REVISION TO MANUSCRIPT DRAFT

Wind Energy Science Discussion

Performance of non-intrusive uncertainty quantification in the aeroservoelastic simulation of wind turbines

The authors would like to thank the two reviewers for their time and for the useful feedback. All inputs that they provided have contributed to the improvement of the paper.

A list of point-by-point replies to the reviewers' comments is reported in the following.

Reviewer #1

Numbered comments

1. [**Reviewer**] *The authors present a well-written and well-motivated application of standard non-intrusive uncertainty calculations to the estimation of loads on a wind turbine. There are, however, a few areas where additional clarity or corrections to the text and figures are required. Abstract: In the first line, "uncertainties" should be replaced by "aleatory uncertainties".*

    [**Authors**] The word "aleatory" has been added, as suggested.

2. [**Reviewer**] *The last sentence should also be made more specific as to what the effects and shortcomings are.*

    [**Authors**] The whole abstract has been reformulated and made more specific.

3. [**Reviewer**] *Section 2, page 1, line 21: "uncertainties are [...] only indirectly accounted for" – the concept of "indirect" uncertainty calculation should be explained, preferably with a citation of an example.*

    [**Authors**] An example has been added to the text.

4. [**Reviewer**] *Section 2.1, page 4, line 14: "give" should read "given".*

    [**Authors**] The typo has been corrected.

5. [**Reviewer**] *Section 2.1, page 4, lines 16-20: The choice of a Beta distribution (actually strictly speaking a scaled Beta distribution, since the input values do not always lie between 0 and 1 – see also Section 2.2, page 5, line 21 for ESD) is not sufficiently motivated. This distribution has some specific purposes in the statistical literature, in particular for expressing an uncertainty distribution over a probability. The reason for the turbulence intensity to be modified by a factor which lies between 0.5 and 2 is not explained, since it implies that the turbulence intensity corresponding to $k\_TI=1$ will not actually be the mean or median of this distribution? A log-normal or truncated Gaussian distribution (with mean or median set to 1) would appear more appropriate.*

    [**Authors**] The focus of the present study is on uncertainty propagation methods that are applicable to wind energy problems and that can converge faster than the standard

Monte Carlo (MC) approach. To perform the necessary comparisons, realistic uncertainties were generated from proprietary datasets. It was observed that the distributions of these datasets could be accurately modeled by scaled beta distributions. In the datasets, TI was not distributed symmetrically, and this is why $k\_TI=1$ is not centered around 1.

It should however be highlighted that neither NIPCE nor Kriging are bound to (scaled) Beta distributions and that other distributions could be readily used. Log-normal or truncated Gaussian distributions would be a perfectly feasible option. This said, in this study the scaled beta distributions nicely met our needs, i.e. representing data that is bound and not necessary symmetrically distributed.

The text in the manuscript has been changed to better explain these points.

6. **[Reviewer]** *Section 2.1, page 4, lines 21-22: The Dimitrov paper does not appear to contain this equation, and the physical motivation behind asserting that SE = SE_ref + a/TI - 1/4 (where a is a constant) is not obvious. The equation is in any case unclear, as TI(k) looks like a function, but appears to be a distribution, from the description on line 24.*

   [**Authors**] The equation is number five in the paper from Dimitrov et al., 2015 (https://doi.org/10.1002/we.1797). The difference between the equation of Dimitrov et al., 2015 and our equation is that in our work TI is not only dependent on wind speed, but also on the uncertain parameter k_{TI}. For varying values of k_{TI}, TI changes and so does the shear coefficient.

   We rewrote a large portion of the section to better explain this point.

7. **[Reviewer]** *Section 2.1, page 4, lines 26-28: The method by which the k_TI values in table 4 have been derived should be explained, to aid reproducibility.*

   [**Authors**] The focus of the paper is on uncertainty propagation and results can be reproduced by using the parameters reported in Table 3. These values are site and wind turbine dependent, and different values would certainly change the outputs, without however invalidating the methods used for uncertainty propagation.

   Lines 26-28 and the corresponding references were removed in the new version of the manuscript, as they did not help with the understanding and were therefore deemed to be superfluous.

8. **[Reviewer]** *Section 3.1, page 8, line 3-4: what does it mean, to say that the mean is below 1%?*

   [**Authors**] The sentence was imprecise, and it has been improved. The sentence refers to the convergence trends and to the variations in mean and standard deviation over the iterations.

9. **[Reviewer]** *Section 3.1, page 8, line 10: "converge" should read "convergence".*

   [**Authors**] This typo has now been corrected.

10. *[**Reviewer**] Section 3.2, page 11, Figure 5: This figure is difficult to understand. Does the y-axis label "difference in" refer to a change between adjacent function evaluations? What is the definition of "potential inexactness" that the grey band is representing, and what information does it give the reader about the other lines on the graph? Finally, the legend says "1.1k MC" whereas the rest of the text indicates 1200 evaluations.*

[**Authors**] The y-axis represents the difference with respect to the MC estimates obtained with 1,100 sample points. As the legend of Figure 5 reports, "The gray area reflects the potential inexactness of the MC benchmark, and it represents the 95% confidence intervals for 1,100 sampling points.". "Potential inexactness" then accounts for the fact that, with a finite number of sampling points (here, equal to 1,100), MC estimates the outputs only up to some possible residual variations. The grey band could be made narrower by increasing the number of samples. The text was updated to clarify this point. The number 1,200 referred to older calculations, while 1,100 is the correct number. The text was corrected accordingly.

11. *[**Reviewer**] Section 3.3, page 12, Figure 6: More explanation is required concerning the pdf values being shown - how should they be interpreted? They are different to the pdf values being shown in Fig 5. The pdf values are presumably also not conditional on k_TI=1, since they do not appear to integrate to 1? Finally, the second graph on the top line has a typo in the title: "MDT" should read "MTD".*

[**Authors**] Figure 6 shows the values and corresponding probabilities of each key output for combinations of k_{AF} and ESD. These values correspond to a 2D slice of the tri-dimensional space. The slice is cut for $k_{TI}=1$.

Two plots are defined for each key output: on the left a plot shows the percent difference with respect to the mean of the various key outputs for the different possible input combinations of k_{AF} and ESD, while the plot on the right shows the corresponding probabilities. The plots were generated by evaluating the UK model, trained with 40 function evaluations, with a large random sample of 1,000,000 points, using $k_{TI}=1$. The probabilities were then computed using this sample, so they are conditional on $k_{TI}=1$.

The pdf shown in Fig. 4 (not Fig. 5, which has no pdfs) corresponds to the sample of 1,100 points obtained from Monte Carlo simulations.

The typo in the title of the graph has now been corrected and a more complete description of Fig. 6 has been added at the beginning of Sect. 3.3.

12. *[**Reviewer**] Section 3.3, page 12, line 7: Isn't the low probability of occurrence of ESD=0 and k_AF=0 an input assumption? Perhaps when the meaning of the pdf plots is more fully explained, this will become clear.*

[**Authors**] Yes, it is. The text has been changed to clarify this point.

13. *[**Reviewer**] Section 3.3, page 13, line 5: The "largest probability" implies total probability greater than 50% of lying within +/- 1% of the mean?*

[**Authors**] The sentence in the text has now been reformulated to highlight that the highest probabilities of occurrence correspond to values of MTD that fall very close to the mean values, and that the deterministic condition prescribed by the standards actually corresponds to the lowest probability of occurrence.

14. [***Reviewer**] Page 13: Mostly these conclusions are justified and well-written. However, some more discussion could be given to the relative influence on the qualitative or quantitative results (i.e. differences with a deterministic approach) of the method itself, versus the specific numerical assumptions made about input parameter values, distributions and covariances*

    [**Authors**] We thank the reviewer for the useful comments and suggestions. We hope that our changes improved the text. We are aware that this work represents only a preliminary step and much remains to be done before these methods for uncertainty propagation are fully understood and become widely applicable. A better analysis of the outputs is a top priority, especially to evaluate the impact of these methods on design. In fact, work is ongoing to integrate the UQ approach within a design framework. A sentence on future work was added to this section, to highlight this point.

Reviewer #2

The authors present the application of two non-intrusive uncertainty propagation techniques: Universal Kriging and Polynomial Chaos Expansion, as means of propagating the effect of uncertainty in wind conditions and blade aerodynamics on wind turbine loads. The manuscript describes the process of setting up the uncertainty propagation models and demonstrates an application on a 10MW research turbine. In the results section, the authors show how the uncertainty in two variables – the airfoil unevenness, and the extent of degradation along the blade span, affect the distribution of various wind turbine load components. The article is well structured and clearly written, and deals with a relevant scientific problem. In my opinion, the manuscript will benefit scientifically if the authors go in further depth in some aspects of their analysis. These recommendations are given in the comments below.

