Assessment of sensitivity and accuracy of BEM-based aeroelastic models on wind turbine load predictions

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Abstract. The general goal of the work reported in this paper is to gain more confidence when performing blade element momentum (BEM)-based aeroelastic simulations, especially when setting-up sub-models and their parameters. Due to limited or no information, the set-up of these methods is often highly uncertain. To achieve this objective, we have developed and used methodologies to perform the analysis of model uncertainty in wind turbine aeroelastic simulations, while assessing their accuracy. This paper presents an example where these methodologies have been applied to a) the different aerodynamic models used in BEM-based aeroelastic tools to account for unsteady airfoil aerodynamics (UAA) and b) key parameters used in one of these models (Beddoes-Leishman). The accuracy of the simulations is assessed by comparing the simulated unsteady loads with measurements from the DAN-AERO MW experiments. One of the main achievements of this work is the ability to assess the uncertainty in load predictions that derives from the uncertainty related to the UAA models and their constants. The study on the sensitivity of the parameters was performed using Sobol indices and showed that for the case under study the normal force standard deviation at outboard blade locations is mostly sensitive to the Beddoes-Leishman model's vortex shedding time constant.

1. Introduction

In the design process, wind turbine design codes which calculate the power and aeroelastic loads on a wind turbine play a prominent role. The backbone of these design codes are the mathematical descriptions of the highly complex aerodynamic phenomena. An additional difficulty arises because the computational effort for design calculations is higher compared to other applications. A typical design requires several millions of model evaluations, needing the use of very efficient, but also very simplified aerodynamic models (i.e., the blade element momentum (BEM) method). The large number of assumptions in BEM models limit their use for wind turbine design. Therefore, over the last decades, several engineering add-ons have been developed which aim to overcome these assumptions. These engineering extensions represent the relevant physical phenomena in a simplified way and include several constants or tuning parameters which are often determined from a limited number of measurements. Additionally, the same basic formulation for an engineering add-on may be implemented differently.

A reliable prediction of the service life of an offshore wind turbine is needed for a cost-optimal well-dimensioned design. However, as mentioned above, the prediction of the wind turbine

response and energy production is performed with models which are affected by different types of uncertainty. One of the model-related uncertainty sources wind turbine designers very often have to deal with is the so called epistemic uncertainty. Epistemic uncertainty is defined as any lack of knowledge or information in any phase or activity of the modeling process [1]. For example, epistemic uncertainty arises when setting-up a given model's parameter for which little or no experimental data is available. The other main source of uncertainty in computational simulations is called aleatory uncertainty, which defines the inherent variation associated with the physical system or the environment under consideration [1]. The epistemic and aleatory uncertainties present in wind turbine simulations put into question how reliable the model predictions are. For this reason, in the wind energy research field, sensitivity and uncertainty analysis is an important topic [2, 3, 4].

This paper presents methodologies to perform sensitivity and uncertainty analysis of BEM-based aeroelastic simulations, considering the epistemic uncertainty associated to the BEM engineering sub-models. In this context, uncertainty analysis denotes an assessment of the effect of input uncertainty on the model output, while sensitivity analysis indicates the evaluation of the contributions of the inputs to the total uncertainty in the analysis output. The above-mentioned methodologies are here demonstrated on the Beddoes-Leishman model and its key parameters. This add-on model is used in BEM calculations to account for unsteady airfoil aerodynamics (UAA).

2. Methodology
In order to achieve this paper's objectives, we created an aeroelastic description of a 80 m rotor diameter, 2MW NM80 wind turbine, which was instrumented and measured within the DAN-AERO MW experiments [5]. Pressure distributions were measured at four radial sections in atmospheric conditions, allowing the evaluation of loads along the blade. Using the baseline aeroelastic model as reference, several aerodynamic models and their internal parameters were varied in order to assess their impact on the blade unsteady loads. To compare simulations and experiments, the wind and operative conditions were chosen to match the experimental ones as close as possible. Aeroelastic simulations performed in this work were fed with turbulent inflow generated, according the experimental wind conditions, by using TurbSim [6]. Uncertainty and sensitivity studies have been carried out through a framework developed by Kumar et al [7] around the uncertainty quantification toolbox `UQLab` [8]. The accuracy of the unsteady aeroelastic load calculations has been assessed by means of skill scores [9], through comparisons between the simulated unsteady loads and measurements.

