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Surrogate Modelling For Fatigue Damage of Wind-Turbine Blades Using Polynomial Chaos Expansions And Non-Negative Matrix Factorization

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Abstract

A computational approach for the estimation of fatigue degradation of composite wind turbine blades by means of time domain aero-servo-elastic simulations is proposed. Wind turbine blades are subjected throughout their lifetime to highly stochastic loading. Fatigue damage of the composite reinforcement of the wind turbine blades has been identified early on in the wind turbine design practice as a factor driving design. A simple fatigue accumulation model is utilized for the spar cap reinforcement of a wind-turbine blade. Non-Negative Matrix Factorization (**NMF**) for the damage accumulation random field is used for dimensionality reduction. An approximate computationally efficient model, relying on Polynomial Chaos Expansion (**PCE**) of the damage state with respect to probabilistically modelled mean wind and turbulence intensity is derived. The framework is exemplified in a case-study of a 1.5MW wind turbine.

Keywords: Composite fatigue; long term fatigue assessment; fatigue degradation; Wind Turbine; thin walled composite beam; Aero-elastic simulation; Gram-Schmidt PCE; NMF.

1 Introduction

In the last few decades, wind energy is gaining ground as an attractive alternative to fossil fuels [1]. Due to the potential of increasing share of energy demand, covered by horizontal axis wind turbines (HAWT), the prediction of their long term structural behaviour becomes an important industry relevant consideration. Reliable long-term structural integrity estimation of wind turbines is imperative for the confident representation of the inescapable uncertainties with respect to the operating life-time of the turbines [2].

In this work we will demonstrate how uncertainty quantification techniques, namely a variation of the well-established Polynomial Chaos Expansion (**PCE**) [3] technique and a dimensionality reduction technique, the Non-Negative Matrix Factorization (**NMF**) [4,5], may be employed to achieve reliable assessment of the stochastic long-

term degradation of composite blades due to fatigue.

In short, the components of the fatigue analysis process are the following:

- 1) N_{MC} number of horizontal axis wind turbine aero-elastic simulations with appropriately sampled wind conditions are performed. IEC 64100-1 [6] standards are used in the present study. Blade time-dependent resultants are sampled at N_t time-instants at as many cross-sections as possible.
- 2) The fatigue damage accumulation of the structural components according to any suited model is estimated. A critical discussion, based on sound mechanics of materials considerations, on the choice of fatigue models is briefly included in the introduction of [7]. Evaluation of time-dependent material stresses is needed. In this work, a 2D FE representation is used

and motivated. This amounts to $N_{MC} * N_t * N_{FE} * 6$ data values, where 6 is the number of stress components evaluated at the material axes. N_{FE} is the number of finite elements used for the structural modelling of the blades.

- 3) Construction of a reduced and parsimonious representation of the fatigue degradation at the material level. In the present work the Non-Negative Matrix Factorization (NMF) technique was used and qualitatively compared with linear Principal Component Analysis (PCA).
- 4) Finally, a probabilistic surrogate model is created with PCE, for simulation of degradation at the level of the cross-section, facilitating efficient long-term fatigue estimation.

The resulting PCE surrogate model may be employed for efficiently and accurately generating fatigue in the cross-section level, corresponding to wind and turbulence measurements.

Retaining all the time-sampled material level stresses and strains of all the aero-elastic runs is practically infeasible. However, the damage model reduces the amount of data needed to represent the material scale damage state information.

The standard approach to summarize the time-dependent nature of the loading, is to apply cycle counting and a linear cyclic damage accumulation rule (*Miner's rule* [8]). It is noted, that although practical, such an approach is not conceptually extendable to a model that accounts for degradation, mainly due to the assumption of the independence of load sequence. Nevertheless, the practical utility of such an approach is expected to remain relevant. That is, until alternative efficient and reliable damage accumulation models for composites are available. A short note on promising research is made at section 2.1.1. Nevertheless, the cycle counting approach (*Rain-flow counting* [9]) is adopted.

