure 10. This observation led to the use of the statistical moments for the selection of an adequate probability distribution model. It was found that the normal distribution was a better approximation of the empirical histogram for all the AoAs when skewness $\gamma_3$ and kurtosis $\gamma_4$ were compared (i.e., $\gamma_3 = 0$, and $\gamma_4 = 3$ for the normal distribution).

In conclusion, uncertainty analysis suggests that there is a non-negligible variability in the lift coefficient derivative $C_{L_{\alpha}}$, obtained from the wind tunnel HFFB data. The fitting of the empirical probability distribution indicates that the current sample population (30 realizations) may not be large enough to identify a unique probability distribution model from the empirical histogram. Further work with a larger sample population may be examined.

![Figure 9](image_url)

**Figure 9.** Empirical histogram of lift coefficient derivative $C_{L_{\alpha}}$ with 30 realizations at each AoA ($\alpha$), compared with fitting distribution models.

### 4. Conclusions

Lift coefficients obtained from wind tunnel experiments exhibit some variability, which can be affected by different experimental configurations. Consequently, experimental error propagation in the lift coefficient and its derivative with respect to the angle of attack (AoA) will have considerable impact on the flutter onset of wind turbine blades.

This paper presented preliminary experimental results and the analysis of randomness in the aerodynamic loads for wind turbine blades at various AoAs. Wind tunnel experiments were
carried out in NEU’s small-scale wind tunnel. The reference blade, used in the experiments, is the NREL 5MW wind turbine blade. The lift coefficients and lift coefficient derivative were both investigated through error analysis.

Table 1 and 2 summarize the statistical moments of these two aerodynamic properties in the blade model. Differences, associated with experimental variability, could be observed from the statistical analysis. As a result, prediction of flutter onset in full-scale wind turbine blades will be influenced by the variability in the lift coefficient derivative. Moreover, continuous probability distribution models were introduced to represent the empirical data histograms. Statistical hypothesis testing and comparison of moments were employed to evaluate the goodness of fit. In general, the normal and log-normal distributions were better approximations for different test scenarios. It was also noted that the sample population is not ideal. Future studies, considering a larger sample size, may be considered.

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