Analysis of two modeling approaches for fatigue estimation and remaining useful life predictions of wind turbine blades

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ABSTRACT

Wind turbines components are subject to considerable stresses and fatigue due to extreme environmental conditions to which they are exposed, especially those located offshore. With this aim, the present work explores two different approaches on fatigue damage estimation and remaining useful life predictions of wind turbine blades. The first approach uses the rainflow counting algorithm. The second approach comes from a fatigue damage model that describes the propagation of damage at a microscopic scale due to matrix cracks which manifests in a macroscopic scale as stiffness loss. Both techniques have been tested using the information provided by the blade root moment sensor signal obtained from the well known wind turbine simulator FAST (Fatigue, Aerodynamics, Structures and Turbulence).

1. INTRODUCTION

Wind turbine blades are components that are subject to highly irregular loading and extreme environmental conditions, especially those located offshore.

One of the aspects that is desirable from operators and original equipment manufacturers (OEMs) perspective is to have information about the damage and remaining useful life predictions provided by condition or health monitoring systems (Frost, Goebel, & Obrecht, 2013). Structural health information is necessary for the wind turbine to continue operating and producing power without exceeding some damage thresholds resulting in unscheduled downtime.

The challenge is thus to decide maintenance actions on components in the way to continuously reduce and eliminate costly unscheduled downtime and unexpected breakdowns, see (Iung, Monnin, Voisin, & Cocheteux, 2008).

For offshore wind turbines, the higher operation and maintenance costs represent a larger overall proportion of the cost of energy than for onshore turbines, even when the large initial investment required for the installation of offshore turbines is included. One of the reasons that these costs are likely to be higher offshore is that the offshore environment will bring with it increased work loading which is relatively uncharacterized due to the lack of existing offshore installations (Myrent, Kusnick, & Adams, 2013).

An understanding of the fatigue behavior of a wind turbine rotor blade is also valuable for the improvement of product development practices. Product development practice up to now has been based on an iterative process whereby a prototype rotor blade is built and tested against real, or realistic, loading patterns. However, this process is costly and time consuming. The ability to simulate the fatigue behavior of the material, the blade structural component and/or the wind turbine rotor blade reduces the cost and allows the development of a wider range of products without the need for increasing the number of physical prototypes (Vassilopoulos, 2013).

In this work, fatigue in the blade root is analyzed. This component has been identified as a critical area for fatigue in several works such as (Sutherland, 1999) which shows, that the edgewise blade root bending moment frequency distribution from a small turbine contains two peaks; one originating from the wind loading, the other a result of the blade being loaded by its own weight. (Caprile, Sala, & Buzzi, 1995) present histograms of mid-size wind turbine blade edgewise and flapwise blade root moments, showing the same peak for the edgewise loading. For larger rotor blades, the edgewise gravity fatigue loading becomes increasingly relevant for life prediction. (Kensche & Seifert, 1990) gives typical root bending moments from measurements on wind turbine blades, both in flap and edgewise direction.

Experimental evidence (Nijssen, 2006) has shown that typical composite materials used in wind turbine rotor blades exhibit strength degradation trends. The degradation of those materials in fatigue conditions has been thoroughly studied in (Vassilopoulos & Nijssen, 2010).

Different methods have been proposed to the degradation of composite materials used in the wind turbine blades. Some of them are based on phenomenological life predictions while others consider the actual mechanical damage modelling. In this work, one phenomenological method and one fatigue damage model are analyzed for wind turbine blades life predictions, these are the rainflow counting and a fatigue stiffness degradation model respectively. Both methods are tested in a high fidelity wind turbine simulator.

2. FATIGUE ESTIMATION BACKGROUND FOR WIND TURBINE BLADES

This section provides a brief theory background for both of the analyzed techniques. The first subsection explains the rainflow counting method and the second subsection explains the stiffness degradation theories from which is proposed the fatigue damage model used in this work to study the stiffness degradation of the blade.

2.1. Rainflow Counting Method

Fatigue is the damage accumulation process on a component produced by cyclic loading. Exposing a material to cyclic loading of constant amplitude will cause fatigue failure after a certain number of cycles. In reality amplitudes of cyclic loading are rarely constant. Most components are exposed to random load fluctuations. A common method to quantify the fatigue impact of fluctuating loads is the combination of a rainflow counting algorithm and a damage equivalent load approach, enabling the relative comparison of different load samples (Martinen, Carlén, Nilsson, Breton, & Ivanell, 2014).