2.1. Assessment of model sensitivity and uncertainty quantification through UQLab
In a companion paper [7], we have proposed a framework for performing uncertainty quantification and global sensitivity analysis using `UQLab` [8]. The framework relies on the computation of so-called Sobol indices, which decompose the variance of a simulation output in terms of the variance of the model inputs. In this work, we use both Monte Carlo (MC) and two types of polynomial chaos expansions (PCE, either solved with the OLS or with the LARS algorithm [8, 7]). In PCE, a polynomial approximation to the aeroelastic model is constructed, and the coefficients of this polynomial are post-processed to yield the Sobol indices. If the model dependence on the uncertain parameters is smooth (and the dimension of the problem not too high), this yields a much faster convergence than MC methods. In this work we use the total order Sobol index to assess sensitivities; more refined indices such as interaction effects are possible but are outside the scope of this work.

2.2. Assessment of model accuracy through skill scores

The assessment of the accuracy of the simulations with respect to a reference set-up is carried out through skill scores. A skill score compares the score obtained by a given model with the score obtained by a reference one using the same verification data. If the alternative model is perfect, it leads to zero error, and the skill score is one. If, on the other hand, the alternative model performs as the reference one, the error will be the same, and the skill score is zero. The skill score for a generic simulation output, x, obtained by using a generic model is given by:

$$SS_{x,model} = 1 - \frac{MSE_{x,model}}{MSE_{x,ref.model}} \tag{1}$$

where $MSE_{x,model}$ denotes the mean squared error, representing the average squared difference between the estimated values by a given model, $x_{model,i}$, and the experimental one $x_{exp,i}$ as follows:

$$MSE_{x,model} = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{x_{model,i} - x_{exp.,i}}{x_{exp.,i}} \right)^2 \tag{2}$$

In Eq. 1 $MSE_{x,ref.model}$ refers to a reference model.

3. Results

This section focuses on two cases of study. In the first one, we assessed the influence of different models accounting for UAA. In the second one, we performed uncertainty and sensitivity analysis of one of the model parameters, using as example the Beddoes-Leishman model parameters.

3.1. Uncertainty and accuracy analysis of unsteady airfoil aerodynamics models on wind turbine loads

In this section, we assess the influence of different models accounting for UAA, typically implemented in BEM-based aeroelastic codes, to the blade span-wise aeroelastic loads. In addition to that, we assess of the accuracy of the simulations by comparing the numerical results to the DAN-AERO MW experimental data. The chosen turbine specifications for this analysis resemble nominal turbine operative conditions, characterized by almost no yaw error, constant rotor speed and pitch angle close to zero.