It should be noted, that in the proposed framework, sophisticated degradation models that account for anisotropic degradation of the material properties may be applied to the fatigue analysis in the context presented herein [7,10,11].

The real limitation of the proposed approach, for blade fatigue damage estimation, is the fidelity of the available composite fatigue degradation models. The present work contributes to the efficient and intuitive probabilistic modelling of spatially varying structure-level damage.

2 Analysis of Wind Turbine Blades and Composite Fatigue Damage Models

2.1 Mechanics of Thin-Walled Composite Blades

In the present section some fundamental mechanics principles, pertaining to the problem at hand are briefly reviewed.

Wind turbine blades consist of a swept, twisted thin-walled, closed cross-section with varying thickness. Warping deformation has a non-negligible effect on their behaviour. For the purpose of assessment of fatigue damage a sizeable amount of time-dependent load cases must be considered due to the stochastic nature of the loading experienced by the structure. Implementation of a direct brute-force 3D finite element approach for that purpose would not be feasible. It should be made clear that this is the case even when the wind loading is taken into account in a simplified, yet sufficiently accurate manner, in the context of the so-called Blade Element Momentum (**BEM**) theory.

On the other hand, modelling techniques for the reliable retrieval of stresses at the material level, through beam-like modelling, such as the Variational Asymptotic Beam Section analysis (**VABS**) [12] analysis or the Anisotropic Composite Beam theory of Giavotto [13] are available.

The efficient high-fidelity time-domain simulation at the structure scale, is covered by the Geometrically Exact Beam Theory (**GEBT**) [14]. In contrast to the Euler-Bernoulli beam theory and to the Timoshenko beam theory, in GEBT, there is no a-priori modelling assumption on the distribution of shear induced strains on the cross-section. Warping deformations are estimated separately in a finite element discretization of the cross-section and re-introduced to the problem in the cross-

section analysis phase. The effect of warping at the structural scale is reflected directly on the stiffness of the structural element. This comes at the cost of a more complicated, perhaps less intuitive, numerical implementation.

2.1.1 Damage Models for Composites and Fatigue

Composite fatigue modelling, is a vibrant and ever expanding research field. The most popular approaches to fatigue damage estimation are chosen mainly due to engineering convenience and rely on refinements of the Goodman diagram and on large experimental campaigns.

It is out of the scope of this work to give a complete treatment of the subject of composite fatigue damage. For a state of the art review the reader is referred to [15] and the more recent [16].

In general, a reliable composite damage model should have the following attributes:

- It should take into account the effect of the anisotropy of the composite in the damage accumulation and progression.
- It should discriminate in some manner between the different damage modes of the composite (fibre fracture, delamination, matrix cracking, micro-buckling)

Probably the most complete and ambitious treatment of progressive composite fatigue damage along the aforementioned lines, is the one exposed in the series of papers from Shokrieh [10]. However, the damage mode estimation procedure in these models relies on the lamina-level damage assumptions of Hashin model, which was developed for unidirectional laminates. The most detailed version of the progressive fatigue damage model cannot be applied to variable amplitude and variable mean stress fatigue loading, such as the highly stochastic loading due to turbulence. Shokrieh and Rafiee, relatively recently, proposed in [11] a simplified approach for that purpose.

A literature review on composite fatigue models incorporating stiffness or strength degradation, revealed that reliable high-cycle fatigue

estimation, with accurate representation of the evolving damage, is an open subject. The most important uncaptured factor, seems to be the anisotropic, evolution of damage and the complex stress redistributions during fatigue [7].

After all the aforementioned considerations, the use of a more sophisticated damage model was not adequately motivated. Therefore, a simple model relying on cycle counting for one component of material stress aligned with the blade longitudinal dimension was used.