Rainflow counting (RFC) method, first introduced by (Endo, Mitsunaga, & Nakagawa, 1967), has a complex sequential and nonlinear structure in order to decompose arbitrary sequences of loads into cycles. The rainflow cycle distributions (often simply called cycle distributions or rainflow spectra) represent the occurrence probability of load cycles with different ranges. Usually, to compute a lifetime estimate from a given stress input signal, the RFC method is applied by counting cycles and maxima, jointly with the Palmgren-Miner rule to calculate the expected damage. The input signal is obtained from time history of the loading parameter of interest, such as force, torque, stress, strain, acceleration, or deflection (Lee, Pan, Hathaway, & Barkey, 2005).

The Fig. 1 depicts the described procedure.

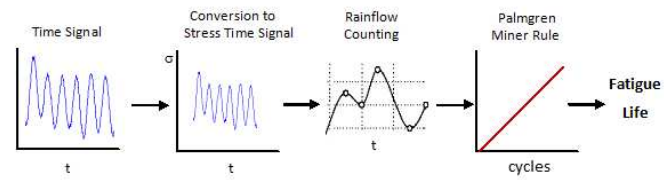

Figure 1. Rainflow counting damage estimation procedure

Different types of RFC algorithms have been proposed in the literature (Downing & Socie, 1982)(Rychlik, 1987). The algorithm used in this paper is introduced in (Niesłony, 2009), and is implemented as a Matlab code. A previous applications of this code to integrate fatigue estimation with model predictive control has been performed in (Sanchez, Escobet, Puig, & Odgaard, 2015). This algorithm calculates the stress for each rainflow cycle in four steps:

- the stress history is converted to an extremum sequence of alternating maxima and minima;
- for each local maximum M_j, the left and right region where all stress values are below M_j is identified, denoted respectively as m_j^- and m_j^+;
- the minimum stress value is computed as: $m_j = min\{m_j^-, m_j^+\}$;
- the equivalent stress per rainflow cycle s_j associated with M_j is given by the amplitude $s_j = M_j - m_j$ or the mean value $s_j = \frac{M_j+m_j}{2}$.

The damage, D, at each stress cycle is computed using S-N curve (Hammerum, Brath, & Poulsen, 2007). The S-N curve is a graphical representation of the stress, s, versus the number of stress cycles, N. An often-used model for the S-N curve is

$$s^{c_W} N = K, \tag{1}$$

where the quantities K and c_W are material properties, being c_W the Wöhler-coefficient. The damage imposed by a stress cycle with a range s_j is computed as

$$D_j \equiv \frac{1}{N_j} = \frac{1}{K} s_j^{c_W} \tag{2}$$

The linear damage accumulation after N cycles can be computed using the Palmgren-Miner's damage rule, given by

$$D_{ac} = \sum_{j=1}^{N} \frac{1}{K} s_j^{c_W} \tag{3}$$

The algorithm steps are illustrated with an example shown in Figure 2.

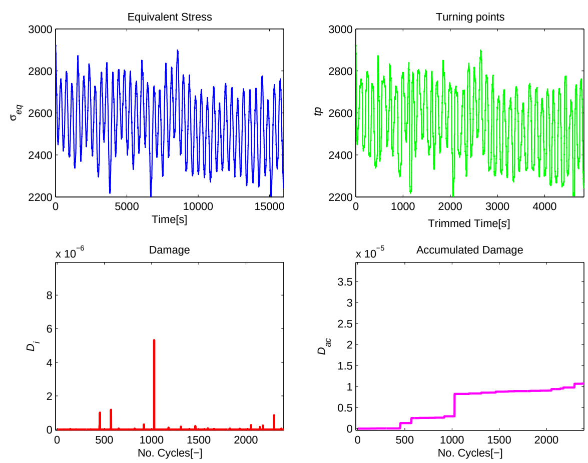

Figure 2. Example of the application of rainflow counting procedure on blade root moment stress signal

On the top left of Figure 2 (a.1) the time signal of the input stress is shown. Then the signal is converted into a sequence of maxima and minima (turning points) shown in (a.2). In the bottom part (b.1) it is shown the calculated damage for each rainflow cycle individually. Finally the accumulated damage is shown on part (b.2).

A common criteria accepted to determine failure when using Palmgren-Miners rule is when the cumulative damage expressed in equation 3 reaches the value $D_{ac} = 1$.