3.1.1. Uncertainty analysis
Aeroelastic simulations matching the experimental conditions were performed by DNV GL and TNO, using Bladed [10], and PHATAS [11]-ECN Aero-Module [12], respectively. The investigation involved a number of UAA models, namely Beddoes-Leishman model [13], Øye model [14] and Snel 1st order [15]. The uncertainty analysis was carried out by simply running simulations replacing the aerodynamic model used to account for UAA. In this evaluation, each sub-model was set-up with a "standard" and constant set of parameters. This study looks at both the mean and standard deviation of the normal and tangential to the chord forces along the blade radius, which are denoted by μ_n, σ_n, μ_t and σ_t, respectively. Figure 1 shows a comparison between experiments and aeroelastic simulations performed by DNV GL and TNO. As depicted in Fig. 1, UAA models do not affect the mean values (μ_n, μ_t) significantly, while there are some differences in σ_n and σ_t. In particular, the Beddoes-Leishman model leads to lower σ_n and σ_t than the experimental values and the other models. With respect to the other models, this difference is due to the fact that the Beddoes-Leishman model accounts for the effect of shed vorticity variation in attached conditions (Theodorsen's effect), leading to lesser variation of forces. Good agreement is observed between DNV GL and TNO results.
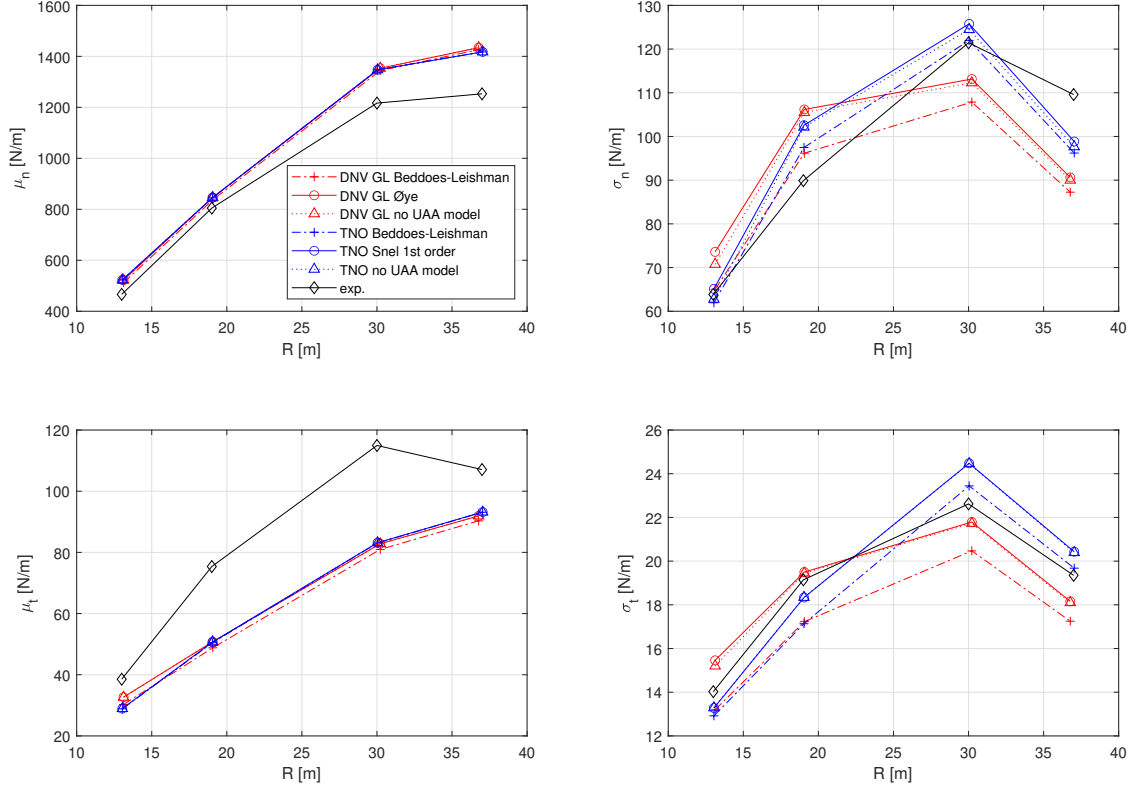
Figure 1. Comparison between experimental blade forces and those computed through aeroelastic simulations by using different unsteady airfoil aerodynamics (UAA) models. μ_n, σ_n, μ_t and σ_t denote respectively the mean and standard deviation of the normal and tangential forces along the blade radius, R. The chosen turbine specifications for this analysis resemble nominal turbine operative conditions, characterized by almost no yaw error, constant rotor speed and pitch angle close to zero.