General comments

1. [***Reviewer**]: In several places in the paper (e.g. page 5, line 3) the authors state that there are some potentially significant sources of uncertainty, which are not considered in order to allow more focus on other relevant uncertainty sources. This is reasonable; however in such a situation it is important to understand what is the effect of not considering these uncertainties. For example, would the ignored uncertainties have the same effect over the entire variable space considered, meaning that they will not mask the relative effects of other uncertainties? Or will their effect mix with that of other uncertainties meaning a larger model error in general?*

    [**Authors**] This is a very good point, which however we have not yet addressed and that -to be fully answered- indeed requires methods like the ones presented in this work. The

problem of uncertainty quantification in wind turbine simulation and design is very complex due to multiple reasons. One of them is exactly the one raised by the reviewer: what are the most "important" uncertainties? Answering this question with a standard MC approach is extremely expensive, to the point of being undoable. To address this problem, we started by testing different uncertainty propagation methods, in order to identify the most suitable one. To run the necessary comparisons, a sub-set of uncertainties that we could quantify was selected. We agree with the reviewer that the next natural step is a detailed assessment of the importance of all uncertainties impacting wind turbine analysis and design.

These thoughts were already included in the outlook for future work, but we have now added one additional sentence to better elaborate on them. In addition, although the introduction already clearly stated the goals of this paper, we have now added a new sentence that clarifies that an in-depth study of the effects of uncertainties is not one of them.

2. *[**Reviewer**] The uncertainty propagation models are trained based on variable spaces with beta-distributed marginal variables. Then the probability density functions for the response surfaces are plotted based on a Monte Carlo simulation which apparently uses the abovementioned marginal distributions. However, these sampling distributions do not fully correspond to the real-world distributions of the uncertainty variables. It is therefore difficult to judge on whether a given load event is critical as it may have a high probability of occurrence in the sampling space used to train the uncertainty propagation model, but low probability in the real world, and vice versa. I suggest that the authors redo the MC analysis (Figure 6) using realistic joint distributions of the uncertainty variables. This is also a key distinguishing point between uncertainty propagation and uncertainty quantification: the response surface only propagates the uncertainty, so in order to quantify the uncertainty of the dependent variable we need to feed the propagation model with the right input uncertainties.*

[**Authors**] This a second very good point raised by the reviewer. However, as clearly stated throughout the text, this work limits its scope to the testing of two propagation methods, analyzing their convergence trends and performing an initial analysis of the uncertain outputs. We did not (and still do not) have access to distributions of the uncertain inputs coming from the real-world. These data sets would be extremely valuable, also to address Comment #1. This work aims at showing that NIPCE and Universal Kriging are two valuable alternatives to MC for the propagation of uncertainties affecting wind turbines. A second goal of this work is to show that the world of UQ has a very large potential to better estimate outputs of interest and help reducing safety factors in wind turbine design.

3. *[**Reviewer**] To me, the authors are considering a manifold of four random quantities: two uncertainty variables (k_{AF} and ESD) combined with two environmental conditions – wind speed, and turbulence intensity (and wind shear as fully dependent on the latter two). I think it will make the paper clearer if the presentation is made along this logic. In this way*

one can also distinguish between point-to-point uncertainty between individual realizations, and the effect of the two uncertainty factors integrated over the joint distribution of the environmental conditions (which is what I believe is the purpose of Figure 6 in the current manuscript).

[**Authors**] The work adopts three random quantities, k_{AF}, ESD and k_{TI}. Shear is linked to TI through Eq. 1. Wind speed is not an uncertain parameter and simulations are run for wind speed bins of 2 m/s from cut in to cut out. We thought of adopting the logic proposed by the reviewer of analyzing the single uncertainties. However, no strong conclusion could be drawn by that approach, and we finally opted for a more aggregated analysis of the results.

4. [**Reviewer**] *It is not clear whether the results reported in Figure 6 are averaged over the wind speed or not. If we were considering integrated quantities such as e.g. fatigue loads, it would be relevant to show the average values. However, when talking about extremes it would be more appropriate to not do any averaging, and instead include the wind speed as one of the factors in computing the pdf of the extreme loads. This also relates to the comments above.*

[**Authors**] The results are not averaged over the wind speed. Quantities such as MTD, ThS, CBRM and CTBM are computed by taking the maximum values across all wind speeds. Quantities such as AEP and the three DELs are instead integrated across the wind speeds assuming the Weibull distribution corresponding to Class IA (k=2, U_{avg}=10).

We added a paragraph in Sect. 3.1 to better explain this point.

Specific comments

5. [**Reviewer**] *Page 3, line 20 (first paragraph of Section 2): This is a classification of the uncertainties according to the physical mechanism that causes them. Another maybe even more relevant classification could be according to their type, e.g., statistical, measurement, model, human-caused… This should make it easier to categorize the uncertainties.*

[**Authors**] Following the reply to Comment #2, the focus of the present work is to test uncertainty propagation methods for three realistic uncertain inputs. An important, but also very challenging, work would be to categorize the input uncertainties and assess their importance. This would be very valuable to the scientific community, although the lack of measurements and field data available in the public domain complicates this task. Although very useful, we believe this aspect to be outside of the scope of the present work.

6. [**Reviewer**] *Page 3, lines 23-25: "Not only the nominal values of all such parameters are uncertain, but additional sources of uncertainty are introduced by manufacturing processes and the status of wear and tear of each individual machine or component". Another uncertainty source which the authors should consider here is the measurement*

uncertainty: the observed value of a given variable is different from its true value due to imperfect observation. This also means that we don't necessarily know the true reference.

[**Authors**] We agree with the reviewer on this point, and we added this source of uncertainty in the text.

7. [***Reviewer***] *Page 4, line 8: The authors describe that turbulence boxes include random realizations of a turbulence field. It would be useful to describe in more details what are the statistical properties of these randomly generated fields – e.g. are they Gaussian, what are the spectral parameters.*

   [**Authors**] Turbulence fields were generated adopting the standard values prescribed by IEC standards. Only TI and shear exponent were assumed uncertain and perturbed.

8. [***Reviewer***] *Page 4, line 12: "…These effects may alter in a significant way the statistics of the wind at a given site. All such effects are difficult to measure and quantify with precision…" What the authors refer to may be considered as a kind of measurement (epistemic) uncertainty due to not being able to quantify the variables with sufficient precision. A specific reference to this type of uncertainty can be found in Tarp-Johansen at al. [1] where this is referred to as "Exposure uncertainty".*

   [**Authors**] When modeling the wind, the distinction between aleatory and epistemic uncertainties may blur. In this work we addressed the first ones, but it is however true that wind is also affected by epistemic uncertainties that should be addressed. We thank the reviewer for having provided a reference we were not aware of. This reference has now been included in the revised version of the manuscript.

9. [***Reviewer***] *Page 4, eq. 1: Please note that in Dimitrov et al. (2015) the reference turbulence intensity TI_{ref} is a function of the turbulence quantile, i.e., the wind shear distribution changes with respect to the turbulence quantile. What kind of turbulence quantile have the authors considered as TI_{ref}? Is that taken into account by the uncertainty factor k_{TI}? I think the authors have to explain the relationship between the turbulence quantile and k_{TI}.*

   [**Authors**] Following Comment #6 of Reviewer #1, the paragraph has been reformulated. The distribution shown in Fig. 3 was determined for a turbulence quantile of 90%.

   [***Reviewer***] *Page 5, line 14: "either uniform or a beta probability distribution" – why either distributions and not one specific?*

   [**Authors**] This was a typo and we corrected it. In the preliminary studies we did not have any indication on k_{AF} and we therefore ran the first analyses adopting a uniform distribution. Later on during the study, one of the authors gained access to real data and provided the values of α and β reported in Table 3.

   [***Reviewer***] *Page 6, line 22: Is the severity of surface degradation k_{AF} assumed to be uniform over the full extent of spanwise degradation (ESD)? I would suggest that a more realistic approach would be to have 1) k_{AF} as a random, spatially-correlated variable over*

the blade span, and 2) the expected value of k_{AF} to gradually increase towards the blade tip. This could still amount to some integrated degradation measure.

[**Authors**] We agree with Reviewer #2 that this could be a better approach for future studies. Nonetheless, the (few) experimental data points used to fill Table 3 suggested a constant k_{AF}.

10. [***Reviewer***] *Page 6, line 9: What was the trend function used in the Universal Kriging approach? One could consider e.g. a polynomial chaos expansion as a trend function – one could even make use of the NIPCE already trained as a standalone model.*

[**Authors**] The trend function used in the UK approach is a reduced quadratic polynomial.

11. [***Reviewer***] *Page 6, line 29 (and Figure 3): what turbulence quantile does TI_{ref} refer to? Why is the turbulence uncertainty factor k_{TI} beta-distributed, normally one could use the standard assumption that the turbulence (standard deviation of wind speed) is log-normally distributed? Again, in continuation to a previous comment, we need an explanation of the relationship between the turbulence probability distribution and the uncertainty factor k_{TI} and what are the implications of replacing the turbulence distribution with k_{TI}.*

[**Authors**] See Comment #9, the whole paragraph has been reformulated to better explain how k_{TI} was defined.