In previous works has been explored how to calculate life predictions using the rainflow counting method, see (Baek, Cho, & Joo, 2008). The way to calculate life for a repeated stress signal implemented in this work is be given by:

$$Life = N_f \left(1 - \sum_{j=1}^{N} \frac{1}{K} s_j^{c_W}\right) \tag{4}$$

where N_f is the lifetime in cycles. The approach presented in equation to calculate the life in cycles, is valid only when a constant load is applied and the accumulated damage expressed in equation (3) is in the range of [0,1].

2.2. Stiffness Degradation Fatigue Theories

As explained in (Vassilopoulos, 2013) strength and stiffness degradation fatigue theories have been introduced in order to model and predict the fatigue life of composite materials by taking into account the actual damage state, expressed by a representative damage metric of the material status. The damage metric is usually the residual strength or the residual stiffness. Failure occurs when one of these metrics decreases to such an extent that a certain limit is reached (Brondsted & Nijssen, 2013). Stiffness degradation theories are not linked to the macroscopic failure (rupture) of the examined material but rather to the prediction of its behavior in terms of stiffness degradation. Failure can be determined in various ways, e.g. when a predetermined critical stiffness degradation level is reached; or when stiffness degrades to a minimum stiffness designated by the design process in order to meet operational requirements for deformations; or even as a measure of the actual cyclic strains, e.g. failure occurs when the cyclic strain reaches the maximum static strain (Zhang, A.P., & Keller, 2008). Methods that are able to assess the development of the remaining stiffness degradation of a material or a structural component during fatigue life are valuable for damage tolerant design considerations. In situations like this, the effect of local failure and the stiffness degradation caused by the failure must be investigated to ensure structural integrity under the given (acceptable) damage. Life prediction schemes for composite laminates have been developed based on these concepts (Eliopoulos & Philippidis, 2011). In addition, this effective medium description requires the gradual strength and stiffness degradation assessment due to cyclic loading. It is obvious that important experimental effort is necessary for the parameter estimation of such a hybrid (strength and stiffness degradation) modeling process.

According to (Van Paepegem & Degrieck, 2002), it is commonly accepted that for the vast majority of fibre-reinforced composite materials, the modulus decay can be divided into three stages: initial decrease, approximately linear reduction and final failure (see Figure 3), where E_0 is the undamaged stiffness, E is the stiffness at a certain moment in fatigue life, N is the number of testing cycles and N_f is the fatigue life in cycles.

In the work of (Schulte, 1985) three distinctive stages are distinguished:

- The initial region (stage I) with a rapid stiffness reduction of 2-5%. The development of transverse matrix cracks dominates the stiffness reduction ascertained in this first stage.
- An intermediate region (stage II), in which an additional 1-5% stiffness reduction occurs in an approximately linear fashion with respect to the number of cycles. Predominant damage mechanisms are the development of the edge delaminations and additional longitudinal cracks

along the fibres.

- A final region (stage III), in which stiffness reduction occurs in abrupt steps ending in specimen fracture. In stage III, a transfer to local damage progression occurs, when the first initial fibre fractures lead to strand failures.

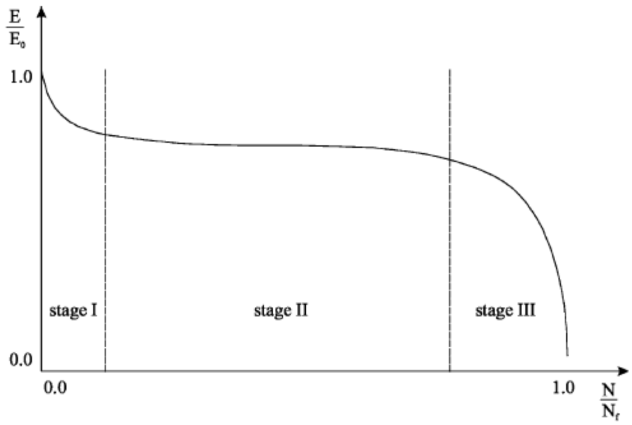

Figure 3. Typical stiffness degradation curve for a wide range of fibre-reinforced materials

3. APPLICATION TO WIND TURBINE BLADE PROGNOSTICS

This section analyzes the application of the rainflow counting algorithm and the fatigue stiffness degradation model for fatigue estimation and remaining useful life prediction of a wind turbine blade. Figure 4 shows the process of applying the rainflow counting algorithm and the fatigue stiffness degradation model to estimate fatigue and calculate remaining useful life predictions for the wind turbine blade using the blade root moment sensor information from the high fidelity wind turbine simulator FAST (Fatigue, Aerodynamics, Structures and Turbulence), (Jonkman & Marshall, 2005).