2.1.2 Outline of Simulation Strategy

In the present work, we are using the MATLAB-based composite thin-walled cross-section analysis tool developed at DTU – **BECAS** for the estimation of the effect of warping. BECAS is based on the theory of [13].

For the aero-elastic simulations we are using the special purpose HAWT simulation tool **FAST** developed by NREL. The module ElastoDyn was chosen for the dynamics. A modal linear representation of the blades that takes into account the effect of cross-section twist on blade deformation was used. The WindPACT 1.5MW blade described in [17] was used for this case study (Figure 1).

Figure 1: Position of the cross-sections studied and BECAS 2D finite element mesh of a cross-section.

The blade geometry was retrieved by NuMAD [18] and the composite material layup was performed in AnSYS-ACP. A set of 2D finite element meshes for BECAS were retrieved from AnSYS-ACP with the correct material layup and fibre orientation. It was validated that the cross-section mechanical properties derived from the BECAS FE models

match well enough with the ones described in the literature for the studied blade [17].

A set of 800, 10-minute aero-servo-elastic simulations in NREL-FAST were performed and cross-section loads were retrieved.

At the cross-section level, stress cycle counting for multiple load cases at all material points for all cross-sections was performed. BECAS was used for retrieving the material strains and stresses. Damage patterns due to short-term fatigue on the blade spar-cap material were retrieved. The damage estimation procedure relied on a Wöhler diagram, a Goodman correction and Miner's rule for damage accumulation.

The evolution of fatigue damage and a stiffness update on the structure scale was not studied. That is due to the issues briefly discussed in Section 2.1.1 that also motivated a simpler fatigue model instead of a more sophisticated one.

3 Uncertainty Quantification

In this section the probabilistic modelling of fatigue damage and the numerical methods proposed are elaborated.

3.1 Polynomial Chaos Expansion (PCE)

Consider the 10-minute accumulated fatigue at the cross-sections of the wind-turbine blade as a stochastic field depending on the 10 minute averaged wind-speed and turbulence intensity. The purpose of PCE is to construct a function of wind speed and turbulence that will return the accumulated fatigue.

In PCE, the probability densities of the input variables are required to be independent. Namely,

$$\begin{aligned} f_{X_1 X_2 \dots X_n}(x_1, x_2, \dots, x_n) \\ = f_{X_1}(x_1) f_{X_2}(x_2) \dots f_{X_n}(x_n) \end{aligned} \quad (1)$$

where x_i denotes the random input variable i , and f_{X_i} denotes the probability density function of input variable x_i .

We define

$$\begin{aligned} \langle \varphi_m(x), \varphi_n(x) \rangle_{f(x)} \\ = \int \varphi_m(x) \varphi_n(x) f(x) dx \end{aligned} \quad (2)$$

where $f(x)$ is the one-dimensional probability density of an input variable x and $\varphi_m(x)$ are univariate functions. We seek a set of functions that satisfy the orthogonality relation

$$\langle \varphi_m, \varphi_n \rangle_{f(x)} = c \delta_{mn} \quad (3)$$

where δ_{mn} is the Kronecker delta and c is an arbitrary real positive constant. The surrogate model results by a linear combination of the multivariate tensor product of these orthogonal functions. When considering classical probability density functions for the input variables, the orthogonal basis consists of a tensor product of so-called *classical* orthogonal polynomials in each of the input variables chosen from the so-called *Wiener-Askey Scheme* [3].

3.1.1 Treatment of Dependency in Inputs

There is a strong dependency of the input variables in the problem at hand. Namely, the 10 minute average standard deviation of the wind speed, σ_1 , is modelled as a conditionally dependent random variable of the 10 minute average hub-height wind speed, V , at hub height according to IEC 64100-1.

The aforementioned *Askey-Scheme* polynomials are not suitable for the construction of a basis orthogonal to an arbitrary joint distribution. That is also due to the fact that there is no set of classical polynomials orthogonal with respect to the Rayleigh distribution. The orthogonality requirement is essential for the fast convergence of the method with increasing polynomial degree [3].

