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Reliability Assessment and Reliability-Based Inspection and Maintenance of Offshore Wind Turbines

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Reliability Assessment and Reliability-Based Inspection and Maintenance of Offshore Wind Turbines

by

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SUMMARY

Wind power installations have become the second largest contributor to installation of electricity capacity in the European Union during the last decade. With this increase in production capability and size, technical and economical efforts should be directed to achieving the optimal structural performance during the life cycle. The deterioration processes, such as fatigue and corrosion, are typically affecting offshore structural systems. This damage decreases the system performance and increases the risk of failure, thus not fulfilling the established safety criteria. Inspection and maintenance actions are the most relevant and effective means of control of deterioration. The risk-based inspection planning methodology, based on Bayesian decision theory, represents an important tool to identify the suitable strategy to inspect and control the deterioration in structures such as offshore wind turbines.

During the last decades, Risk Based Inspection (RBI) approaches have been applied in the oil and gas industry, giving a theoretical background that can also be applied for offshore wind turbines. Unlike other offshore structures, offshore wind turbines represent low risk to society due to their offshore location, no pollution risks and low human risks since they are unmanned. This allows the allocation of lower reliability level compared to e.g. oil & gas installations. With the incursion to water depths between 20 and 50 meters, the use of jacket and tripod structures represents a feasible option that improves technical aspects concerning structural robustness, dynamical performance and damage distribution. Structural components such as support structures, transition nodes and towers, have critical design elements or zones that need special thorough design concerning fatigue damage.

In this work, a framework for optimal risk-based inspection and maintenance planning for Offshore Wind Turbines (OWT) is developed. Fatigue prone details (in cast iron and welded steel) at the jacket or tripod steel support structures are addressed. For wind farms additional efforts are needed when wake are to be accounted for. Wake effects imply increased turbulence and thus decrease in OWT fatigue life and performance. In wind farm locations and single/alone locations of offshore wind turbines are considered, and probabilistic models for assessment of the fatigue reliability are developed.

Further a reliability-based approach to calibrate Fatigue Design Factors (FDF) for offshore wind turbine support structures is described. The FDF values are calibrated to a specific minimum reliability level and a particular inspection and maintenance strategy. Generally, lower FDF values are obtained for offshore wind turbines than for oil & gas structures and reduced FDF values are obtained when inspections are taken into account. Thereby, the basis is available for selecting a cost-effective fatigue design for offshore wind turbines substructures.

Additionally, the integration of condition monitoring information to optimize the damage-mitigation activities is considered. This work is contemplating the updating through Bayesian statistics and Monte Carlo Markov Chain techniques. The new information and uncertainty is incorporated with an orthogonal polynomial approximation for assessment of fatigue reliability.

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CONTENTS

Technical articles included in this thesis:
The following publications are compiled in the last part of this thesis and stand for extended-work covering the overall work.

Technical articles part of the work:

The following technical papers are part of the work but not included in the compilation of technical papers. The articles above cover the topics of the following publications.

I RBI Optimization of Offshore Wind Turbines
IFIP – International Federation of Information Processing, Work-Group 7.5 Reliability and Optimization of Structural Systems. 2008, Toluca, México.

V Reliability Assessment and Reliability-Based Inspection and Maintenance of Offshore Wind Turbines
5th EAWE-PhD Seminar 2009. European Academy of Wind Energy. Durham, UK.

VII Framework for Probabilistic Calibration of Fatigue Design Factors for Offshore Wind Turbines Support Structures
IFIP – International Federation of Information Processing, Work-Group 7.5   Reliability and Optimization of Structural Systems. 2010, Munich, Germany.

VIII RBI Optimization of Offshore Wind Turbines
Accepted in a special issue of the International Journal of Structure & Infrastructure Engineering.

X Non-parametric Bayesian Updating for Offshore Wind Turbine Support Structures
International Conference on Applications of Statistics and Probability in Civil Engineering. ICASP 2011, Zurich, Switzerland.

CHAPTER 1

INTRODUCTION

The Offshore Wind Industry (OWI) plan to supply around 563 TW/year in 2030 that is approximately the 15% of total European Union (EU) electricity demand. This production aim by European Commission [1] entails a total installed capacity of 150 GW for 2030. Moreover, the European Environment Agency estimates a technical potential of offshore wind of 30,000 TW/year, which is approximately 7 times the whole EU demand [2]. Currently, the installation of a power production of 11 TW/year is planned with an already installed capacity of 3 GWh.

The OWI exploits a synergy of onshore and offshore activities with the goal to reduce the use of fossil fuels and enhancing the internal energy market through the transnational grid that will save around 48 million toe (tons of oil equivalent) and 292 million of tones of CO_2 for 2030's annual installed capacity - this is 30% of the EU's Kyoto obligation [3]. From an industrial outlook, OWI can further boost the maritime industry that actually represents the 40% gross domestic product (GDP) of EU's economy.

Wind turbines at onshore places have several environmental impacts: Visual and noise impact, risk for human beings and flying fauna, and disruption of human and wild life. These impacts can be significantly reduced by going offshore. Not all is "frosting in the cake", offshore wind installations are 50% more expensive, operate under harsher conditions and the future scenario reflects an increasing competition in vessels for installation and maintenance of offshore wind installations and grid. The capital costs of offshore wind installations depend on site-conditions (water depth, wind speeds, wave, current, soil conditions, etc).

The energy production from offshore wind turbines is determined by: turbine height, efficiency of the turbine and wind conditions (related with the location). For onshore wind turbines the total cost of the wind turbine can approximately be divided in 78% for the wind turbine itself, 3% for the foundation, 5% for the electric installations, 5% for the grid connection, 2% for consultancy, 2% for land rental, 3% for financial costs and 2% for road construction [4]. Offshore wind turbines cost about 20% more than the onshore turbines and also offshore tower and support structure cost 2.5 times more than similar structures at onshore location [6].

One of the main reasons of going offshore is the high wind speeds at low heights with 50% larger full load-hours per year than onshore places (3150 full load-hours in average per year against 2150 at land places). Danish wind farms have recorded high load-hours of 4700 [5].