12. [***Reviewer***] *Page 9, Table 4: are these statistics based on the full data set over all wind speeds? Have the results been Weibull-weighted according to a certain wind speed probability, or is the wind speed probability considered uniform? Is the "standard deviation" the sample standard deviation, or the uncertainty in the mean estimate?*

[**Authors**] These statistics are based on a sample of 1,100 MC function evaluations. Each function evaluation corresponds to 12 transient simulations at different wind speeds from cut-in to cut-out, considering six turbulent seeds. The extreme loads (MTD, ThS, CBRM, CTBM) are computed extracting the maximum overall value of each simulation for each quantity. The DELs (DEL ThS, DEL CBRM, DEL CTBM) and AEP are computed for each dynamic simulation and Weibull-averaged according to the Weibull of wind class 1A. The standard deviation is computed as the amount of dispersion of the key outputs of the 1,100 function evaluations.

Text has been changed to include the above information.

13. [***Reviewer***] *Page 10, line 7: give a definition of the collocation ratio*

[**Authors**] The collocation ratio is defined as the ratio between the number of function evaluations used to train the model and the total number of terms in the chaos expansion.

The definition has now been added to the text.

14. [***Reviewer***] *Page 10, line 8: what is the sampling distribution of the MC? Is that the same as the MC sample used to train the models?*

[**Authors**] The sampling distribution of the MC is random. Yes, it is the same used to train the models.

15. [***Reviewer***] *Page 10, line 11: the UK converges faster than the NIPCE. Could that be because Kriging is in essence an interpolation scheme, and the response is linear enough (as the authors point out themselves) so that a few points are sufficient to establish a reasonable extrapolation?*

[**Authors**] Yes, we believe this to be a correct interpretation of the results.

16. [***Reviewer***] *Figure 6: there are some "wrinkles" in the contour plots. Could these be caused by having few data points (40 function evaluations only)? What if we added more data – maybe the contours would resemble more straight lines (= closer to linear dependencies)?*

[**Authors**] The contour plots in Fig. 6 are computed by evaluating 1,000,000 random sample points in the UK model trained with 40 function evaluations. We did ask ourselves the same question at the time of analyzing the outputs of the simulations. We then generated similar contour plots training the model with more evaluation points. However, the plots did not change substantially, and we therefore concluded that the wrinkles are likely associated to non-linearities of the aeroservoelastic model.

17. [***Reviewer***] *Page 13, line 24: "…the deterministic conditions prescribed by international design standards generate maximum values of loads and power production, which however are typically associated with a very low probability of occurrence". This is guaranteed only if the sampling distribution used to propagate the uncertainty is the same as the real-world distribution of the random input variables. As discussed in the general comments, this is not necessarily the case with the present data sets.*

[**Authors**] The uncertain input parameters reported in Table 3 come from real datasets and can be assumed to be realistic. It is true that a higher number of uncertain parameters will likely increase the uncertainty of the outputs. Nonetheless, the variations observed in this work suggest that the adoption of uncertainty propagation methods may help reducing safety factors, possibly drastically.

Technical comments:

18. [***Reviewer***] *Page 4, line 14: "give turbine" -> "given turbine"*

[**Authors**] The typo has been corrected.

19. [***Reviewer***] *Page 8, line 10: "converge" -> "convergence"*

[**Authors**] The typo has been corrected.

We have taken the opportunity to make several small editorial changes to the text, in order to improve readability. A revised version of the manuscript is attached to the present reply, with the main changes highlighted in blue.

The authors

Performance of non-intrusive uncertainty quantification in the aeroservoelastic simulation of wind turbines

Pietro Bortolotti[1], Helena Canet[1], Carlo L. Bottasso[1], and Jaikumar Loganathan[1,2]

[1]Wind Energy Institute, Technische Universität München, D-85748 Garching, Germany
[2]GE Global Research, Aero Thermal Lab., Hoodi Village, Bangalore, India

Correspondence: Carlo L. Bottasso (carlo.bottasso@tum.de)

Abstract. The present paper characterizes the performance of non-intrusive uncertainty quantification methods for aeroservoelastic wind turbine analysis. Two different methods are considered, namely non-intrusive polynomial chaos expansion and Kriging. Aleatory uncertainties are associated with the wind inflow characteristics and the blade surface state, on account of soiling and/or erosion, and propagated throughout the aeroservoelastic model of a large conceptual off-shore wind turbine.

5   Results are compared with a brute-force extensive Monte Carlo sampling, which is used as benchmark. Both methods require at least one order of magnitude less simulations than Monte Carlo, with a slight advantage of Kriging over polynomial chaos expansion. The analysis of the solution space clearly indicates the effects of uncertainties and their couplings, and highlights some possible shortcomings of current mostly deterministic approaches based on safety factors.

1 Introduction

10   The analysis and design of complex engineering systems is typically based on sophisticated numerical models. While in the past these have been mostly based on deterministic formulations, more recently probabilistic approaches have been gaining an increased attention because of their ability to account for uncertainties in both the models and their inputs. Although numerous applications of probabilistic methods can be found in many areas of engineering, so far formal uncertainty quantification has been applied to a lesser degree in the wind energy field. In fact, probabilistic approaches have been used to estimate wind turbine

15   extreme loads, as reported by Dimitrov (2016) and Graf et al. (2018) among others, but comprehensive analyses and design procedures that account for uncertainties have been lagging behind. This can probably be attributed to the inherent complexity of the models describing the behavior of wind turbines and the environment in which they operate. Indeed, wind (and water, in the offshore case) excitations are highly unsteady and characterized by complex phenomena. Additionally, comprehensive wind turbine simulation environments are obtained by coupled multi-physics models, which account for the effects of structural

20   dynamics, aero and hydrodynamics, closed-loop controls, and their mutual interactions. As a consequence of the inherent complexity and computational cost of the resulting simulation tools, most of the analysis and design methods are currently based on deterministic simulation models and uncertainties are, to a large extent, only indirectly accounted for. For example, instead of computing extreme loads from the tails of probability distributions —which would be the probabilistic approach—, artificial deterministic wind time histories are routinely used to generate in a simpler way such limit cases (IEC61400-1, 2005).

The behavior of wind turbines and of the environment in which they operate is profoundly affected by uncertainties. Therefore, time is ripe for investigating rigorous mathematical formulations to evaluate the robustness of designs and to establish confidence levels on outputs of interest. In the literature, already a few authors have taken the first steps in this direction. One of the first wind energy related publications in this field is the paper by Witteveen et al. (2007), where an intrusive formulation of

5　polynomial chaos expansion (IPCE) is used to investigate the effects of uncertainties affecting the Onera dynamic stall model with regard to a 1 MW wind turbine blade. The authors conclude that the model is very sensitive to input uncertainties and that IPCE is able to reconstruct the output statistics with one order of magnitude fewer function evaluations than a standard Monte Carlo (MC) approach. In Petrone et al. (2011), the aerodynamic design optimization of a wind turbine blade is presented, where uncertain levels of contamination affect the airfoil polars along the span of the blade. A Simplex Stochastic Collocation (SSC)

10　method is used for the propagation of the uncertainties, and convergence is compared against the standard MC approach. SSC is found to be significantly more efficient than MC, in the sense that it requires a much smaller number of evaluations of the model for convergence. Multi-objective design solutions are also presented in the same work, investigating trade-offs between maximum power coefficient and minimum sound pressure levels. Another approach for the robust design optimization of wind turbine rotor blades is presented by Campobasso et al. (2016), where uncertainties are assumed in the chord and twist distribu-

15　tions as well as in the prescribed pitch angle. Additional recent efforts in this area have been dedicated to the development of novel stochastic models for the aerodynamic analysis of wind turbine blades (Fluck, 2017).

Modern simulation and design frameworks are typically based on validated comprehensive aeroservoelastic models. Drastic rewritings of such complex codes to incorporate stochastic formulations are clearly undesirable. To enable the use of legacy codes as black boxes within a probabilistic approach, studies have been recently focusing on the augmentation of aeroser-

20　voelastic solvers with non-intrusive uncertainty propagation methods. In addition to enabling the reuse of existing software, non-intrusiveness also allows one to rapidly reap the benefits of any modeling improvement, as the problem of uncertainty quantification is essentially decoupled from the details of the underlying simulation model. This approach is followed by Abdallah et al. (2015) using MC. The method, however, is non-intrusive but also typically extremely expensive, because it performs a straightforward exhaustive sampling of the solution space. More sophisticated spectral methods are used in Matthäus et al.