3.1.2. Accuracy analysis The accuracy of the aeroelastic simulations is assessed by means of skill scores, as depicted in Table 1. The simulations performed without a UAA model are assumed to be the reference models. Generally, the simulation accuracy regarding μ_n and μ_t is quite poor, which is due to discrepancies between experiments and aeroelastic code results. At the time of writing, the reason behind this difference is not fully understood and efforts are now directed into this within the IEA Task-29 project [16]. UAA models do not considerably improve the average loads, as confirmed by skill scores close to zero. Experiments and simulations show a better agreement on σ_n and σ_t. For both DNV GL and TNO simulations, only the Beddoes-Leishman model improves the accuracy of the prediction of σ_n, most likely because of the inclusion of the Theodorsen's effect as mentioned above. The reason behind the little or no improvement associated to the use of the UAA models with respect to the reference case (with no UAA model) could be related to the fact that the test case under study has very limited unsteady aerodynamics and therefore the exclusion of a UAA model already gives a fairly good approximation. Another reason could be related to the use of non-optimal model's constants. The following section explores another test case where dynamic airfoil aerodynamics is more

present, and investigate the constants used by the Beddoes-Leishman model.

model	SS_{μ_n}	SS_{σ_n}	SS_{μ_t}	SS_{σ_t}
DNV GL Beddoes-Leishman	0.1786	0.2537	-0.2371	-1.6422
DNV GL Øye	-0.0020	-0.1418	0.0020	-0.2269
TNO Beddoes-Leishman	-0.002	0.2677	-0.012	-0.341
TNO Snel 1st order	-0.0079	0.0058	0.0001	-0.0324
no UAA model	0	0	0	0

Table 1. Skill scores for different unsteady airfoil aerodynamics (UAA) models in predicting the mean and standard deviation of the normal and tangential forces, denoted respectively by SS_{μ_n}, SS_{σ_n}, SS_{μ_t} and SS_{σ_t}. Skill scores equal (or close) to zero indicate that the accuracy of the given model is the same of that of the reference model (no UAA model in this case). Positive skill scores instead denote that the given model's accuracy is better than that of the reference model, while negative skill scores indicate worse accuracy.

3.2. Uncertainty, sensitivity and accuracy analysis of parameters used by unsteady airfoil aerodynamics models on wind turbine loads
In this section we apply a procedure to perform uncertainty and sensitivity analysis of model parameters by taking into account, as an example, some of the parameters used by the Beddoes-Leishman model. In addition to that, we assess the accuracy of the best combination of these parameters, by comparing the numerical results to the DAN-AERO MW experimental data, and finally evaluating the skill scores. To better test the effect of the Beddoes-Leishman model's parameters, we chose an experimental set-up that leads to a pronounced UAA. More specifically, this test case specifications are characterized by 6° yaw error and a pitch angle of -4.5°.

3.2.1. Sensitivity analysis In this section, we present the sensitivity analysis of four Beddoes-Leishman model's parameters on the standard deviation of the force normal to the chord line, σ_n, at around 75% of the blade radius. In other words, we assessed the contribution of four Beddoes-Leishman model's input parameters to the overall uncertainty (due to the variability of the four constants) in predicting σ_n at around 75% of the blade radius. The Beddoes-Leishman model's parameters which were chosen for the sensitivity analysis are: time constant connected to the leading-edge pressure gradient, Tp, time constant connected to leading-edge separation of the airfoil, Tf, time constant connected to vortex shedding, Tv, and time constant connected to the vortex advection process, Tvl. These constants are typically calibrated by means of wind tunnel tests, and they depend on the specific airfoil under consideration. We do not have information on how to calibrate the Beddoes-Leishman constants for the airfoils implemented by the blade under study, showing a typical example of epistemic uncertainty. Damiani et al. [17] have determined these parameters for three different airfoils experimentally, showing that indeed these constants vary depending on the airfoil shape. In our analyses, we assumed that the aforementioned constants vary within the range of variability determined by Damiani et al.. Each uncertain variable was considered uniformly distributed within its range as depicted in Figure 2.

The results of the sensitivity analysis are depicted in Figure 3. The Sobol indices were evaluated by means of MC and two types of PCE methods. Figure 3 shows that the Tv constant mostly contributes to the overall uncertainty, followed by the Tf constant. σ_n at around 75% of the blade radius is shown not to be sensitive to the Tp and Tvl constants (with total indexes respectively equal to 0.001 and 0.0001). This information can be used, for example, to exclude

Tp and Tvl from an attempt to calibrate the simulations, while focusing on the Tv and Tf constants.