The operation and maintenance (O&M) costs are expected to decrease from approximately 16 to 12 €/MWh in the next 10 years [5]. The average of these operational and maintenance cost correspond to 23 and 45 percent of the expected annual investments in wind turbines in EU in 2020 and 2030 [6], respectively (based in the electricity production)

As described above a significant growth of OWI can be foreseen the next years, [7]. Offshore structures are highly exposed to deterioration due to the harsh environmental conditions that degrades the material. The detrimental processes have properties that will 'define' the suitable manner to handle them. The metal-corrosion process is certainly a time-

dependent process that depends in multiple factors such as chemical arrangement of the metal and outer oxidizing agents, temperature and exposure. In the literature methods can be found to control the corrosion or design to accomplish a specific life considering corrosion process [8]. In this work chemical deterioration processes are not considered but only the mechanical ones.

Mechanical deterioration of structural systems in a marine environment has been studied in different engineering areas from which treatment, control and research have flourished from mainstream industry such as oil and gas (O&G), ships and harbor industry.

With the interest of going offshore, wind industry has to face meso- and micro-meteorological wind and wave influences, water depth and soil conditions. The wind properties represent the main reason for going there. The load conditions made the fatigue failure a main long-term design driver for the mechanical components. The wave influence may also represent a harmful force to OWT for particular cases where depth is significant, poor soil conditions present and the wave-impact area of the support structure is considerable. It is assumed in this work that wind condition is dominating the load cases for any support structure. This supposition is based in the technical and future conditions of OWT. These assumptions are that the load influence is impacting at hub height, creating a fast-shift of stresses in the support structure, see [12] and [37]. Additionally when the towers' dimensions and swept area is increasing, the wind influence is larger compare with the wave condition.

When depths are larger than 20-25 meters, monopoles are considered not suitable according to experts' opinions [9]. Moreover, a comparison with alternative support structures such as tripod and lattice structural systems reflects that the reduction in material could be up to 50% in cases when water depth of 35 mts, see[10] and [11] . These alternative support structures represent a better structural redundancy at failure scenarios, increased stability for hydrodynamic loads and poor site conditions [12].

Analyzing the future expected offshore projects (see figure 1.1), the majority tend to be placed at sites relatively close to the shore and with less than 60 meters depth which make it convenient to use tripod and jacket support structures.
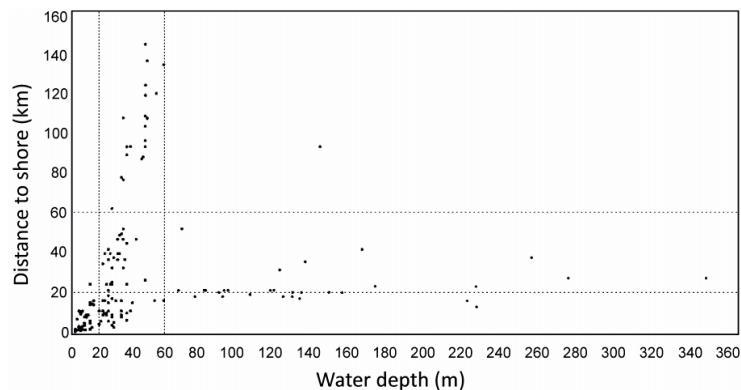
Figure 1.1 – Probable future development trends of the offshore industry in the 2025 timeframe including operating, under construction, consented, in consenting process or proposed by project developers according to EWEA [**6**].

This incursion in deeper water imposes the OWT to a harsher environment that decreases the structural performance and reliability. Structural reliability methods (SRM) have been extensively used in applications in different areas of engineering [44-46]. With the use of SRM is possible to quantitatively estimate the reliability and perform a life-cycle analysis of structural systems. In the petroleum industry, SRM have contributed to assessment of reliability and risk analysis for facilities at offshore places that are exposed to extreme events and long-term damage conditions.

The OWI can take advantage of this SRM-applications in O&G industry by migrating these techniques to assure a suitable performance of the OWT while technical and economical aspect are taken into account for optimizing inspection, maintenance, operation and repair actions, see [13-15]. Risk-based inspection (RBI) planning and risk management for deteriorating structures have increased in number of applications in other areas [16], e.g. bridge engineering [17], industrial areas [18], which also illustrate the potential in the wind energy industry. In this work, RBI is considered for OWT. Within the assessment of reliability, Bayesian updating techniques are considered using stochastic structural mechanics and probabilistic methods.

1.1 SCOPE AND LIMITATIONS

The main objective is the application of RBI approaches for offshore wind turbines' structural components that are prone to fatigue failure. This method is mainly considered for use in the support structure but it can be generalized to other components as shown in [19]. The following scope and limitations are included in this work:

❖ Apply RBI approach to OWT support structure.
  ▪ Consider and describe the essential differences with other RBI-approach in the civil engineering field
  ▪ Consider offshore wind turbines influences in the adapting of RBI
  ▪ Describe and demonstrate the application of a probabilistic calibration procedure for code-base safety factors using the former framework

❖ Use and describe a probabilistic modeling for the assessment of reliability and consider the main characteristic of offshore wind turbines

❖ Application and description of updating procedures within the RBI approach:
  ▪ Describe classical Bayesian statistics
  ▪ Describe and apply Non-parametric Bayesian statistics and Monte Carlo Markov Chain techniques for updating
  ▪ Inclusion of uncertainty through Polynomial Chaos Expansion (PCE) approximation in assessment of reliability

1.2   OUTLINE OF THE THESIS

This thesis finds its main incentive in the application of SRA through a RBI format. The organization highlights the principal accomplishments in this work, mentioning partially the work related with structural reliability for OWT and remark the application of other statistical and mathematical tools within the RBI-format and assessment of reliability.

In chapter two is described a review of offshore environment influences and general structural issues for offshore wind turbines, considering especially the dynamical and aerodynamical performances.

Chapter three addresses the fatigue failure aspects for OWT. Former work in assessment of fatigue modeling and reliability of structural components is briefly described. Next, the external loads and related measurements are described.

In chapter four, the RBI approach is briefly explained (applied to OWT) based on its applications in different areas, but describing the main differences with the OWT case. Features of the used design and limit state equations and inspections are described.

In chapter five, the application of Bayesian statistics for updating is described sing the RBI format. Classical and non-parametric Bayesian methods are considered using Monte Carlo Markov Chain methods. The PCE approximation is used for modeling the uncertainty in SRA. In chapter six, a summary and conclusion of this work is shown. Achievements and suggestion for future work are included.