Classically, dependencies are dealt with the application of iso-probabilistic transforms of the joint densities of the random variables, such as the *Rosenblatt* transform, so that the expansion is valid in the transformed space.

In this work, an alternative approach is followed, first considered in [19]. A multi-dimensional inner

product, is directly used for the construction of the orthogonal polynomial basis set. Namely,

$$\langle \varphi_m, \varphi_n \rangle_{f(V, \sigma_1)} = \iint \varphi_m(V, \sigma_1) \varphi_n(V, \sigma_1) f(V, \sigma_1) dV d\sigma_1 \quad (4)$$

$$\langle \varphi_m, \varphi_n \rangle_{f(V, \sigma_1)} = \delta_{mn} \quad (5)$$

Figure 2. Visualization of the polynomial basis functions, orthogonal w.r.t. (4)

The *Gram-Schmidt* procedure is utilized for the construction of the jointly orthogonal basis set. The general purpose 2D numerical integrator of MATLAB was used for estimating the required integrals. Starting from an arbitrary linearly independent basis set, in our case polynomials on σ_1 and V such as

$$\{1, \sigma_1, V, \sigma_1 V, \sigma_1^2, V^2, \dots\} \quad (6)$$

we evaluate a sequence of linear combinations of the polynomials that have the desired orthogonality property (5). For visual illustration, plots of the some of the derived basis functions for the joint PDF of wind-speed and turbulence are given in Figure 2.

3.2 Dimensionality reduction for spatial fatigue damage

3.2.1 Non-negative matrix factorization

The most widely used method for dimensionality reduction of random fields is the so-called Karhunen-Loève expansion. In the context of engineering analysis under uncertainty its use was pioneered by Ghanem and Spanos in [20].

An alternative dimensionality reduction technique that is constrained in order to return strictly positive coefficients and positive component vectors, as required by the problem at hand, is the so-called Non-Negative Matrix Factorization (NMF) or (NNMF)[4]. It is presented directly in the context of the problem at hand.

For the N_{MC} runs and for the accumulated fatigue at the N_{FE} finite element points along the blade, 10 minute accumulated fatigue damage is computed. In our case, $N_{FE} = 7707$. This amounts to an output data matrix Z of size $N_{FE} * N_{MC}$. Note that all elements of Z are positive, since they represent 10 minute accumulated fatigue. We seek a decomposition of Z such that

$$\argmin_{W, H} \sum_{k=1}^p ||W_{ik} H_{kj} - Z_{ij}|| \quad (7)$$

Both W and H have positive or zero components. Also p is the number of non-negative factors we pre-define. The number of rows of W is N_{MC} and the columns are p non-negative weight vectors (components). The entries of each column may be seen as a weight, for the rows of H . The rows of H are vectors of size N_{FE} that may be considered as "latent" underlying fatigue components. For details on a probabilistic interpretation of NMF, the reader is referred to [5]. NMF fatigue components are computed using the fatigue data for all blades at all cross sections. Only the first two components are chosen for the following analysis, since they were found to approximate the spatial distribution of cross-section fatigue data well. The relative reconstruction error using 2

NMF components is $\frac{\sum_{i,j} |WH - Z|_{ij}}{N_{FE} * N_{MC} * Z_{ij}} \cong 3.1 * 10^{-3}$. It has to be noted, that due to the structure of the

problem this decomposition is not unique and its efficiency is problem and data dependent. Also a non-linear scaling was performed in order to treat numerical issues related to the small values of 10 minute accumulated fatigue DEL, that are beyond the scope of this paper.

As shown in *Figure 3*, the non-negative matrix factorization components (NMF-C) for this particular problem, are qualitatively and quantitatively similar to those of a principal component analysis (PCA-C). Moreover, both methods seem to reveal the spatial distribution of fatigue damage in the cross sections. Similar patterns were observed in all cross-sections that are not included due to space limitations. It is worth to be noted, that we can already distinguish the nature of the damage. The c1 component seems to correspond to edge-wise bending fatigue and the c2 component due to flap-wise bending.