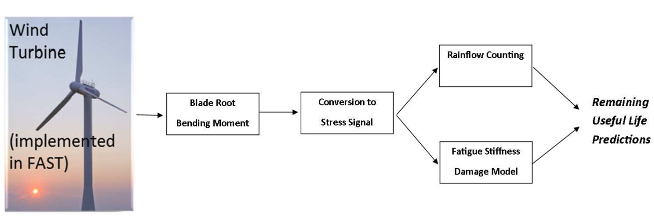

Figure 4. Scheme of the application of the analyzed approaches for wind turbine blade remaining useful life predictions

To analyze the two approaches three different blade root moment bending loads are obtained from the wind turbine simulator working on three different constant wind speeds of 14, 16 and 18 m/s. Figure 5 presents three different blade root moment (BRM) bending loads (obtained from FAST simulator) corresponding to the different wind speeds. The blade root moment signals present a sinusoidal wave due to the cyclic behavior of wind turbines and with different mean values because of the different wind speeds considered. These loads are converted in stresses dividing by the appropriate section modulus in order to be used as inputs for the rainflow counting algorithm and the fatigue degradation damage model.

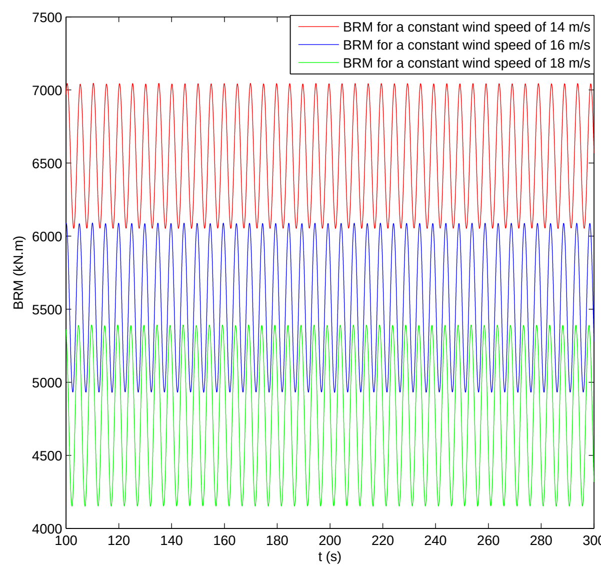

Figure 5. Blade root moment bending loads obtained in FAST for constant wind speeds of 14, 16 and 18 m/s

3.1. Life prediction approach based on rainflow counting algorithm

For real-time applications, applying the traditional rainflow counting algorithm is very challenging and computationally heavy. Significant amounts of data must be stored and processed periodically to obtain a magnitude of the data in equivalent regular cycles. In addition the algorithm must be applied to a stored set of data.

Loads in wind turbine structure arise from several factors (Jelavic, Petrovic, & Peric, 2008), being the main cause the spatial variations of wind speed caused by the turbulent nature of wind. The paper (Jelavic et al., 2008) concludes that the most pronounced contribution to the blade root loading happens at the frequency given by the blades speed, and this loading is the main source of fatigue at the blades.

Using the RFC method the accumulated damage is obtained as function of the cycles of the blade root moment stress signal. In case that the input signal is expressed as bending moments it is necessary to convert the fatigue load to fatigue stress dividing by the appropriate section modulus (Burton, Jenkins, Sharpe, & Bossanyi, 2011). Some previous works such as (Burton et al., 2011), (Vassilopoulos, 2013) for wind turbine blade fatigue assessment and life prediction that describe the rainflow counting algorithm have been reviewed. A number of subproblems must be solved sequentially in order to produce the final result, the steps applied in this work are the following:

1. Derive the individual fatigue load spectra for each mean wind speed and for each radius. In this work the wind and load information is obtained from the wind turbine FAST simulator.
2. Synthesize the complete fatigue load spectrum at each radius from the separate load spectra for each mean wind speed.
3. Convert the fatigue load cycles (expressed as bending moments) to fatigue stresses by dividing by the appropriate section modulus. The section modulus with respect to a particular principal axis is defined as Second Moment of Area of the cross-section about that axis divided by the distance of the point under consideration from the axis. The blade root bending moments are divided by the section corresponding to a wind turbine blade root.
4. Find an appropriate S-N curve for the material considered.
5. Cycle counting. This is done by applying rainflow counting algorithm.
6. Adoption of the fatigue failure criterion.
7. Calculate the cumulative damage according to Miners rule and obtain the fatigue life prediction. In section 4.2, is explained the damage assessment and assumptions that result in a prediction in the scope of this work.