CHAPTER 2
OFFSHORE WIND TURBINE STRUCTURE AND EXTERNAL AGENTS

The purpose of this chapter is to give a brief review of general structural aspects and external factors that affect the reliability and performance of the OWT. In the first part is mentioned the related work concerning the structural system and the second is focus on loads at offshore places.

2.1 STRUCTURAL SYSTEM

2.1.1 STRUCTURAL CONNECTIONS

Some elements are structurally more important due to their contribution to system's robustness and its performance. In the offshore context, structural joints participate as an important global or local failure-damage estimator. The abrupt changes in material and geometry are encounter in connections, are sensitive and prone to the damage. The offshore steel structural systems are generally fabricated with hollow sections. Past work in offshore structural connections and assembles, see [20]; show the influence of damage in the connections where stress concentration plays an detrimental role. This influence has been theoretical and experimentally [21,22] addressed .

Welded steel joints have been stochastically and experimentally studied, e.g. [23] and [24]; and criteria for the assessment of reliability have been proposed for welded joints at offshore structures considering inspections, see [25]. Work as [26] and [27] precisely address the high concentration of stresses in OWT connections and structural solutions are proposed. Concerning the global performance, criterion to relate local and global failure has been devised to estimate the failure scenario, see Straub and Faber in [28].

This work is mainly addressing 'hot spots' or details at connections where discontinuities in geometrical dimensions, components and material, make these parts prone to fatigue failure. Only high-reliability components are considered. These components are technically or economically not feasible to change and the consequences of failure are costly. The fatigue prone details that could be analyzed to the presented methodology are the following:

a) Support Structure connections – welded steel detail
b) Transition node between tower and support structure – Welded steel detail
c) Transition part between tower and nacelle (yaw system) – cast iron detail

2.1.2 BLADES

The **blade** components have two notable characteristics: it is a moving and material-composite element. Commercially 3-blade wind turbines dominate the market with maximum size around 60 meters. The choice of blade number is based on energy need; the fewer the number of blades, the faster the rotor needs to turn to extract certain fixed maximum power from the wind input. Comparing the option of two and three blades setup, the two bladed

option would lead to a larger energy output according to the coefficient of performance (C_p) curve with generally wider plateau that covers intermediate tip speeds. Unfortunately, this two-blades setup brings high tip speeds and acoustic noise, and the blade needs small area that causes an increase of stress [29], larger fatigue and raises the risk of aerodynamical instabilities [30].

As composite member, the fatigue damage depends on the materials, e.g. type of resin, reinforce fiber, layers, mechanical properties, orientation of the fiber, etc. The improving of blade technology to resist more fatigue cycles requires better modeling of relative large stress ranges [31].

The fatigue failure prone details can be found all over the blade and hub in:

      d)   Hub – cast and welded steel details
      e)   Blade-inner girder and connection – Welded and cold-formed steel details
      f)   Blade – carbon fiber details.

2.1.3 TOWER AND SUPPORT STRUCTURE

The **tower** element is the largest component of the OWT. This consists in a hollow structural member that accomplishes the function of transmitting the load to the support structure. Important stress concentration sectors are in the extremes where nacelle and transition node are. The tower's dimensions are directly in function of wind conditions and indirectly of the location, blade size and power capacity. Due to the dimensions, the hollow section is built with cold-form plates and weld-seams are located over all the length.

The **transition node** (transition zone) accomplishes the connection of the support structure and tower. It is relevant the fatigue design of these structural members for possessing abrupt changes in geometry. Commonly with the use of monopile, tripod and gravity based support there is not an immediate or unfavorable change in geometry (considering that circular hollow structure continues) but in the case of jacket-type support structure, this element should adopt an appropriate configuration to transfer properly the forces.

The stresses in the transition zone worsen due to the unusual load cases. The maximum vertical load is relatively small compared with the horizontal and the overturning moment on the foundation. The ratio of moment to horizontal load is varying hastily with the time, when is compared with other typical offshore cases and the wave direction may not be synchronized with the existing wind direction. Another remarkable feature of OWT load, lies in the fact that wind load only contributes to approximately 25% of the horizontal load but ca. 75% of the overturning moment that is applied at hub height, [32].

According to the EWEA [**7**], 65.2% of online OWT **support structures** at the end of 2009 consist in monopile foundation, 23.1% Gravity, 2% jacket, 0.8% tripod and 0.8% floating foundation and the rest is unknown. The average depth at offshore place is around 9 m not taking into account Alpha Ventus project (30 meters depth and using jacket) and the Hywind floating turbine (220 meters depth). Moreover, the average shore distance is 14.4 Km.

According to the previous mentioned, the jacket support structure is far for being the most popular but with the necessity of bigger turbines and going to deeper water; the jacket and tripod support structures will represent a feasible technical alternative.

Nowadays, not all the set of technical problems have been solve for OWT with typical monopile foundation [33]. However, the experience gained in O&G industry may help finding the technical solutions for the particular case of tripod and jacket support structures. The design, construction and practical recommendations in O&G industry may be applied but some differences have to be taken into account:

   1) Unusual load cases and extreme load considerations
   2) Mechanical, Electrical and Control system components
   3) Varying characteristics of exchangeable component
   4) Interaction with external agent for benefit per se
   5) Structural risk criteria mainly based on economical lost that human affectation

Particular sectors or components should be design for a liable performance for fatigue failure, regarding: Fatigue assessment requirements, location of details and consequences of failure. The fatigue failure prone details can be found all over these structural parts on:

g) Tower top – yaw system – cast and welded steel details
h) Tower bottom and body – welded steel details
i) Transition node – welded steel details
j) Jacket support structure – welded and cast steel details

2.2 DYNAMICAL AND AERODYNAMICAL ASPECTS

2.2.1 DYNAMIC OF WIND TURBINES

As a compose system, the wind turbine stand for coupling dynamical characteristics of several systems or components. When all this elements are taken separately, it is possible to estimate the dynamical properties of each one by simply applying structural dynamics' theory [34], [35]; however when these parts are jointly working the definition can vary depending, e.g. governing coupling modes, geometrical and structural configuration, mechanical properties, etc [36]. In figure 2.1, the common terminology for degree of freedom of wind turbines is shown.