25　(2016) and Murcia et al. (2017). In these three studies, the impact of uncertainties in the soiling of the airfoils and the wind inflow is estimated in terms of the statistics of rotor performance and extreme loads.

The present study expands and refines the work presented in Matthäus et al. (2016), with the primary goal of identifying the most suitable approaches for the propagation of uncertainties throughout aeroservoelastic wind turbine models. A second goal of this work is that of establishing the performance and convergence properties of such methods for this specific application.

30　The in-depth study of uncertainties and their effects on wind turbines is not amongst the goals of this paper, although it is clearly a long term objective of crucial importance. Among the various approaches that are available in the literature (Sudret, 2007), non-intrusive polynomial chaos expansion (NIPCE) and Kriging (Krige, 1951) are considered here, because of their generality and typical good performance on a wide range of different applications.

The study is conducted with reference to a conceptual offshore 10 MW wind turbine, which is representative of the edge of

35　the current technology. The machine is modeled with the code Cp-Lambda (<u>C</u>ode for <u>P</u>erformance, <u>L</u>oads and <u>A</u>eroelasticity

by <u>M</u>ulti-<u>B</u>ody <u>D</u>ynamic <u>A</u>nalysis), which implements a multi-body formulation for flexible systems with general topologies. The element library includes rigid bodies, non-linear flexible elements, joints, actuators and aerodynamic models (Bottasso et al., 2006; Bauchau, 2011). Uncertainties are assumed both in the wind characteristics, using actual field measurements, and in the aerodynamic properties of the rotor blades, on account of soiling and erosion. Simulations are performed over a range

5 of wind speeds covering the entire operating regime of the machine. The two considered uncertainty propagation methods are compared in terms of their ability to reconstruct the main statistics of key performance indicators and design drivers, including maximum blade tip deflection, ultimate and fatigue loads at various spots on the machine and, finally, annual energy production (AEP). An exhaustive sampling by the classical MC approach is used as benchmark to define the convergence and accuracy of the tested methods. The resulting probabilistic simulation framework can quantify the effects of uncertainties for

10 a comprehensive black-box aeroservoleastic simulator, in support of the analysis and design of wind turbines. This work is an intermediate step towards the inclusion of robust design methods in the procedures described in Bortolotti et al. (2016), which are at present purely deterministic (except than for the standard treatment of wind by the use of multiple realizations of turbulent fields (IEC61400-1, 2005)).

The paper is structured as follows. Section 2 first discusses sources and models of uncertainty for wind turbine aeroservoe-

15 lasticity, and then briefly presents the two methods considered here for the propagation of such uncertainties. Next, the wind turbine model is presented at the beginning of Sect. 3, followed by a comparison of the convergence trends for the two methods in Sect. 3.2, while an analysis of the results is discussed in Sect. 3.3. Conclusions and recommendations for future work are finally given in Sect. 4.

2 Sources of uncertainty and propagation methods

20 Uncertainties are commonly categorized into two macro families: aleatory and epistemic uncertainties. The former source of uncertainty emerges from the underlying randomness of a process, as for example described by the probability distribution of the wind speed at a certain site. The latter, on the other hand, originates from a lack of knowledge and data. This work considers the effects of aleatory model parameters and inputs with established underlying probability distributions.

Wind turbines are subjected to several sources of uncertainty. In addition to the inherently stochastic character of the wind,

25 which varies in time and space for a multitude of reasons, uncertainties are also present in the aerodynamic characteristics of the machine, in the mechanical properties of the materials, structures and foundations, as well as in the characteristics and performance of many of the sub-systems of a wind turbine. Not only the nominal values of all such parameters are uncertain, but additional sources of uncertainty are introduced by manufacturing processes and the status of wear and tear of each individual machine or component. Additionally, one should not forget that measurements are also uncertain (Tarp-Johansen et al., 2002),

30 so that an absolute real ground truth can not be established in general.

Due to its preliminary character, this study limits its attention to uncertainties affecting the wind inflow and the aerodynamics of the blades. These are typical and relevant examples of aspects of a turbine model that can often only be described in statistical terms, but that also have a profound impact on the behavior and overall performance of the system. It should however be

remarked that the methods analyzed here are general, and in principle applicable to problems other than the ones considered in this work.

2.1 Uncertainty in the characterization of the wind

Wind is a natural phenomenon where air particles move dynamically following three-dimensional paths as the result of a number of driving effects. In general, such a complex process can only be measured and described in terms of its statistics. International standards, such as IEC61400-1 (2005), represent wind profiles by a combination of deterministic mean parameters —typically, mean hub-height speed, shear exponent (SE), vertical and horizontal inflow angles— and a turbulence model, which, for an assigned mean turbulence intensity (TI), describes the stochastic variability of the flow field. Each realization of the turbulent wind field is associated with a random seed. By combining the mean flow field with the fluctuations produced by the turbulence model, one obtains a representation of the wind field in space and time. Sufficient durations and number of realizations are typically necessary for the statistics of the generated wind fields to reach convergence.

However, effects such as solar irradiation, seasonal and long term climate changes, vegetation growth and complex terrain conditions play important roles in increasing uncertainties in the characteristics of the wind (Sathe et al., 2011; Ernst and Seume, 2012). These effects may alter in a significant way the statistics of the wind at a given site. All such effects are difficult to measure and quantify with precision, in turn introducing uncertainties in the assumed wind characteristics used for the simulation and design of wind turbines. This is clearly a problem of crucial importance. In fact, for a given turbine and control system, the assumed wind input plays a fundamental role in determining performance and loading, including lifetime and safety.

This work assumes that both TI and SE are uncertain. However, field data often exhibit a correlation between SE and TI that, according to Dimitrov et al. (2015), can be modelled as

$$\mathrm{SE} = \mathrm{SE_{ref}} + \frac{\mathrm{TI_{ref}} - \mathrm{TI}}{\mathrm{TI}\, c_{\mathrm{SE}}}. \tag{1}$$

In this expression, $\mathrm{SE_{ref}}$ is a reference value for the shear exponent, c_{SE} a correction factor that can be generally assumed equal to 4, and $\mathrm{TI_{ref}}$ is the value of the turbulence intensity at a wind speed of 15 m/s. Here an uncertain multiplicative factor k_{TI} is used to perturb an initial distribution of TI over wind speed; when k_{TI} equals 1, TI at 15 m/s equals $\mathrm{TI_{ref}}$. Therefore, through Eq. (1), k_{TI} also introduces a corresponding uncertainty in SE.

Here and in the following all uncertain parameters are modelled with scaled beta distributions. Such distributions are preferred to other possible choices for two reasons: first, they are highly flexible in shaping the probability density function on account of given statistical data and, secondly, they generate bounded distributions with lower and upper limits. This is a necessary feature when modeling parameters that cannot assume negative values. It should be noted, however, that neither NIPCE nor Kriging are bound to scaled beta distributions, and truncated Gaussian, log-normal, uniform distributions or others could also be readily used. The parameters of the beta distribution for the uncertain factor k_{TI} are reported in Sect. 3.1.

2.2 Uncertainty in rotor aerodynamic properties

A second important source of uncertainty in wind turbine simulation and design lies in the aerodynamic characteristics of the rotor. Among other effects, the performance of the airfoils —measured in terms of the aerodynamic coefficients of lift, drag and moment— is considered as a possible major source of uncertainty.

The estimation of airfoil aerodynamic coefficients can be obtained by experimental and numerical techniques. Both approaches are challenging and lead to uncertainties of an aleatory and epistemic nature, especially in the stall and post-stall regimes. Although potentially very significant, such uncertainties are not considered further in this work, which focuses instead on blade surface conditions.

During operation, the surface of a blade may be contaminated by the deposition of dust, dirt, insects and pollen. Additionally, the blade surface can also be altered due to erosion caused by sand and rain. All these effects are typically and particularly prominent at the leading edge, which has a fundamental role in dictating the behavior of airfoils. As a result, changes in surface conditions during operation may result in significant uncertainties in power capture and loading.

Several studies have quantified the impact of erosion and contamination on aerodynamic performance (Khalfallah and Koliub, 2007; Sareen et al., 2014; Zidane et al., 2016). The exact pattern and location of surface changes during operation is a random process, which is largely governed by local effects, such as the local relative speed of the flow with respect to the blade and the local manufacturing surface quality, for example in terms of gel coat thickness and bonding strength (Khalfallah and Koliub, 2007). In the current study, an uncertain level of airfoil profile unevenness is simulated by using the random variable k_{AF}, modeled with a scaled beta probability density function. Variable k_{AF} is assumed to vary within the values of zero and one, where zero corresponds to the nominal (clean) state of an airfoil, while one corresponds to a contaminated or fully rough state of operation. The airfoil aerodynamic coefficients between these two states are linearly interpolated for any intermediate value of the random variable, as shown in Fig. 1.