Figure 4 shows the convergence of the total Sobol indices and the standard deviation of the standard deviation of the normal force at around 75% of the blade radius with increasing number of model evaluations. Regarding both the Sobol indices and the standard deviation, PCE methods achieve convergence for a significantly lower number of model evaluations than those necessary for MC to achieve convergence. It is noted that for both cases, MC does not show a proper convergence. We have however decided to show the comparison between MC and PCE methods' convergence to stress how MC approach results computationally too expensive in this kind of applications, due to the very large amount of needed model evaluations. PCE methods are instead shown to be a viable solution, as they converge for limited number of evaluations.
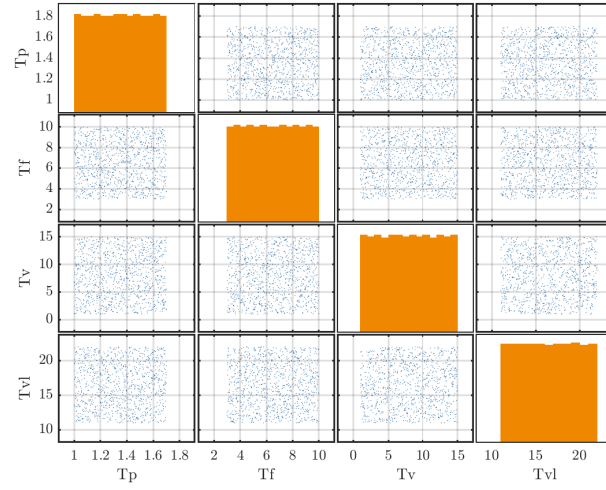

Figure 2. Marginal probability density functions of four Beddoes-Leishman model's uncertain parameters, and example of sampling locations. The figure shows that each uncertain parameter is uniformly distributed within the depicted ranges of variability.
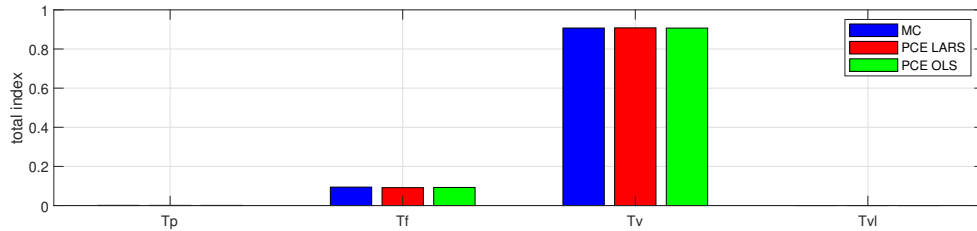