1.	Longitudinal (fore-aft)
2.	Lateral (sidewards)
3.	Yaw
4.	Tilt
5.	Roll
6.	Pitch*
7.	Flapwise (flatwise)
8.	Torsion (twist)
9.	Edgewise (lead-lag)
10.	Azimuth

*Pitching is an active-stall and pith-regulated turbines' mechanism to regulate wind load.
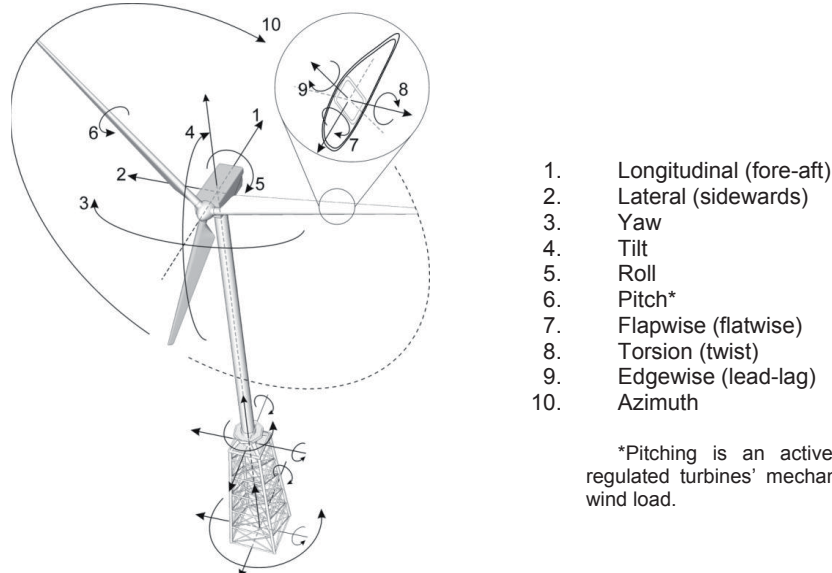
Figure 2.1 - 'Common' degree of freedom of offshore wind turbines.

The tower's natural frequencies show independency toward the speed of the rotor, although a gyroscopic coupling of the tower top-motion and rotor, results in a rotor-speed dependent ratio and phase that exist between lateral and longitudinal components of tower's mode shapes, see [30]. Moreover, the flexibility of nacelle and rotor as little influence on the tower's bending modes, see figure 2.2.

Considering different support structure and transition node, the influence in dynamical modes may change for the change of mass and rigidity that affects the natural period of the OWT. Additionally, there is influenced of the soil interaction [37] that adds flexibility to the system. The choice of support structure influences the tower frequencies, see [12]; and indirectly the scour condition (and wave impact) by modifying the entire system frequencies (top, baseline and surface relative frequency).

2.2.2 AERODYNAMIC OF WIND TURBINES

The active control and mechanical parts give to the OWT, its main characteristic for being differentiated with offshore structures. Rotor speed makes vary the natural frequency of asymmetric modes at standstill (see figure 2.2).
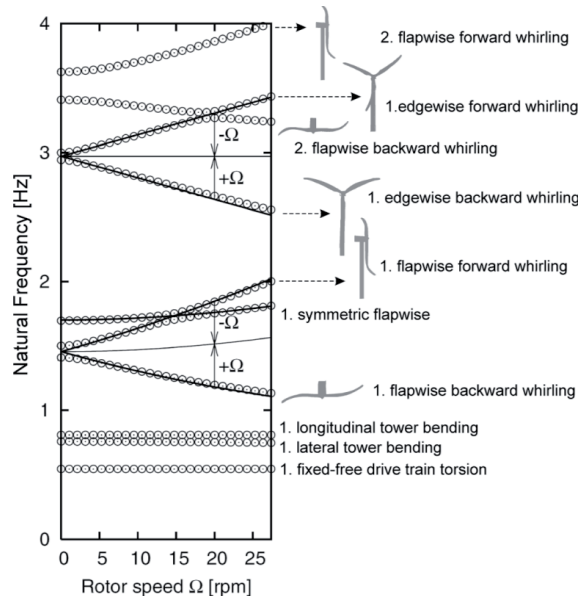
Figure 2.2 - Campbell diagram of ground-fixed natural frequencies (○) for the first 10 structural modes of a 600 kW three-bladed turbine with illustrations of asymmetric standstill modes.14 Lines denote approximations to the computed frequencies and the center frequencies of the rotor whirling modes given ±Ω added to the ground-fixed natural frequencies, taken from **[36]**.

In the figure 2.2, the natural frequencies are shown with the effect of the rotor speed. The blade's modes are coupling the drivetrain's torsional mode (main shaft, gearbox and generator). Furthermore, tower bending and torsional modes with symmetrical and asymmetrical motion.

There are two special instability problems in aerodynamics that may afflict wind turbines due to blade and rotor dynamic: Stall-induced vibrations and classical flutter. The first one originated for the stall-condition that produces airfoils state depending of the blade orientation. The second arises when the torsional blade mode couples with the flapwise bending mode, causing the fluttering. An deeper treatment of the aerodynamical topic related with wind turbines is found in [30] and [36].

2.3 EXTERNAL LOADS

The **wind** as phenomenon in the atmospheric boundary layer (ABL) is originated for the interaction of air masses due to the evaporation, heat-transfer and the friction. The turbulence at free flow condition is mainly the product of the wind shear due to the friction of the layers. Assuming homogeneous source of turbulence, the layers can be classified as: Convective boundary layer (CBL), Stable Boundary Layer (SBL) and neutral boundary layer. These regimes are affected by changes of temperatures, humidity of fluxes that come from the sun heat radiation, see figure 2.3.
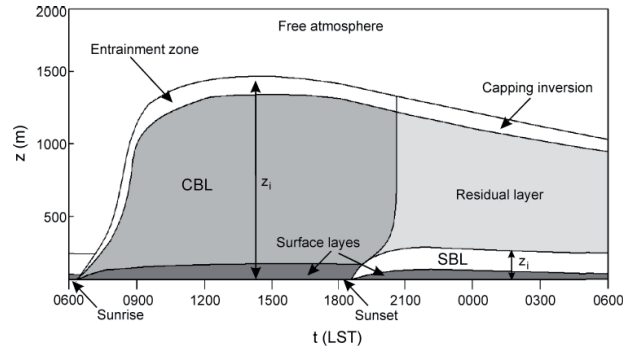
Figure 2.3 - The evolution of the atmospheric boundary layer with height during an ideal diurnal cycle. The convective boundary layer (CBL), stable boundary layer (SBL), surface layer, residual layer, entrainment zone, and boundary-layer height, z_i, are distinguished. Local standard time (LST) is used in the x-axis, taken from [**38**].