Uncertainties in the actual extension of surface degradation along the span of the blade are modelled by introducing a second parameter, termed extent of spanwise degradation (ESD). Parameter ESD is defined as the non-dimensional span length —measured from blade tip— where factor k_{AF} affects the airfoil coefficients. Since surface degradation typically occurs in the outer portion of the blades, ESD is assumed to follow a beta distribution between zero, which corresponds to a fully clean blade, and 0.5, which implies that the outer 50% of the blade is affected by surface degradation with a severity dictated by k_{AF}.

2.3 Methods for uncertainty propagation

As anticipated in Sect. 1, the current literature offers a vast range of methods for the propagation of uncertainties. A detailed overview of the various formulations can be found in Sudret (2007). Among the many options, based on the results presented in Matthäus et al. (2016), the present study considers the regression-based order 3 NIPCE and Universal Kriging (UK), as implemented in DAKOTA (Adas et al., 2015), to propagate the uncertainties discussed in Sects. 2.1 and 2.2.

In Matthäus et al. (2016), the methods of spectral projection and linear regression were tested to determine the polynomial coefficients of NIPCE, the latter typically yielding the best results. In terms of polynomial order, tests were conducted between
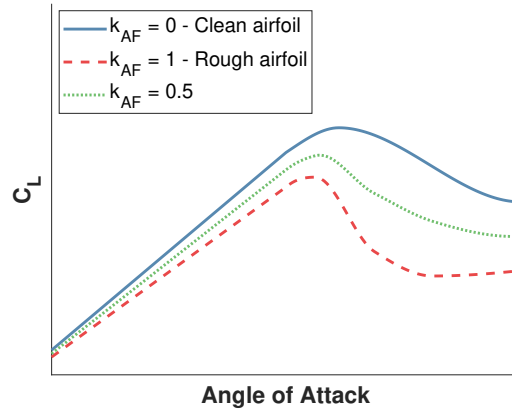
Figure 1. Interpolation of the airfoil aerodynamic coefficients between the fully clean and fully rough conditions.

order one and 16. The best results were obtained for order three, while above this value the solution first stopped improving and then deteriorated. It was also found that Universal Kriging is superior to Ordinary Kriging, mostly due to its better adaptability to a general trend in the response.

3 Application to a 10 MW wind turbine

Here uncertainties in the wind characteristics and in the airfoil polars are propagated throughout the aeroservoelastic model of an offshore wind turbine, with the goal of comparing the performance of the uncertainty quantification methods and of establishing their main convergence characteristics. First, Sect. 3.1 introduces the turbine model together with the assumed uncertainties. Convergence of the statistics is then discussed in Sect. 3.2, while the analysis of the effects of uncertainties on some key outputs is finally presented in Sect. 3.3.

3.1 Wind turbine model and associated uncertainties

The AVATAR wind turbine is considered in this work, as a representative case of a large offshore wind turbine. This conceptual machine was developed by a consortium of academic and industrial partners within the EU project AVATAR (AVATAR Consortium, 2014-2017), and its main characteristics are summarized in Table 1. In this study, the standard configuration defined by the consortium is used, while the blade inner structure is the one developed at Politecnico di Milano (Croce et al., 2017). Table 2 lists the airfoils used along the span of the blades.

For airfoils DU97-W-300 and DU91-W2-240, which occupy the outermost part of the blade, surface conditions are specified by the two parameters k_{AF} and ESD, by interpolating between fully clean and fully rough aerodynamic coefficients. The clean and rough polars of the two airfoils, which are based on the work performed in the AVATAR project (Méndez et al., 2017), are

Table 1. Principal characteristics of the 10 MW AVATAR wind turbine.

Wind turbine model	10 MW offshore
Wind class	IEC 1A
Rated electrical power	10.0 MW
Drivetrain & generator efficiency	94.0%
Rotor diameter D	205.76 m
Hub height H	127.0 m
Nacelle uptilt angle Φ	5.0 deg
Rotor cone angle Ξ	2.5 deg
Cut-in wind speed V_{in}	4 m/s
Cut-out wind speed V_{out}	25 m/s
Max tip speed $v_{\text{tip}_{\max}}$	90 m/s
Blade mass	52,874 kg
Tower mass	630.0 ton

Table 2. Spanwise positions of the airfoils.

Airfoil	Thickness	Position	Airfoil	Thickness	Position
Circle	100.0%	0.0%	DU00-W2-350	35.0%	36.31%
Circle	100.0%	0.61%	DU97-W-300	30.0%	45.63%
DU-600	60.0%	17.00%	DU91-W2-240	24.0%	65.00%
DU00-W2-401	40.1%	28.47%	DU91-W2-240	24.0%	100.00%

reported in Fig. 2. On the other hand, only clean aerodynamic coefficients are used for the airfoils located closer to the blade root, as surface degradation is less likely to happen in this region.

Uncertainties are considered in k_{TI}, k_{AF} and ESD. As previously explained, the wind parameter SE is not assumed as an independent uncertain variable, but it obeys the relationship of Eq. (1), assuming SE_{ref} equal to 0.15 and TI_{ref} equal to 4.9%

5   (see Fig. 3). All uncertainties are assumed to follow the beta distributions whose parameters are reported in Tab. 3. The distribution of turbulence intensity is taken from a measurement campaign conducted in a wind park in the North Sea. The distribution for $k_{\text{TI}} = 1$ is reported in Fig. 3.

An extensive MC is first performed to characterize the solution space. The three uncertainties are propagated throughout the aeroservoelastic model in a power production state at 12 different wind speeds from cut-in to cut-out, considering six turbulent

10   seeds. Eight outputs of interests are analyzed, namely maximum blade tip deflection (MTD), ultimate and damage equivalent load (DEL) of the thrust measured at the main shaft (ThS), ultimate and DEL combined blade root moment (CBRM), ultimate

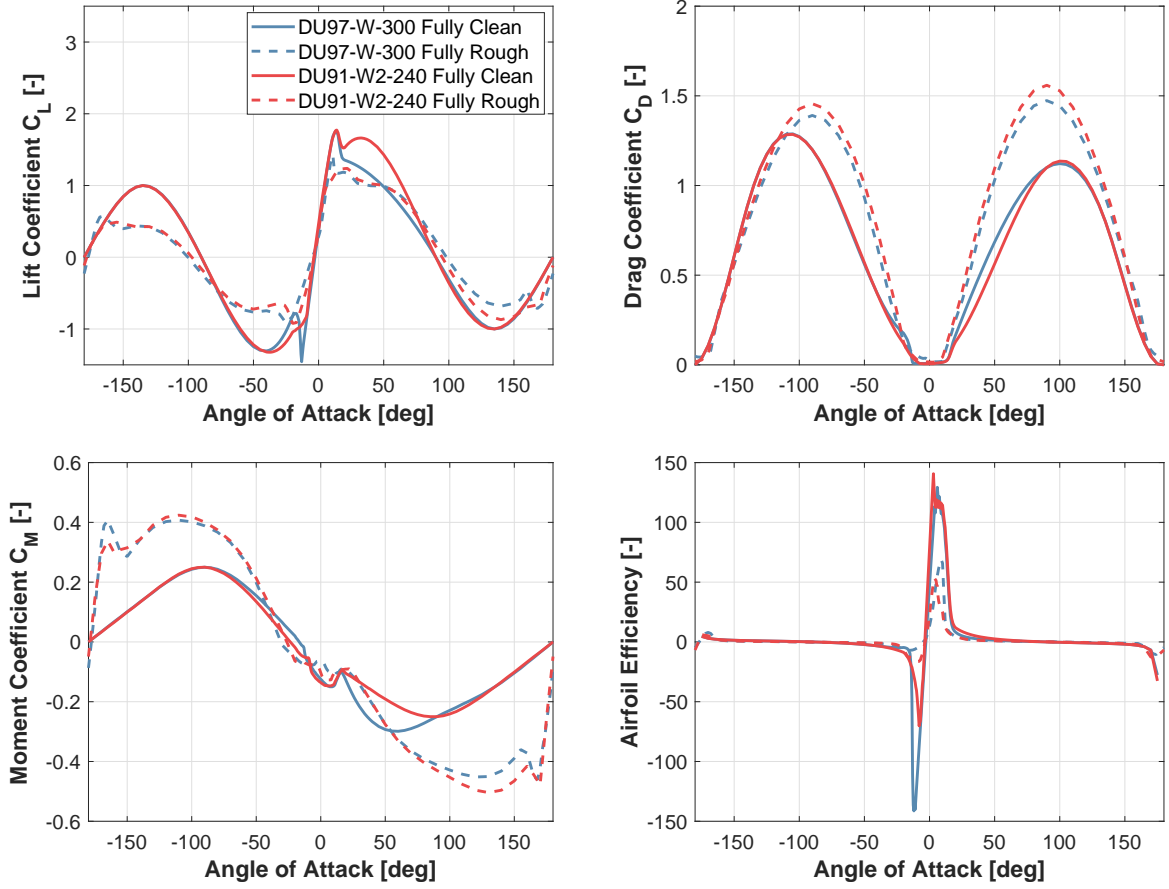**Figure 2.** Fully clean and fully rough aerodynamic coefficients C_L, C_D, C_M and airfoil efficiency vs. angle of attack for airfoils DU97-W-300 and DU91-W2-240.