Since the damage equivalent loads can be well approximated by two latent factors, instead of the FE evaluation of fatigue at all cross-section at every blade, the weights of the latent factors (entries of matrix W) are used to represent the blade damage. A surrogate model of the cross-section damage NMF components is computed via PCE. Scatterplots of the weights of the 2 NMF coefficients for the sample considered, are given in *Figure 4*. An additional parameter, depending on the total number of rotor revolutions in the 10 minutes of the simulations is added to account for the effect of gravity.

It was observed that the operating regime has a pronounced effect on fatigue accumulation. Namely, the second fatigue damage component c2, obtains a local maximum at 14m/s. This seems to be due to the contribution of pitch-to-feather control for the maintenance of rated rotor speed that indeed corresponds to mean speed of 14m/s. The first component of spar-cap fatigue damage, which seems to be mostly due to edge-wise bending, does not seem to be relieved during the pitch control regime.

It was found that average wind-speed together with operating conditions, is a good predictor for blade fatigue. The edge-wise fatigue feature c1, positively correlates with the number of revolutions and wind-speed whereas c2 negatively

correlates. This is consistent with intuition, since at higher wind-speeds blades are controlled in order to expose their flat region towards the wind resulting in lower lift. Therefore while rotating, the self-weight of the blade produces cyclic edge-wise bending.

Figure 3. PCA and NMF factors of damage for a blade cross-section.

Figure 4. Scatterplot of input data and fatigue damage coefficients. Turbulence is expressed as percentage of 10 minute average wind speed.

3.3 Polynomial Chaos Expansion of Fatigue Damage

A polynomial chaos surrogate fit was carried out for fatigue damage modes, obtained by non-negative matrix factorization. Polynomials up to order 4, both in V and σ_1 were used for the construction of the orthogonal basis. Discriminating with respect to different operating conditions, was deemed necessary to ensure the quality of the polynomial chaos fit. The operating conditions enter as a factor in the regression problem, that discriminates with respect to mean $V > 14m/s$ and $V \leq 14m/s$. The fitting procedure is performed with 800 samples separately for damage components c1 and c2. The

Least Angle Regression (LAR) algorithm [21] of UQLab [22] is employed that has been shown to reliably produce good results in the context of polynomial chaos expansions [23].

As seen in Figure 5, the fatigue damage accumulated loads seem to be well represented by the PCE/NNMF surrogate models. The normalized relative error in estimation, computed according to (8) for all fatigue components is of the order of 7%. The Leave-one-out Cross-validation error for the PCE is also of the order of 10%. This relatively high error value is reasonable since there are many factors unaccounted for in the performed fit.

$$\text{NRMSE}(y_{\text{sim}}, y_{\text{PCE}}) = \frac{\sqrt{\frac{\sum (y_{\text{PCE}} - y_{\text{sim}})^2}{N}}}{\max(y_{\text{sim}}) - \min(y_{\text{sim}})} \quad (8)$$

Figure 5. Plot of simulated 10 minute accumulated, mean cross-section fatigue damage

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against PCE/NNMF estimated for all cross-sections.

4 Conclusions

Adoption of complicated models for composite strength and stiffness degradation, is not sufficiently motivated by the reliability of the presently available models. Fatigue models are conservative on the amount of information they require for convenient application in design practice.

A computational approach for the representation of fatigue damage in wind turbine blade spar-caps was presented. The damage was successfully represented with NMS and intuitive observations were made. A computationally efficient polynomial chaos model was derived for the 10 minute accumulated fatigue.

Future work will be devoted to the formulation of surrogates that are suited to different sources of uncertainty. More detailed damage accumulation models ought to further be investigated as part of future work.

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