Wind profile can be modeled by the logarithmic equation:

$$U(z) = \frac{u_*}{\kappa} ln\left(\frac{z}{z_0} - \psi_m\right) \qquad (1)$$

where U is the wind speed, z is the height above the ground, u_* is the velocity scale or friction velocity, κ is the Von Kármán constant (constant, ca. 0.4), z_0 is the roughess length according to the height at which the wind speed become zero and ψ_m is the diabatic correction of the logarithmic wind profile.

At Offshore places wind profile is characterized by higher speed at lower heights with z_0-values around 0.001 to 0.0002 that contrast with values of 0.1 to 0.03 for countryside and open land places.

The turbulence intensity defined with the equation (2) can be divided in free-flow ambient turbulence and in case of any other phenomenon causing more turbulence; this can be named additional turbulence.

$$I = \frac{\sigma_u}{U} \qquad (2)$$

where σ_u is the standard deviation of along-wind wind speed fluctuations and U is the wind speed.

Wind farm turbulence have been measured and studied extensively, see [39-41], to come up wind proper models to take into account this detrimental wind variation for coding purposes.

The **sea** dynamic as wind is a complex phenomenon that is originated by the centrifugal, gravitational and attraction forces in and out of earth. Moreover this is influenced by air masses in the ABL and interacts with the places' geomorphology. In this work is not giving a dominant approach to wave condition and is considered as additional secondary load process that does not govern the long term fatigue failure scenario, if it is compare with wind load. It has to be mention that wave conditions at different sea states could be a dominant load when normal wind condition (operational state of the OWT) and poor soil conditions exist at a considerable depth, see [42]. However, the model use to consider turbulence was calibrated for offshore conditions [53].

CHAPTER 3

ASSESSMENT OF FATIGUE RELIABILITY

3.1 INTRODUCTION

The OWI is a multidisciplinary business that in favor of competitiveness looks for improving its costs jointly with better technology. This technological improvement will have impact when more reliable energy production systems are achieved. The OWI is a capital-intensive industry with capital costs accounting for up to 80% of the production costs which is larger than for the fossil fuel industry [4]. This condition makes the OWI's safety an imperative commitment for the sake of the economic benefit. Unlike the O&G industry, OWI does not represent high risk of society and this converts this situation appropriate to use minimum reliability levels concerning the mechanical, electrical and structural components in order to attain the production goals.

90% of all OWT support structures are made of steel. Mechanical components in nacelle stand for low reliability components that can be studied from a qualitative outlook [43]. This qualitative assessment of reliability uses failure statistics that are not attached to any particular failure mode but disruption of the power production. This is helpful when deterioration mechanisms are increasing-monotonic and rate-dependent processes for the mechanical parts. These mechanical and electrical parts are feasible to be repaired or changed, not having any economical or technical impediment.

Unlike wind-energy converter components, the structural components have a high reliability and are not feasible to be removed, changed and in certain cases even not to be inspected or repaired. In a structural failure scenario, some structural components could generate collateral damage to the structure and neighboring ones, e.g. blade failure affecting tower or hitting surrounding wind turbines or e.g. buildings. A qualitative reliability approach for high-reliability components is not technically viable and more sophisticated reliability methods in a life-cycle approach represent a proper solution for assessing reliability depending on the failure mechanism, load nature and deterioration time.

Structural reliability methods (SRM), see [44 - 46] that have been developed in the past decades, provide a basis to address this problem; in a similar manner as they are directed to other mainstream industry and adjacent engineering areas, e.g. O&G industry, aeronautical engineering and marine engineering. This dissertation finds its innovation in the application and migration of one of these well-known techniques, Risk Based Inspection (RBI) into offshore wind industry. In this way, a first step is established for life-cycle analysis of fatigue failure for offshore wind turbine structural components within a RBI framework.

3.2 BACKGROUND

The following review to previous work is considering the fatigue limit state for tower and support structures. Also, some work is considered for wind turbines components from a general viewpoint. Ultimate limit states (extreme events) are not considered, but it is noted that there in some cases is an interaction between the two limit states.

Probabilistic methodologies for the fatigue limit state have been developed and applied to wind turbines during the last two decades. Most of the initial work was directed to consolidate the modeling based on recorded loads. Veers [47] established a general fatigue reliability format to estimate the fatigue life for wind turbine components using SRM. This approach represents a good beginning considering the state-of-art of multidisciplinary areas in wind turbine industry: materials, measurements, electrical and mechanical devices (control system), wind turbine scale, cluster of wind turbines, offshore considerations, etc.

Lange in [31], considers a probabilistic treatment of the load measurements to establish a reliability framework for wind turbines (blades) where different probabilistic load models are compared for components and where the load and resistance factor design (LRFD) format is calibrated with the model.

Most recent work by Veldkamp [48] represents an important effort to analyze in detail the probabilistic aspects of the main variables (loads, materials, different components, site and wake conditions) to assess the fatigue structural reliability in the design life and a cost optimization framework is presented. Tarp-Johansen in [49] presented a reliability analysis and calibration approach where less uncertainties than Veldkamp [48] are used. A linear fatigue accumulation principle is used instead of the equivalent damage concept used in Veldkamp [48].

Sørensen et al. in [50] and [51] proposed a formulation for evaluating the reliability with linear and bi-linear fatigue accumulation limit state equations integrated in a model for reliability-based optimization for offshore wind turbines. Further in [19] and [52], a fatigue probabilistic model was proposed based on the equivalent load concept integrating a code-based model for including free flow and in-wind farm wake turbulence models.

The model proposed in [52] is used as basis for the probabilistic modeling in this thesis. The model has the following general characteristics:

a) Simplification of operational states to standstill and operation. During the design life the OWT changes between the operational states, depending on the availability and size of the wind resource. This model is not taking into consideration both states but only a single state where the accumulation of damage is monotonically increasing during the life-cycle of the OWT.

b) Possibility to address different components. When it is likely to have different hot spots or components prone to fatigue failure, it is advantageous to use a model that can be applied to different details / zones at the support structure, transition node and yaw mechanism all having differences in the load influence.

c) Loading-influenced formulation (wave, wind and turbulence). One of the drawbacks of former work is that the effect of loads from particular geographical sites, e.g. sea location and wind farm location, is not explicitly taken into account. This model includes these factors by using an influence function which is a product of measurements and/or modeling for particular load cases that can be simulated with certain probabilistic properties.

d) Response-influenced formulation (control system and structural layout influence). Nowadays, there are several support structures that can be used potentially depending on the site conditions and energy production. Additional, the control system of OWT is an important characteristic of wind turbines compared with most civil structures. These previous factors affect the response dramatically by limiting the maximum and minimum stresses and varying the response. When a general probabilistic model is used the

simplicity and generality are important to made viable the computing and cover most of the typical cases.

e) Use of code-based turbulence model. With this it is possible to establish the accomplishment of the minimum reliability requirements in the code, see Frandsen [53].