3.2. Prognostics approach based on fatigue stiffness degradation model

This section analyzes a fatigue stiffness damage model application based on the model proposed by (Van Paepegem & Degrieck, 2002). In order to apply this model, it is assumed that the blade is a solid beam. This assumption simplifies the application of the stiffness damage model which is derived for a specific material fiberglass which is commonly used in wind turbine blades. The blade root bending moment sensor information from the high fidelity simulator as the input load which translates in compressive stress. The damage model is used to obtain remaining useful life predictions subject to different wind speed scenarios generated by the wind turbine high fidelity simulator FAST (Jonkman & Marshall, 2005).

The model proposed in (Van Paepegem & Degrieck, 2002) defines the model as the sum of an initiation function and a propagation function based on theoretical considerations and a sound modeling of the observed fatigue damage mechanisms. The original model proposed functions for the tensile and the compressive stresses. The model used in this work is the one proposed for the compressive stresses since the damage loads considered for this study are the ones that come from the flapwise bending moments at the blade root. Therefore, choosing the flapwise bending moments as the considered damage loads involves the use of the model for compressive stresses. This model has been tested for bending fatigue experiments in (Van Paepegem & Degrieck, 2002). The impact of control contingency strategies for reducing flapwise blade root moment damage loads have been previously studied in the work of (Frost et al., 2013), which makes these type of loads interesting for future research work in damage reduction and the increase of remaining useful life of wind turbine blades. The damage initiation function simulates the sharp decline of the stiffness in the first stage of fatigue life. Matrix cracking is the predominant mechanism in this stage and according to (Van Paepegem & Degrieck, 2002). The failure index $\sum(\sigma, D)$ is constant for strain controlled fatigue experiments. The saturated crack density should depend on the level of the cyclic strain amplitude applied. The fatigue failure index for the purposes of this work is given by:

$$\sum(\sigma, D) = \frac{\sigma}{(1-D)X_C} \tag{5}$$

The damage initiation function uses the fatigue failure index 5 and is defined as:

$$f_i(\sigma, D) = \left[c_1 \sum\ (\sigma, D)\ \exp\left(-c_2 \frac{D}{\sqrt{\sum\ (\sigma, D)}} \right) \right]^3 \tag{6}$$

The damage propagation function uses the fatigue failure index 5 as well and is defined as:

$$f_p(\sigma, D) = c_3\, D\, \Sigma(\sigma, D)^2 \left[1 + \exp\left(\frac{c_5}{3} \left(\Sigma(\sigma, D) - c_4 \right) \right) \right] \tag{7}$$

Practical implementations of equations 6 and 7, requires to make a distinction on the level of the damage growth rate equation dD/dN, because the damage increment is calculated after each cycle and this damage increment is extrapolated to the next simulated cycle. The final layout of the fatigue damage model states as follows:

$$\begin{aligned} \tfrac{dD}{dN} = & \left[c_1 \Sigma \exp\left(-c_2 \tfrac{D}{\sqrt{\Sigma}} \right) \right]^3 + \\ & c_3\, D\, \Sigma^2 \left[1 + \exp\left(\tfrac{c_5}{3} (\Sigma - c_4) \right) \right] \end{aligned} \tag{8}$$

where the damage variable D is a measure for the stiffness reduction in the considered material element due to matrix cracks, σ is the stress measure, X_C is the ultimate compressive static strength, c_1 and c_2 are material constants. The constant c_1 determines the amplitude of the damage initiation rate, while the exponential function is a decreasing function of damage D. Once a certain damage value has been reached, the contribution of the damage initiation function becomes negligible. c_3 is the damage propagation rate, c_4 is a sort of threshold below which no fibre initiates and c_5 is a model parameter used to keep the exponential function strongly negative as long as failure index $\sum(\sigma, D)$ remains below the threshold c_4, but switches to a large positive value once the threshold has been crossed.

3.3. Damage prognostics

For predicting remaining useful life (RUL) of a composite structure such as a wind turbine blade, we are interested in predicting the time when the damage grows beyond a predefined acceptable threshold (Saxena, Celaya, Saha, & Goebel, 2010). The time or cycle at which it occurs is known as the expected end of life (EOL).