	α	β	Region
k_{TI}	3.4	6.0	[0.5 , 2.0]
k_{AF}	2.0	6.0	[0.0 , 1.0]
ESD	2.5	4.0	[0.0 , 0.5]

Table 3. Probability density functions for turbulence intensity factor k_{TI}, airfoil roughness k_{AF} and non-dimensional spanwise extent of erosion ESD.
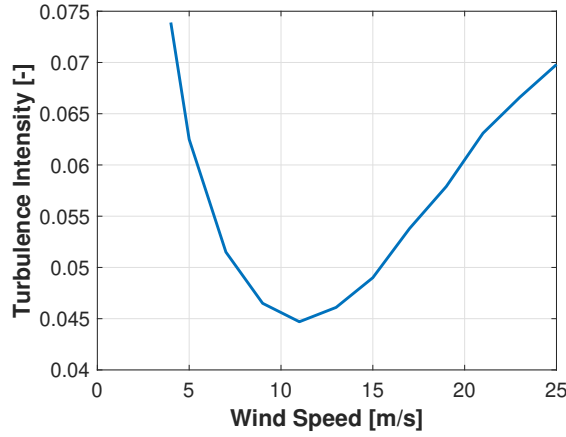
Figure 3. Turbulence intensity distribution for varying wind speed.

and DEL combined tower base moment (CTBM), and finally annual energy production (AEP). MTD and ultimate ThS, CBRM, and CTBM are obtained by computing the maximum overall value across all time steps and wind speeds. DELs and AEP are instead averaged via the Weibull distribution corresponding to wind class IA, which is characterized by a shape factor of 2 and an average wind speed at hub height of 10 m/s (IEC61400-1, 2005).

5　　The MC analysis was stopped at 1,100 evaluations, where the convergence of mean and standard deviations for all quantities consistently returned variations below 1% of their average values. While convergence is rapidly obtained for the mean values of the eight outputs of interest, standard deviations require a significantly higher number of evaluations to reach convergence. The statistics of the outputs are reported in Table 4.

　　Here, six seeds were used to limit the computational cost of the MC analysis, following accepted international standards
10　(IEC61400-1, 2005). However, as reported in the literature (Dimitrov et al., 2015; Graf et al., 2018), this number might not always be adequate. This is confirmed also here, as the use of only six seeds does not guarantee the full convergence of all quantities, especially in terms of standard deviations, as shown by Fig. 4. While the differences in AEP and DELs are indeed small, this is not true for the ultimate loads. A better understanding of the convergence of results with the number of turbulent realizations should be the subject of future work, as discussed in Sect. 4.

15　**3.2　Convergence analysis**

The convergence of the uncertainty propagation methods is studied first. The analysis considers mean and standard deviation of AEP, maximum tip displacement, thrust, combined blade root moment, combined tower base moment and the corresponding damage equivalent loads.

　　Order-three NIPCE and UK, both as implemented in Dakota (Adas et al., 2015), are tested against the MC benchmark
20　presented in Sect. 3.1. To ensure a fair comparison, a MC sampling strategy is adopted for both NIPCE and Kriging. The number of training data samples follows the relation $R = r\, N_t$, where r is the collocation ratio, varying from 0.6 to 8, and N_t is

Table 4. Main statistics of the eight outputs of interest for 1,100 MC function evaluations. MTD: maximum tip deflection; ThS: thrust at main shaft; CBRM: combined blade root moment; CTBM: combined tower base moment; DEL: damage equivalent load; AEP: annual energy production.

	Mean	Standard deviation	Coefficient of variation
MTD	6.99 m	0.11 m	1.58 %
ThS	2.08 MN	0.02 MN	1.02 %
DEL ThS	0.34 MN	0.05 MN	13.79%
CBRM	56.29 MNm	0.63 MNm	1.12 %
DEL CBRM	29.51 MNm	2.61 MNm	8.83 %
CTBM	236.05 MNm	2.20 MNm	0.93 %
DEL CTBM	46.79 MNm	7.82 MNm	16.72 %
AEP	53.71 GWh	0.29 GWh	0.54 %
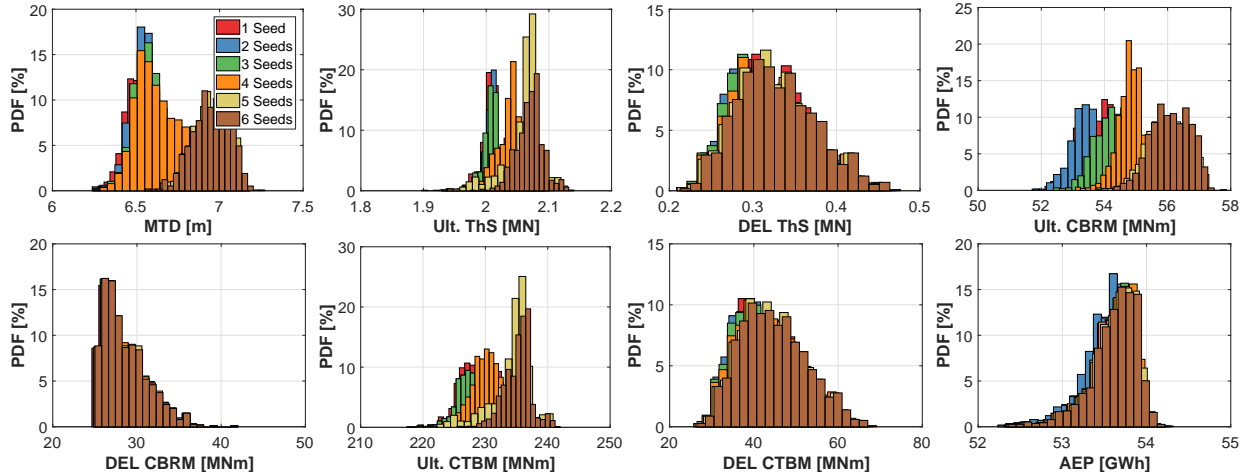
Figure 4. Probability density functions of key output metrics for varying number of seeds. Each case is based on 1,100 sampling points.

the total number of terms considering a total-order expansion. The collocation ratio is defined as the ratio between the number of function evaluations used to train the model and the total number of terms in the chaos expansion. On the resulting response surface, an extensive MC sampling with 100,000 points is conducted to extract mean and standard deviation.

Both NIPCE and UK appear to be capable of estimating the eight outputs of interest at a much reduced number of function evaluations compared to MC. In addition, UK consistently converges faster than the other two methods, with a reduction of one-two orders of magnitude with respect to MC for the estimation of the output mean and standard deviation. The plots reported in Fig. 5 provide for a visualization of these results. In the figure, a gray area represents the 95% confidence intervals for the finite (here equal to 1,100) number of sampling points used in the MC analysis. The grey band could be made narrower by increasing the number of samples.
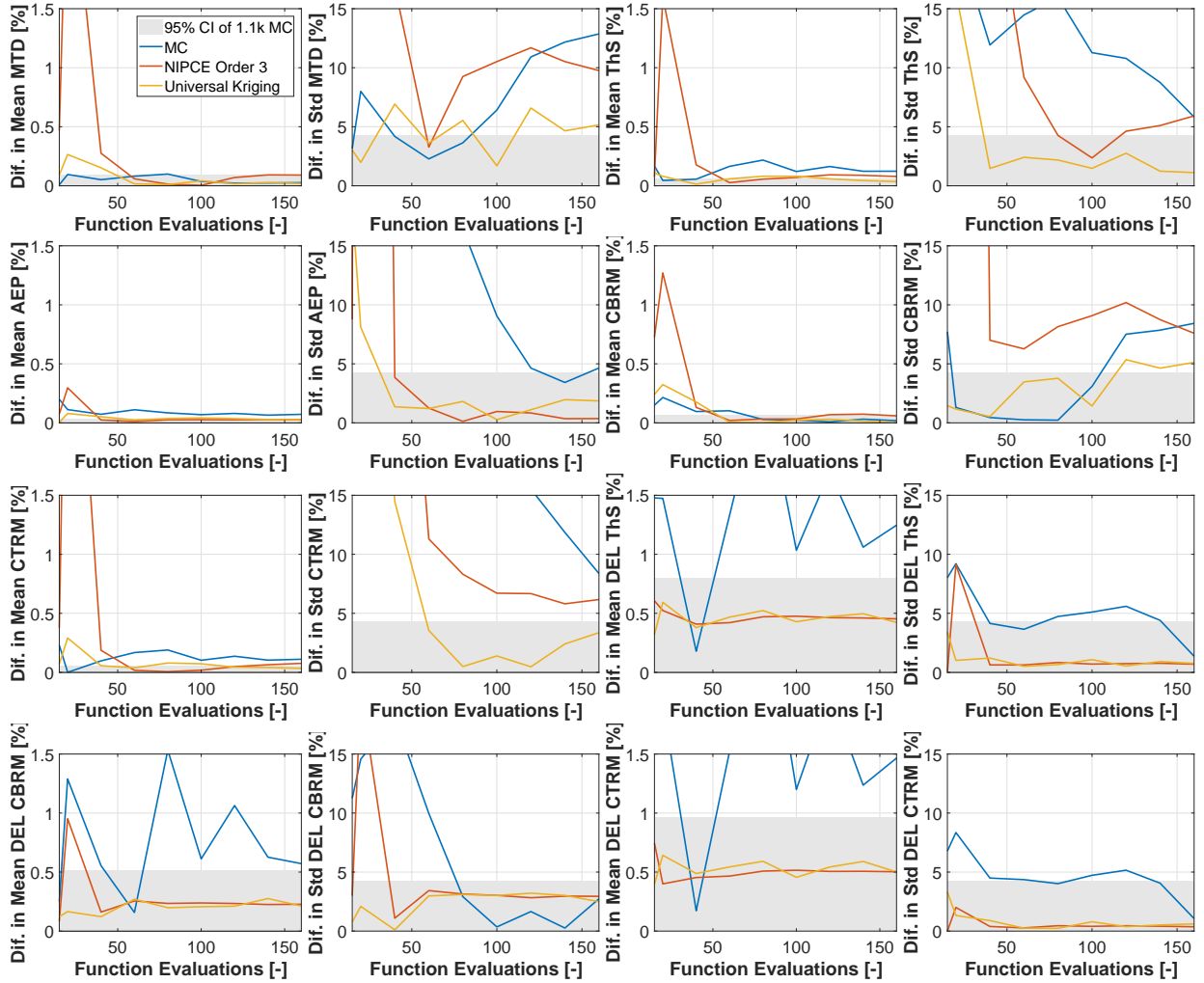