For OWT the physical modeling, simulation tools, design and control system are important for assessment of the structural reliability. In Kühn [54] general descriptions are presented on design methodologies, physical modeling including dynamics, aerodynamics, soil-substructure interaction and design optimization for OWT. Cheng [55] describes efforts in the understanding of reliability through statistical analysis of the response for design consideration when extreme events occur. Van der Tempel's [56] work focus on support structures and gives a detailed study and treatment of design procedure from time- and frequency-domain approach.

Saranyasoontorn in [57] devised a probabilistic framework where simulation techniques of loads are jointly used with reliability methods for short-term load estimation. Another work is the one of Agarwal [58], where statistical load extrapolation is used in a similar approach to evaluate the reliability considered in [57]. These prior works present a rich source of information in physical modeling, design approaches, simulation and extrapolation methods, that shows a broad outlook of OWT performance and modeling.

3.3 MEASUREMENTS AND UNCERTAINTY

In the probabilistic and stochastic modeling of loads, materials and other external agents affecting the OWT, it is necessary to understand their characteristics by using the information from measurements and other sources. OWI is a well-monitored industry with facilities [59], devices and mechanisms for recording, measuring [60] and monitoring at experimental [61] and operational stages [62].

3.3.1 WIND

The wind resource is typically measured before and after the installation of OWTs, see [63]. Meteorological (met-) mast measurements are the primary facilities used to measure the wind characteristics [64] at the site. The information that is possible to gather is the following:

    a) Wind speed profile
    b) Short- and long-term wind histories
    c) Turbulence intensity in the wind profile (wind a different heights and directions
    d) Wind roses for the frequency of wind direction occurrence at certain heights
    e) Wind speed roses at certain heights

With this information it is possible to obtain wind speed probability distributions and statistical parameters in short- and long-term wind histories. It is clear that with this availability of wind information it is possible to have an overwhelming amount of data. However, there are algorithms to analyze the data and calculate the necessary parameters to describe the gained information, e.g. estimation of the distribution and parameters of *n*-minutes mean wind speeds by e.g. the Weibull correction method, Wasp [65] or Correlation Method. A brief summary can be found in [63]. The average wind speed distribution of 10-minutes interval occurring during a specific interval is described by the Weibull distribution:

$$F(U) = 1 - exp\left(-\left(\frac{U}{\beta_U}\right)^{\alpha}\right) \tag{3}$$

where α and β_U are the wind shape and scale parameters, respectively. In table 3.3.1 (taken from [63]), the Weibull distribution parameters are illustrated using different prediction methods.

Table 3.3.1 Results for 48 m height at Vindeby taken from [63].

Prediction Method	Mean wind speed (m/s)	Weibull scale parameter (m/s)	Weibull shape parameter
Weibull	7.9	8.9	2.1
WAsP	8.1	9.2	2.4
Correlation	7.9	8.9	2.2
Observed (1993-1997)	8.1	9.1	2.3

OWI has benefited from recent advances in remote sensing technology, such as SODAR (Sound detection and ranging) and LIDAR (Light Detection and ranging), see [66,38]; and other applications such as ceilometers and satellite measurements that contribute to minimize site efforts for measuring wind speed and turbulence conditions, see figure 3.1.
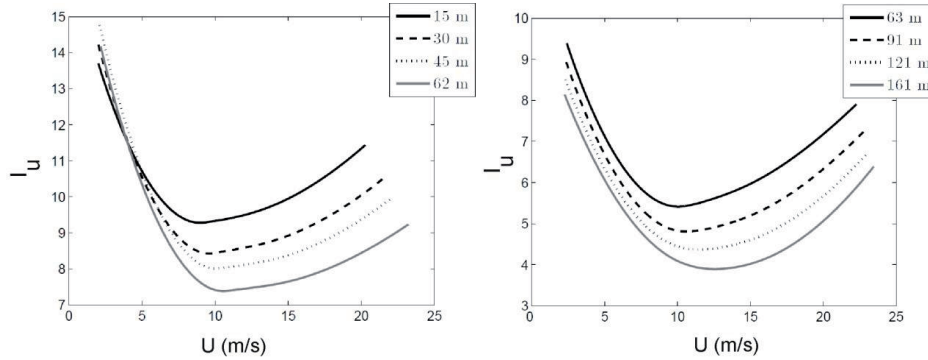
Figure 3.1 - Turbulence intensity, I_U, variation with mean wind speed, U, for different heights measured at the M2-platform at Horns Rev. The observations of the cup anemometers are shown in the left panel and the LIDAR observations in the right panel. The lines result from a lest-squares fit of the data taken from [**38**].

Turbulence is defined as the standard deviation of wind speed for a measured time interval T and with the turbulence intensity is defined as the ratio of the turbulence to the mean wind speed in an interval T (see equation 2). The variance of the wind speed is estimated from

$$\sigma_u{}^2 = \int_T \frac{(U(t) - \overline{U})^2}{T} dt \tag{4}$$

where $\overline{U}$ is the mean wind speed and T is the time interval. The turbulence can statistically be approximated by a Lognormal distribution:

$$F(\sigma_u) = N\left(\frac{ln(\sigma_u) - \mu_N}{\sigma_N}\right) \tag{5}$$

where

$$\mu_{\sigma_u} = exp\left(\mu_N + \frac{\sigma_N{}^2}{2}\right) \tag{6}$$

$$\sigma_{\sigma_u} = \mu_{\sigma_u}\sqrt{exp(\sigma_N{}^2) - 1} \tag{7}$$

According to IEC 61400-1 [67] the value of σ_{σ_u} is

$$\sigma_{\sigma_u} = 1.4 \, I_{ref} \tag{8}$$

where I_{ref} is the expected value of the turbulence intensity at 15 m/s (IEC-61400-1). Further, the model for the mean turbulence is:

$$\mu_{\sigma_u} = I_{ref}(0.75U + c) \tag{9}$$

where c is a factor in m/s. In addition to free flow turbulence, inside a wind farm wake effects originating from upwind surrounding turbines are present. The deficit of the wind speed is high in the next two diameter distances (near wake interval) from the turbine and decreases until a minimum, see [68]. Further, the turbulence increases in wake compared to free flow. This in-wind farm effects can be considered by an effective or equivalent turbulence model. The concept of an equivalent turbulence is representing the real turbulence such that it basically produce the same fatigue damage by combining and considering the effects of free flow conditions.