The wind turbine is expected to continue operating and producing power without exceeding the end of life (EOL) threshold for the blade given by the accumulated stiffness fatigue damage $D = 0.8$ provided by equation 8, which is set as the maximum stiffness reduction allowed for the purpose of this work.

Once the (EOL) threshold is determined, the remaining useful life can be readily obtained as $RUL_n = EOL - n$. Where n stands for the current time or cycle.

A simplified algorithmic description for the RUL prediction is provided below.

1. The stiffness damage at the current cycle and the future loads are required.
2. Calculate damage for the next cycle provided by equation (8).
3. Increase the number of cycles to failure.
4. If the current damage is less than EOL repeat steps 2-4.
5. If current damage is greater than EOL the RUL is equal to the number of cycles to failure accumulated.

4. ANALYSIS OF RESULTS

In this section both methods are tested to estimate fatigue damage accumulation and calculate remaining useful life predictions using the blade root bending loads given by the wind turbine simulator FAST (Jonkman & Marshall, 2005), in three different constant wind speeds scenarios. In section 4.1 is simulated the damage progression with the fatigue stiffness degradation model which is later embedded into a prognostics algorithm to calculate remaining useful life predictions. Section 4.2 tests the rainflow counting method with the same blade root moment loads used in the stiffness degradation model, the cumulative damage for the three wind scenarios is obtained as well.

4.1. Fatigue stiffness degradation model

Figure 6 shows the damage progression for different wind speeds using the stiffness degradation damage model of equation 8. The parameters $X_c = 341.5$ (MPa), $c_2 = 30$ (-), $c_4 = 0.85$ (-) and $c_5 = 93$ (-) were chosen taking as a reference the ones proposed in (Van Paepegem & Degrieck, 2002). In (Van Paepegem & Degrieck, 2002) the model is tested for different values of the damage propagation rate c_3, which shows that final failure occurs much earlier if this parameter is increased. In the case of this work, after several simulation tests, the value for the parameter was chosen as $c_3 = 4 \times 10^{-4}$ (1/cycle).

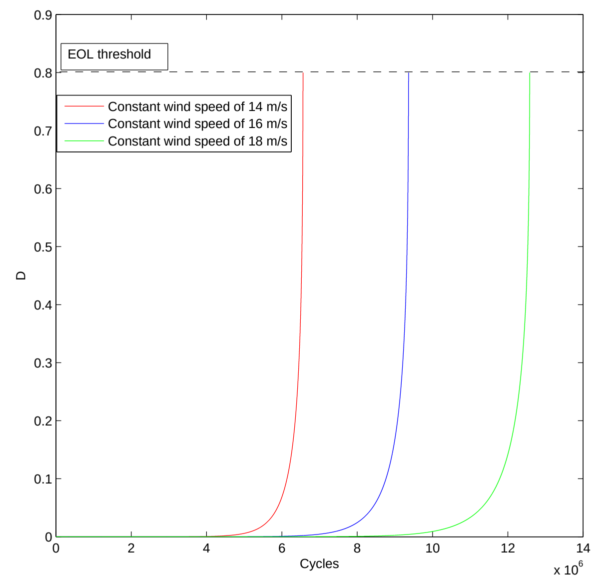

Figure 6. Damage progression in the stiffness degradation model for different loads due to three different wind speed scenarios

From Figures 7-9, it can be observed the curves for remaining useful life predictions for the wind turbine blade on three different wind scenarios of constant wind speeds of 14, 16 and 18 m/s. The remaining useful life predictions shown are the mean value of 500 samples and the value $\alpha = 0.9$.

The results show that the damage progression is faster for lower wind speeds, resulting in the reach of the end of life threshold earlier as it can be seen in the Figure 6. This is due to the fact that wind turbine is operating in control region 3. In region 3, the wind turbine rotational speed is maintained constant at the rated speed by pitching the turbine blades (Frost et al., 2013). In lower wind speeds the angle of attack of the blades against the wind is higher and that translates into higher flapwise blade root bending loads. When the wind speed is higher the angle of attack of the blades needs to be