Figure 5. Convergence of mean and standard deviation for key output quantities. The gray area reflects the potential inexactness of the MC benchmark, and it represents the 95% confidence intervals for 1,100 sampling points.

3.3 Effects of uncertainties on outputs of interest

The results obtained by UK with 40 function evaluations are then subjected to a more detailed analysis. Response surfaces for the eight outputs of interest and their corresponding probability density functions are shown in Fig. 6. The plots are generated by first training the UK model with 40 points and then evaluating it with a random sample of 1 million points. Given the three-dimensionality of the solution space, two-dimensional surfaces are plotted for a constant k_{TI} equal to one.
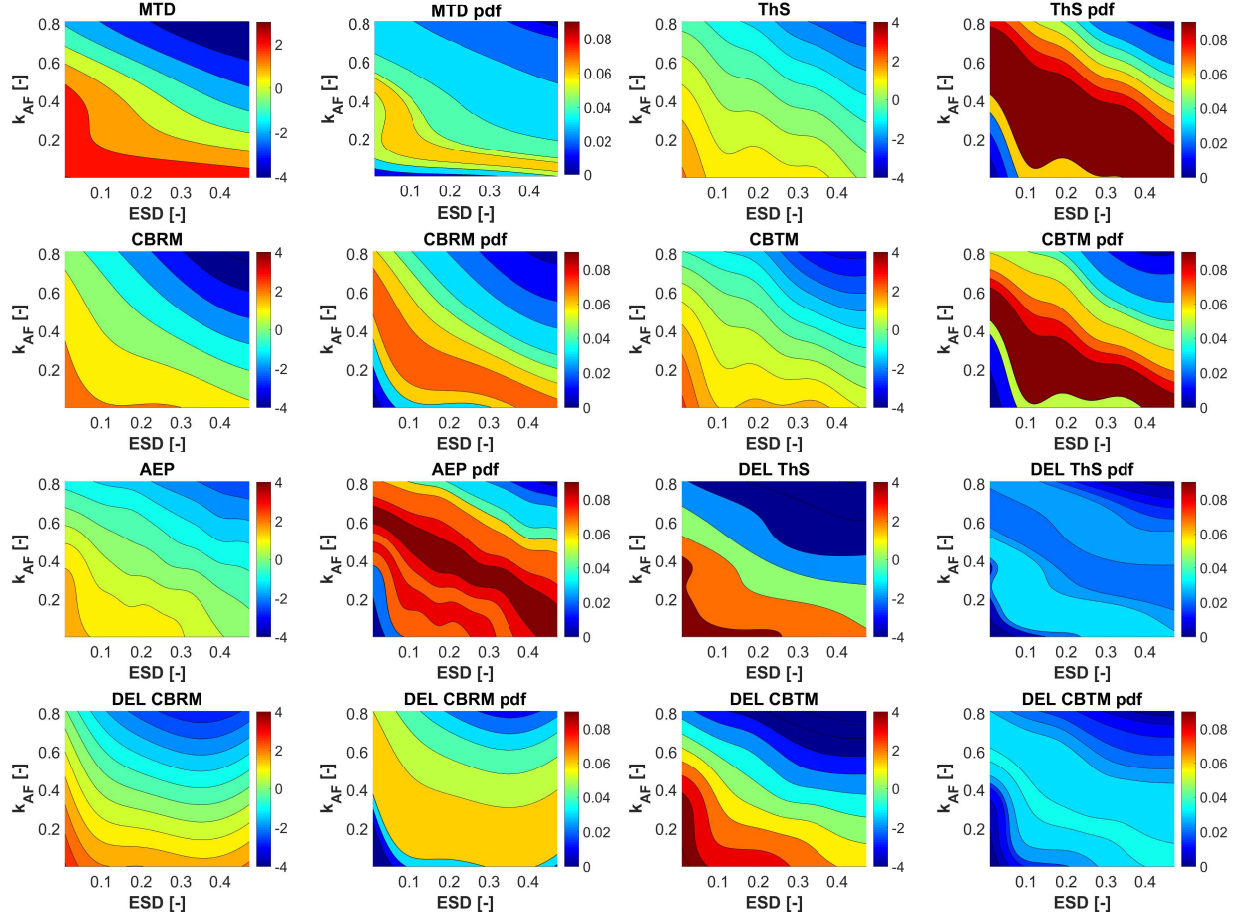

Figure 6. Key outputs (in percent difference with respect to the mean value) and corresponding probability density functions, for k_{TI} equal to one.

The contour plots visibly show non linearities. Additionally, they also show that the condition corresponding to a fully clean rotor, namely ESD and k_{AF} equal to 0 (bottom left corner of each plot in Fig. 6), generates the highest values for all eight outputs of interest (left plots). However, according to the input distributions of Table 3, these conditions also have a very low probability of occurrence (right plots). For MTD and the three key loads ThS, CBRM and CTBM, this means that the deterministic simulations prescribed by the standards overestimate the actual output values. Since the variations in the outputs

are limited, and typically in the range of $\pm 3\%$, these results might appear to suggest that the conventional safety factors equal to 1.2 or 1.3 may be excessive. It is however clear that this analysis is purely limited to the effects of surface roughness and some wind inflow parameters, and a more comprehensive analysis should be conducted before drawing any final conclusion or recommendation. It should also be remarked that the non-intrusive uncertainty propagation methods used here would indeed allow for such a more general analysis in a rather straightforward manner.

MTD provides for an interesting example. International standards prescribe MTD to be 30% lower than tower clearance. The top left plots in Fig. 6 show that the largest probability of occurance corresponds to MTD values that fall within $\pm 1\%$ of the mean, while very low probabilities are associated to the value of MTD obtained in the deterministic condition prescribed by the standards (k_{AF} and ESD equal to 0). Similarly, a deterministic analysis overestimates AEP by about 3%, while the uncertainty analysis shows an equal probability within a range of $\pm 1.5\%$ from the mean value.

In addition, the contour plots of MTD and AEP indicate a fairly linear behavior of the solution space, where the two outputs show a maximum variation along the 45 degree bi-sector. This follows from the fact that, as expected, the rotor is more loaded for clean airfoils and a low extent of erosion (both k_{AF} and ESD equal to zero), generating higher AEP and MTD. These variations are apparently approximately linear, and as a result the region of maximum probability aligns with the expected values of k_{AF} and ESD.

4 Conclusions and outlook

This work has reported on the first steps towards the development of a framework for the non-intrusive propagation of uncertainties throughout black-box aeroservoelastic wind turbine models. Non-intrusiveness is key to the reusability of legacy models, and for rapidly reaping the benefits of modeling improvements without the need for a deep rewriting of such complex codes.