The turbulence model used in [67] and proposed by Frandsen [53], is used in this work. It has the following general characteristics:
  a) Simple implementation of the model avoiding major modifications of calculations.
  b) When formulating the equivalent concept, the material properties get included in the load calculation (Wöhler exponent of S-N curve).
  c) The model can be calibrated to site conditions
  d) The main assumption is the proportionality of turbulence and response of the OWT.
  e) Limitation in maximum number of wind turbines (eight surrounding wind turbines).
  f) Uniformity assumption of wake conditions around the OWT.
  g) The fatigue is considered to be linearly accumulating.

The equivalent turbulence is modeled by:

$$\sigma_e = \left[(1 - N_w p_w)\sigma_0{}^m + p_w \sum_{j=1}^{N_w} \sigma_w{}^m \right]^{1/m} \tag{10}$$

$$\sigma_w = \sqrt{\frac{0.9\,U^2}{(1.5 + 0.3 d_j\,\overline{U\ c_c})^2} + \sigma_0{}^2} \tag{11}$$

where σ_e is the effective turbulence, N_w is the number of neighboring wind turbines, p_w is the probability of wake conditions, d_j is the normalized distance of the jth OWT, c_c is a constant equal to 1(m/s), σ_w and $\sigma_{u,j}$ are the maximum equivalent center wake for wake and free flow turbulence.

3.3.2 OFFSHORE

At offshore locations, wind fields behave different than at land. The sea surface roughness is much smaller than at land [39]. Waves are depending on micro and macro phenomena such as: earth translational and rotational movements, moon gravitational influence, geographic and geomorphology of the location, ABL's temperature changes and surface wind conditions. These phenomena impact in tide, waves and current at offshore locations. The sea states can be measured by buoys and met-masts which generally provide:
  a) Sea level at different time of the day, year and specific conditions.
  b) Wave heights
  c) Current and tide information
  d) Wave roses from frequency of wave direction occurrence

According to the statistics, wind and wave correlation is generally strong for sea locations while at offshore locations that are close to the shore, this linearly correlated relation decrease due to the fact that large significant wave heights are developed with small mean wind speeds [58], see figure 3.2. Further, refraction can change the wave direction. A

loading decoupling between wind and wave can exist. This effect is changing the concentration of damage in sectors of the OWT.

(a)   (b)
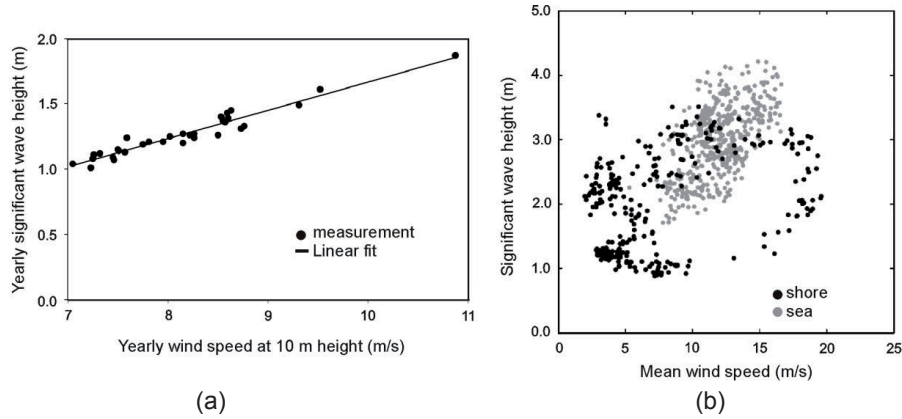
Figure 3.2 – (a) Yearly average significant wave height as function of yearly average wind speed at 10 m height from NESS/NEXT database, grid point NL-1 from [48]. (b) Wind-wave scatter diagram for winds from the sea and shore during storms [58].

In this dissertation, the wave, wind load and their intrinsic characteristics are jointly taking into account through the *influence function* that is considering the following:
   a) Wind load directly correlated with the wave load (load cases, simulated and recorded time history load)
   b) Free flow turbulence
   c) Stress effects in structural details
   d) Control system
   e) Structural layout

The influence function α_{Δ_σ} is defined as the ratio of stress ranges to the mean wind speed for a characteristic case, see figure 3.3. This function can be obtained through measurements or simulation. Taking realistically, direct measurements of stresses in steel details for long periods are not common in OWT and neither devices have been implemented that were reliable due to their deterioration in long terms. Indirectly an estimation of stresses conditional on the mean wind speed can be done by using vibration and acoustic measurements at mechanical parts in the OWT, e.g. the nacelle. The disadvantage of recordings is that the resulting influence functions are limited by the setup of the installed wind turbines.