Figure 3. Sensitivity analysis results of four Beddoes-Leishman model's parameters on the standard deviation of the normal force at around 75% of the blade radius. The sensitivity analysis is here assessed by means of total Sobol indices determined by means of Monte Carlo and two types of polynomial chaos expansion methods.
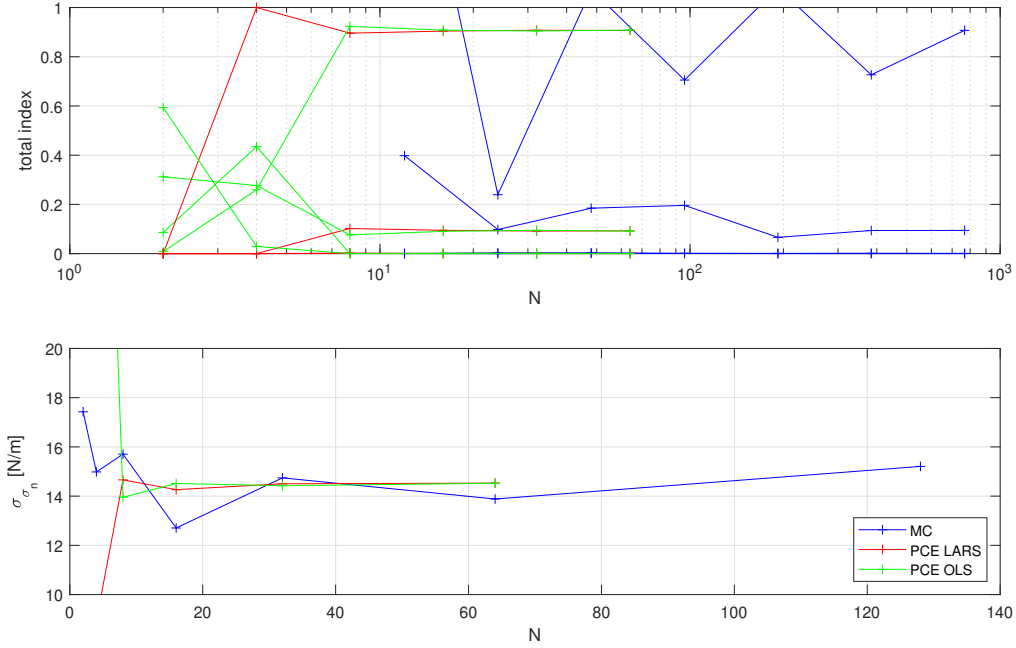
Figure 4. Convergence of the total Sobol indices (top subplot) and the standard deviation of the standard deviation of the normal force at around 75% of the blade radius, σ_{σ_n}, (bottom subplot) with increasing number of model evaluations, N, for different methods: Monte Carlo and two types of polynomial chaos expansion.

3.2.2. Uncertainty analysis The variation of the Beddoes-Leishman model's input parameters leads to a variation of the calculated output loads' mean and standard deviation. This variation is represented in Fig. 5 through error bars, representing the standard deviation around the average force value, shown through solid lines. Regarding TNO simulations Tp, Tf, Tv and Tvl were varied, while DNV-GL only varied Tp and Tf constants, as Tv and Tvl are hard coded in Bladed. It is seen that the mean loads are not significantly affected by the variation of the Beddoes-Leishman model's parameters. The standard deviation of the loads, representative of the blade fatigue loading, is more sensitive to these parameters, especially at mid-outboard sections. At such locations, for the TNO's simulations, the standard deviation of predictions reaches significant values up to 10% of the average values. Error bars corresponding to DNV GL's simulations are smaller due to the fact that only Tp and Tf constants were varied, and, as shown in the sensitivity study, Tv is mostly contributing to the total uncertainty.