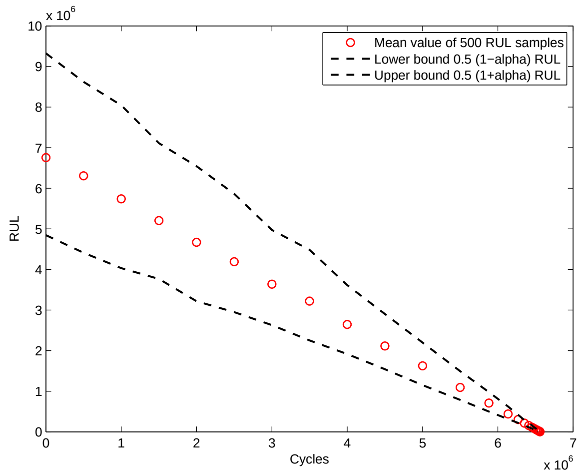

Figure 7. Remaining useful life predictions for different cycles on a wind speed of 14 m/s

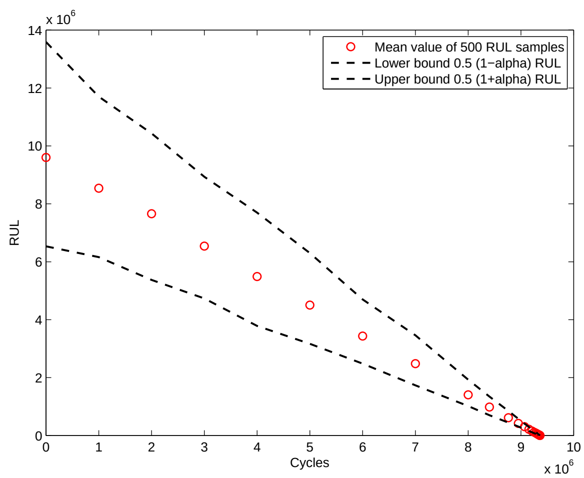

Figure 8. Remaining useful life predictions for different cycles on a wind speed of 16 m/s

lower to maintain the wind turbine rotating at the rated speed, therefore the flapwise damage loads are lower. It is consequently observed in Figures 7-9 that the RUL predictions for lower winds are shorter than those for the higher winds.

4.2. Rainflow counting algorithm

In the Figure 10, it is shown the cumulative damage obtained applying the rainflow counting algorithm for the case of three different loads due to three different wind speeds scenarios of 14, 16 and 18 m/s. The parameters used in this work are $c_w = 10$ which is a common value for glass fibre composite materials (Burton et al., 2011). Wind turbine rotor blades will probably be required to sustain 10^9 fatigue cycles during the 25 years of their expected operational life

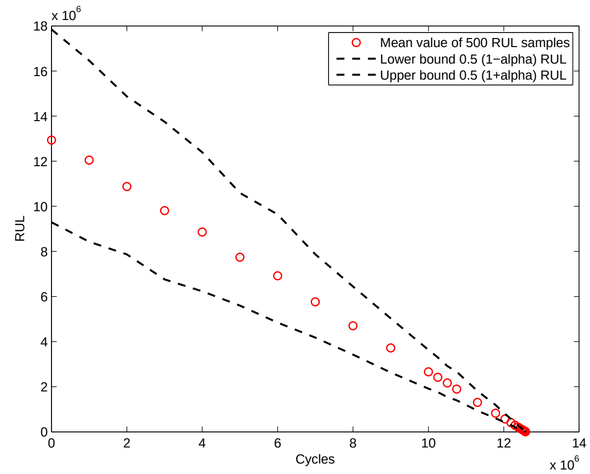

Figure 9. Remaining useful life predictions for different cycles on a wind speed of 18 m/s

(Vassilopoulos, 2013) which translates in $N = 10^9$, assuming $K = 7.0173 \times 10^{76}$. Figure 10 shows that the damage slope is

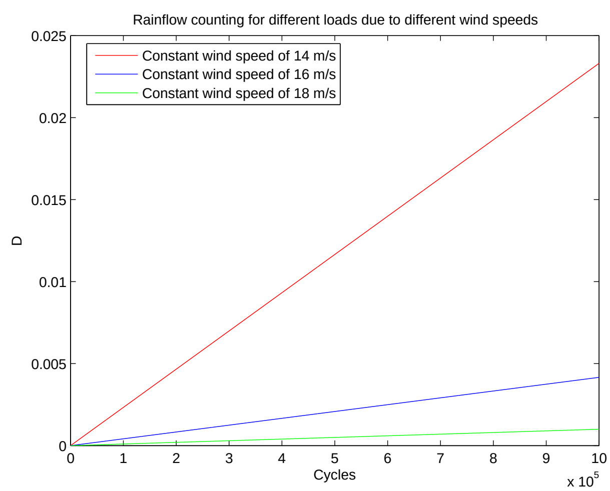

Figure 10. Cumulative Damage obtained with rainflow counting algorithm for different loads due to three different wind speed scenarios

higher for lower winds which have a higher mean stress values, this translates into a faster damage accumulation, i.e. a shorter life of the blade. It is assumed that future wind speed will remain constant for the purpose of the rainflow counting application in this work. The results are presented in Fig. 11, showing the calculated life predictions for each wind scenario.