NIPCE and UK were applied to a large state-of-the-art conceptual wind turbine, considering both power capture, tip deflection and some typical design-driving loads as performance indicators. Uncertainties were considered in both the wind inflow conditions and the roughness of the blades, on account of soiling and/or erosion. For both methods, comparisons to standard brute-force Monte Carlo predictions indicate a good performance in terms of quality at a significantly lower computational cost. Of the two, UK appears to consistently converge faster than NIPCE.

The analysis of the results indicates non-linearities and couplings among the various sources of uncertainty. In addition, it was found that the deterministic conditions prescribed by international design standards generate maximum values of loads and power production, which however are typically associated with a very low probability of occurrence. Although the results obtained here are not comprehensive enough to draw any significant conclusions, they do suggest that the use of formal mathematically-based methods of uncertainty propagation may lead to a revision of typical safety factors, in the interest of more cost-competitive —but still fully safe— designs.

The present study should be refined in several important aspects. To start, the problem of turbulent realizations deserves specific attention. Here the number of turbulent seeds typically recommended by design standards was used, but appeared

not to be always sufficient for guaranteeing convergence of the statistics. If the number of seeds needs to be increased in a substantial manner to ensure convergence, this might require a change in the methodological approach, as the computational cost might become prohibitive. In this sense, the use of surrogate models, instead of the high-fidelity ones used here, might become attractive. An additional problem of interest is the computation of extreme states, which populate the tails of the

5 probability distributions and often act as design drivers. Here, ad hoc sampling strategies have been developed by the statistical research community, and could be applied to the problem at hand (Graf et al., 2018). Other sophisticated sampling methods, such as Latin Hypercube Sampling or Hammersley Sampling (Hosder et al., 2007; Eldred et al., 2009), have been described in the literature and will be topic of future studies. Furthermore, additional sources of uncertainty should be investigated. In fact, in principle many parameters and inputs can be assumed to be uncertain. However, a comprehensive knowledge of the

10 role played by the various uncertainties and their couplings is still largely missing. A ranking of uncertainties and a deeper understanding of their effects is a very worthwhile endeavour, which might have a significant role in the future design of wind energy systems.

References

Abdallah, I., Natarajan, A., and Sørensen, J.D.: Impact of uncertainty in airfoil characteristics on wind turbine extreme loads, Renewable Energy, 75, 283–300. doi:10.1016/j.renene.2014.10.009, 2015.

Adams, B.M., Bauman, L.E., Bohnhoff, W.J., Dalbey, K.R., Ebeida, M.S., Eddy, J.P., Eldred, M.S., Hough, P.D., Hu, K.T., Jakeman, J.D., Stephens, J.A., Swiler, L.P., Vigil, D.M., and Wildey, T.M.: Dakota, A Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 6.0 User's Manual, Sandia Technical Report SAND2014-4633, July 2014. Updated November 2015 (Version 6.3). Available at https://dakota.sandia.gov.

AVATAR, Advanced Aerodynamic Tools for Large Rotors, http://www.eera-avatar.eu.

AVATAR Deliverable 4.12, Effect of blade flexibility and structural tailoring on loads, August 2017. http://www.eera-avatar.eu.

Bauchau, O.A.: Flexible Multibody Dynamics, Mechanics and Its Applications, Springer, ISBN: 978-94-007-0335-3, 2011.

Bortolotti, P., Bottasso, C.L., and Croce, A: Combined preliminary-detailed design of wind turbines, Wind Energy Science, 1(1), 71–88. doi:10.5194/wes-1-71-2016, 2016.

Bottasso, C.L., Croce, A., Savini, B., Sirchi, W., and Trainelli, L.: Aero-servo-elastic modeling and control of wind turbines using finite-element multibody procedures, Multibody System Dynamics, 16(3), 291–308, doi10.1007/s11044-006-9027-1, 2006.

Campobasso, M.S., Minisci, E., and Caboni, M.: Aerodynamic design optimization of wind turbine rotors under geometric uncertainty, Wind Energy, 19(1), 51–65, doi:10.1002/we.1820, 2016.

Dimitrov, N., Natarajan, A., and Kelly, M.: Model of wind shear conditional on turbulence and its impact on wind turbine loads, Wind Energy, 18(11), 1917–1931, doi:10.1002/we.1797, 2015.

Dimitrov, N: Comparative analysis of methods for modelling the short-term probability distribution of extreme wind turbine loads, Wind Energy, 19, 717–737. doi:10.1002/we.1861, 2016.

Eldred, M.S., and Burkardt, J.: Comparison of non-intrusive polynomial chaos and stochastic collocation methods for uncertainty quantification, Proceedings of 47th AIAA Aerospace Sciences Meeting, doi:10.2514/6.2009-976, 2009.

Ernst, B., and Seume J.R.: Investigation of site-specific wind field parameters and their effect on loads of offshore wind turbines, Energies, 5, 3835–3855, doi:10.3390/en5103835, 2012.

Fluck, M.: Stochastic Methods for Unsteady Aerodynamic Analysis of Wings and Wind Turbine Blades, Ph.D. Thesis, University of Victoria, 2017.

Graf, P., Dykes, K., Damiani, R., Jonkman, J., and Veers, P.: Adaptive stratified importance sampling: hybridization of extrapolation and importance sampling Monte Carlo methods for estimation of wind turbine extreme loads, Wind Energy Science, 3(2), 475–487, doi:10.5194/wes-3-475-2018, 2018.

Hosder, S., Walters, R.W., and Balch, M.: Efficient sampling for non-intrusive polynomial chaos applications with multiple uncertain input variables, Proceedings of 48th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, doi:10.2514/6.2007-1939, 2007.

IEC 61400-1, Wind Turbines - Part 1: Design Requirements, Ed. 3, International Standard IEC 61400-1, 2005.

IEC 61400-12-1, Power Performance Measurements of Electricity Producing Wind Turbines, 2005.

Khalfallah, M.G., and Koliub, A.M.: Effect of dust on the performance of wind turbines, Desalination, 209(1-3), 209–220, doi:10.1016/j.desal.2007.04.030, 2007.

15

Krige, D.G.: A statistical approach to some basic mine valuation problems on the Witwatersrand, Journal of the Chemical, Metallurgical and Mining Society of South Africa, 52(6), 119–139, 1951.

Matthäus, D., Bortolotti, P., Loganathan, J., Bottasso, C.L.: Propagation of uncertainties through wind turbine models for robust design optimization, AIAA SciTech Forum, doi:10.2514/6.2017-1849, 2017.

5 Méndez, B., Munduate, X., Sørensen, N., García, N.R., Prospathopoulos, J., Papadakis, G., Voutsinas, S., and Ceyham, O.: 2D Airfoil polars for the AVATAR rotor - WP2 Deliverable 2.1, September 2015.

Murcia, J.P., Réthoré, P.E., Dimitrov, N., Natarajan, A., Sørensen, J.D., Graf. P., and Kim, T.: Uncertainty propagation through an aeroelastic wind turbine model using polynomial surrogates, Renewable Energy, 118, 1–13, doi:10.1016/j.renene.2017.07.070, 2017.

Petrone, G., Nicola, C.D., Quagliarella, D., Witteveen, J., and Iaccarino, G.: Wind turbine performance analysis under uncertainty, Proceed-
10 ings of 49th AIAA Aerospace Sciences Meeting, doi:10.2514/6.2011-544, 2011.

Sareen, A., Sapre, C.A., and Selig, M.S.: Effects of leading edge erosion on wind turbine blade performance, Wind Energy, 17(10), 1531–1542, doi:10.1002/we.1649, 2014.

Sathe, A., Mann, J., Gottschall, J., and Courtney, M.S.: Can wind Lidars measure turbulence?, Journal of Atmospheric and Oceanic Technology, 28, 853–868, doi:10.1175/JTECH-D-10-05004.1, 2011.

15 Sudret, B.: Uncertainty Propagation and Sensitivity Analysis in Mechanical Models - Contributions to Structural Reliability and Stochastic Spectral Methods, Rapport d'activité scientifique, Université Blaise Pascal - Clermont II, 2007.

Tarp-Johansen, N., Madsen, H., and Frandsen, S.T.: Partial Safety Factors for Extreme Load Effects. Technical report Risø-R-1319(EN), Risø National Laboratory, Denmark, 2002.

Witteveen, J.A.S., Sarkar, S., and Bijl, H.: Modeling physical uncertainties in dynamic stall induced fluid–structure interaction of turbine
20 blades using arbitrary polynomial chaos, Computers and Structures, 85, 866–878, doi:10.1016/j.compstruc.2007.01.004, 2007.

Zidane, I.F., Saqr, K.M., Swadener, G., Ma, X., and Shehadeh, M.F.: On the role of surface roughness in the aerodynamic performance and energy conversion of horizontal wind turbine blades: a review, International Journal of Energy Research, 40(15), 2054–2077, doi:10.1002/er.3580, 2016.