It is seen that the error bars are not large enough to include the experimental values, and therefore the uncertainty affecting the Beddoes-Leishman constants cannot explain the aforementioned differences between experiments and simulations. Thus, the reason for the differences in the DAN-AERO test case needs to be found considering other sources of model uncertainty or perhaps even errors in modelling or in measurements. However, the effect of the considered four Beddoes-Leishman model's constants on the loads is significant, especially considering that, very often, users of aeroelastic tools are not aware of these parameters, or these constants are hard-coded.
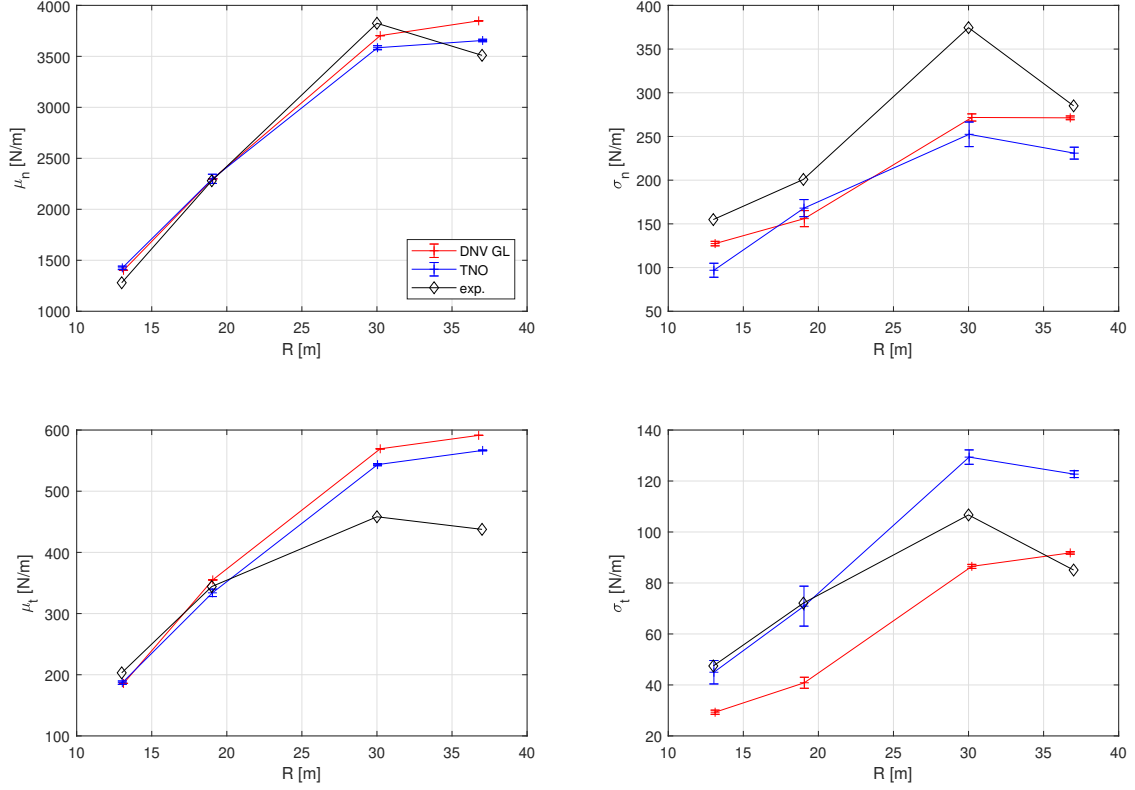
Figure 5. Comparison between experimental blade forces and those computed through aeroelastic simulations using different values for the Beddoes-Leishman model's parameters. μ_n, σ_n, μ_t and σ_t denote respectively the mean and standard deviation of the normal and tangential forces along the blade radius, R. Error bars represent the standard deviation of the calculated loads due to the variation of the model's input parameters. The error bars are established around solid lines which represent the simulations' average values. This test case specifications are characterized by around 6° yaw error and a pitch angle of around -4.5°.

3.2.3. Accuracy analysis All simulations performed during the course of the uncertainty analysis were evaluated by means of skill scores. Table 3 shows details of the model's set-up leading to the "best" skill scores and the reference model set-up, representing the standard values that DNV-GL and TNO use generally in their simulations. The simulations obtained by means of the standard model set-up were used as reference ones for the skill score calculation. Skill scores related to the specific application led to discordant conclusions based on the parameters that were assessed. In this demonstration, we have called "best" configurations the ones leading to a highest accuracy in predicting σ_n, mostly representative for blade turbine fatigue. Tp and Tf characterizing both "DNV GL best" and "TNO best" are shown to achieve almost the same values. The actual skill score values are shown in Table 2. It is noted that, both "DNV GL best" and "TNO best" lead to an improvement in predicting σ_n with respect to that of the reference set-up. Regarding the "DNV GL best" configuration, there is also an improvement on σ_t. Little variations on both μ_n and μ_t are instead resulting from the uncertainty analysis.

model set-up	Tp	Tf	Tv	Tvl
DNV GL best	1.7	10	-	-
DNV GL reference	1.7	3	-	-
TNO best	1.69	9.8	11	21.4
TNO reference	1.35	6.5	8	16.5

Table 2. Different combination of the Beddoes-Leishman model's parameters which characterize different model set-up assessed in Table 3. Reference model set-up represents the standard values that DNV-GL and TNO use, in general, for their simulations. We have called "best" configurations the ones leading to a larger accuracy in predicting σ_n (as depicted in Table 3), mostly representative for blade turbine fatigue.