Wind Speed (m/s)	Life prediction (cycles)
14	9.77×10^8
16	9.96×10^8
18	9.99×10^8

Figure 11. Results of life predictions using the rainflow counting method

4.3. Comparison of the approaches

There is extensive research that has been performed analyzing rainflow counting algorithm and the stiffness degradation models (see (Nijssen, 2006) (Vassilopoulos & Nijssen, 2010) (Vassilopoulos, 2013)).

In this section, a brief summary collected from the mentioned literature for both of the approaches analyzed in this work is provided based in the input information that they require, the output information we get from them and the advantages and disadvantages that each one presents.

In Figure 12 is summarized the input and output information for both of the approaches analyzed in this work.

Approach	Input Information	Output Information
Rainflow Counting	• Numbers of cycles to failure on current load condition. • Stress or strain measure for each cycle.	• Calculated damage for each load cycle
Stiffness Degradation Model	• Current state of stiffness damage. • Stress measure for the current cycle.	• Stiffness damage increment for the current cycle and this damage increment is extrapolated to the next simulated cycle.

Figure 12. Input-output information for Rainflow Counting Algorithm and the Fatigue Stiffness Degradation Model

Advantages and Disadvantages of Rainflow Counting Method

The main advantage of rainflow counting method is that the estimation of the model parameters is based on linear regression analysis that can be performed by simple hand calculations.

The rainflow counting method presents the following disadvantages:

- Needs experimental data for the specific material in order to have an S-N curve for the specific material.
- Different model parameters should be determined for different loading conditions.
- Do not take into account any of the failure mechanisms that develop during the failure process.
- As an empirical method, its predictive ability is strongly affected by the selection of a number of parameters that must be estimated or even, in some cases, assumed.
- The linear behavior observed in cumulative damage methods based on Miner's rule such as the rainflow counting is not an accurate representation fit to the behavior observed in realistic scenarios.

Advantages and Disadvantages of the Fatigue Stiffness Degradation Model

Among the advantages of fatigue stiffness degradation model can be mentioned the following:

- The ability to quantify the stiffness reduction at any point during realistic loading applied to the structure constitutes the major advantage of stiffness degradation methods for life prediction.
- Modeling the loss of stiffness of a material after cyclic loading can be a powerful tool in the development of life prediction schemes, especially when dealing with variable amplitude or spectrum loading, since it offers a meaningful physical alternative to empirical damage accumulation rules such as the Palmgren-Miner rule.
- The remaining useful life can be assessed by non destructive evaluation since the stiffness degradation theories are based on a damage metric that does not need the failure of the material in order to derive it.
- Stiffness degradation exhibits greater changes during the entire fatigue life.

One of the disadvantages of stiffness degradation models is the important experimental effort that is necessary for the parameter estimation of the fatigue damage model.

5. CONCLUSIONS

Two approaches for fatigue estimation and remaining useful life predictions for wind turbine blades were analyzed and tested in this paper. The advantages and disadvantages of both methods were investigated and both methods were tested using a blade root moment bending signal given by a high fidelity wind turbine simulator.

The damage definition used in the two methods is different. In the fatigue stiffness damage model the damage is defined as the stiffness reduction in the material due to cyclic loading while the damage in the case of the rainflow counting algorithm it is not explicitly related to a physical characteristic of the material or the considered structure. Therefore, the numerical results obtained for each one of the methods cannot be directly compared or analyzed. However both of the approaches demonstrated that the higher is the mean stress value due to wind speed, the damage accumulation occurs faster which translates in shorter life and RUL predictions for the wind turbine blade.

As a future work, other methods such the ones proposed by (Bendat, 1964) or (Dirlik, 1985) could also be considered for comparison. Moreover, the results of the analysis and tests done in this work can be used to assess the design of a wind turbine controller that can be capable of adapting the damage and remaining useful life predictions provided by the models in order to enable a damaged turbine to operate in a reduced capacity and optimize the trade-off between the remaining useful life predictions of a wind turbine blade and energy production demands.

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