model set-up	SS_{μ_n}	SS_{σ_n}	SS_{μ_t}	SS_{σ_t}
DNV GL best	-0.0069	0.4373	0.0003	0.2565
DNV GL reference	0	0	0	0
TNO best	0.1226	0.3696	-0.0131	-0.1761
TNO reference	0	0	0	0

Table 3. Skill scores for different model setup in predicting the mean and standard deviation of the normal and tangential forces, denoted by SS_{μ_n}, SS_{σ_n}, SS_{μ_t} and SS_{σ_t}. The model setups are characterized by different Beddoes-Leishman model's parameters as depicted in Table 2. Reference model setup represents the standard values that DNV-GL and TNO use generally in their simulations. We have called "best" configurations the ones leading to a larger accuracy in predicting σ_n, mostly representative for blade turbine fatigue.

4. Conclusions

This paper has presented methodologies to deal with the uncertainty wind turbine designers often face when setting up models or model's parameters of which little or no information is available, denoted as epistemic uncertainty in the literature. The proposed methodologies included skills scores method and Sobol indices for model sensitivity quantification and were applied to two test cases from the DAN-AERO MW experiments. These methodologies have been applied to study the uncertainty related to the aerodynamic model add-ons used in BEM-based unsteady aeroelastic loads calculations to account for unsteady airfoil aerodynamics and also the key parameters used by one of these models (Beddoes-Leishman). The applied methodologies for uncertainty quantification have allowed to establish error bars around predictions during the validation exercise. The sensitivity study on the parameters in the Beddoes-Leishman model showed that standard deviation of the force normal to the chord line at outboard locations is mostly sensitive to the time constant connected to vortex shedding, and to lesser extent to the time constant connected to the airfoil leading-edge separation. The physical or numerical reasons underlying these findings are still an open point and will be part of future investigation.

One of the main underlying motivations inspiring the presented research work was to investigate whether model uncertainty (or epistemic uncertainty) could explain the differences between the DAN-AERO experiments and BEM-based aeroelastic simulations. Such differences were seen within the IEA Task-29 project for several aeroelastic tools and hadn't been fully understood yet. In order to carry out such investigation, as a first step, we had to develop a computationally affordable methodology to perform the uncertainty analysis of epistemic uncertainty on wind turbine aeroelastic response. The affordability of the method represents in fact an important prerequisite as uncertainty analysis can require a very large number of aeroelastic evaluations. This step has been achieved and demonstrated in the paper, for

simplicity, by taking into account only the parameters used by unsteady airfoil aerodynamics models. As noticed, the uncertainty underlying these models cannot alone explain the aforementioned differences between experiments and simulations (i.e., the error bars are not large enough to fall into the experimental values). Therefore, the reason for the differences in the DAN-AERO test case needs to be found considering other sources of model uncertainty or perhaps even errors in modelling or in measurements. In future investigations, the presented methodology can play a role in providing an affordable way to perform uncertainty analysis accounting for a potentially large number of epistemic uncertainty sources.

In general, regardless the application case, numerical predictions based on BEM theory are always affected by epistemic uncertainty. Therefore, evaluating the effect of such uncertainty on simulation results can always increase the confidence of designers in their simulations. Even the relatively simple test case reported in this paper has shown that "invisible" (to most users) constants can lead to significant variations of loads. In wind turbine design, this uncertainty is normally accounted for by means of safety factors, which likely lead wind turbines to be more expensive than they should be. Systematically accounting for epistemic uncertainty in wind turbine simulations might contribute relaxing such factors. This paper outlines and demonstrate an affordable methodology to perform uncertainty analysis and accuracy assessment through skill scores which it is believed to have a general validity and applicability. Moreover, another important opportunity that derives from performing a model sensitivity study is to identify which parameters have the most effect on the quantities of interest, giving directions towards which variables to calibrate (or focus on) to make simulations more representative to real conditions.

5. Acknowledgements

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