On the other hand, simulation can be used to theoretically obtain the influence function for multiple cases. For loading, code-based load cases [67] can be simulated by generating wind fields with turbulence and wave conditions for different setups of the OWT. Moreover, different structural components can be considered and also a variety of support structures (monopile, tripod, jacket, suction bucket and concrete gravity), material properties (cast iron, steel, carbon fiber) and control systems can be included. This complexity in modeling and characterization of the OWT can be summarized and integrated in the reliability analysis by the influence coefficient that in principle reflects the loading distinctiveness conditional on the wind turbine properties.
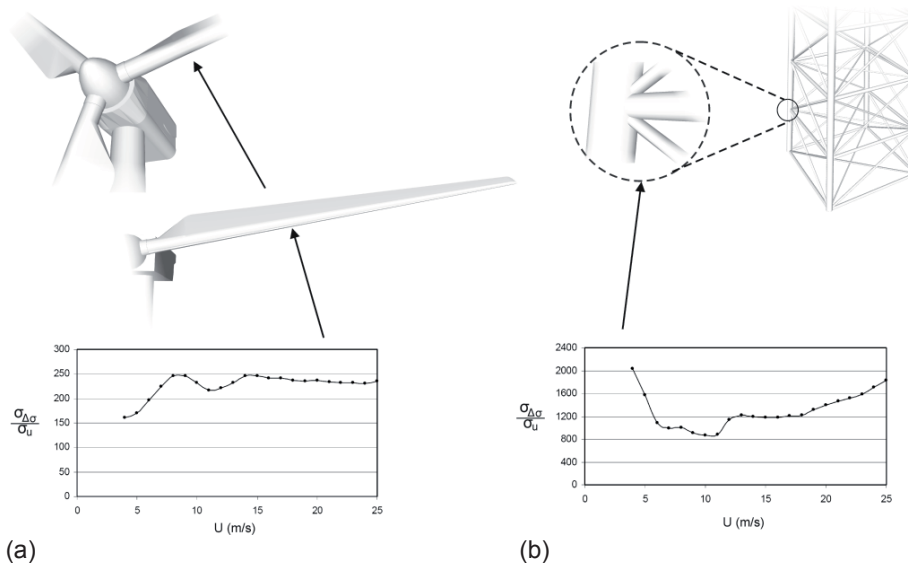
Figure 3.3 – (a) influence function for blade flap moment – pith controlled wind turbine. (b) Influence function for mudline bending moment – pitch controlled wind turbine, from **[52].**

3.3.3 MONITORING OF OFFSHORE WIND TURBINES

For OWTs, surveillance actions can be classified depending on the measurement time and/or interval of monitoring: Real-time and long-term monitoring. Real-time condition monitoring systems are typically implemented inside the nacelle. The mechanical and electrical components in the nacelle are mostly low reliability components where monitoring efforts are intended to maximize their performance and reduce the downtime periods. A general view of monitoring systems and devices are described in [69] and [70].

Examples of these OWI's monitoring systems are considered in the research projects CONMOW [71], Cleverfarm® [60] and [72] where use of e.g. vibration and acoustic sensors makes it possible to measure the velocity and acceleration in mechanical parts. Besides sensors, a fault detection architecture provides damage-detection algorithms to monitor the inside components. Additional to the SCADA system (System of Control and Data Acquisition), online resources for prediction coming from meteorological satellite measurements [60] are integrated.

When this thesis is concerned about high reliability components, the low-reliability component measurements coming from the SCADA system are not directly relevant or useful. Nowadays, load monitoring algorithms for wind turbines have been developed for components such as blades and rotor component, see [73] and [74]; where optical and temperature sensors give the information for load counting [62].

Inspection and supervision of the state of the OWT details can be considered as long term activities for monitoring. Commonly, inspection activities are mostly carried out for OWT's structural components in reachable areas.

3.4 FATIGUE

The loss of strength as a result of cyclic stressing over a period of time is a general phenomenon that takes place for most materials. This failure scenario can take place in situations where loads are under the design loads for extreme, ultimate limit states, no matter whether static or dynamic conditions are considered. This failure phenomenon was first noticed in the nineteenth century by Albert [75] and one of the first researching this

phenomenon was Wöhler [76] that investigated the fatigue endurance in railway axles under constant amplitude loading. Palmgren [77] and Miner [78] proposed a cumulative linear damage model that considers variable amplitudes for fatigue life prediction.

In short, fatigue life of a component can be summarized in three phases: crack initiation, crack propagation and final fracture. From an engineering outlook these periods can be defined in two stages: crack initiation life N_I that is defined by the number of loading-straining cycles required to develop a microcrack and N_P that is the number of cycles required to propagate a crack to critical dimensions. The last phase may be neglected by stating that it can be a sudden state of the crack or very close to the failure. The total fatigue life N_T can be expressed as:

$$N_T = N_I + N_P \tag{12}$$

The fatigue problems in components are addressed by estimating the 'total fatigue life' in terms of the stress-strain statistical properties and environmental conditions. The approach proposed by Wöhler together with the Palmgren-Miner linear cumulative damage rule represents a simple formulation for estimate the fatigue life.

Several approaches for adopting safety measures for fatigue failure scenarios have been considered. The safe-life approach (1950's) through fatigue tests intended to predict the replacement time for components (aircraft components). This approach often represented a very conservative safety measure for decisions on replacement depending on whether or not visual damage was present. This replacement could be of the entire system.

The fatigue-safe approach (1960's) is aimed for failure modes and paths taking into account structural redundancy. Somehow, it was understood that the system robustness will give it sufficient capacity to operate during crack propagation period and individual failures.

Finally, the damage tolerance approach (1970's) is based upon more sophisticated fracture mechanics techniques and rules. The overall assumption is that the system is imperfect and flaws may be found at stress-hot spot sectors where the failure and crack grow can be predicted, detected and supervised. This approach involves the calculation of crack growth rates by fracture mechanics models.

The fatigue crack propagation is influenced by the micro-structural nature of the material, mean stress, frequency of load application, the environment and the constraints of forces on it. There have been many efforts to describe the crack development by different crack growth laws. The Paris-Erdogan law [79] is one of the broadest used:

$$\frac{da}{dN} = C \cdot \Delta K^m \tag{13}$$

where a is the crack size, N is the number of cycles, ΔK is the stress intensity factor range, C is the crack growth rate and m is an exponent. These last to are regarding the material constitution. The stress intensity factor range is a parameter that considers the energy release rate and crack driving force by the following definition:

$$\Delta K = Y \cdot \Delta \sigma \cdot \sqrt{\pi a} \tag{14}$$

where $\Delta \sigma$ is the stress intensity factor range in the stress cycle and Y is the geometry-function that takes into consideration the shape and geometry of the specimen and crack. In the assessing of fatigue life at the level of the crack, the stresses are substantially affected by the following factors:

    a) Surface finish. There are three characteristics that will affect the fatigue endurance: surface irregularities, condition of the surface (cold worked or softened) and residual stress conditions.

b) Size of detail. It has been observed that fatigue endurance varies with the size of specimen (detail, component). E.g. when the welded flaws is large in volume there is a higher probability of failure due to imperfections, see [80].

c) Load type (Bending, axial or torsion loads) and mean stress level influence the crack growth.

d) Temperature.

e) Stress concentration factor: geometrical shape of the detail or component.

f) Notch sensitivities (size and material).

g) Miscellaneous effects: corrosion, electrolytic plating, cyclic frequency, etc.

These factors are not directly taken into account in this work except the stress concentration factor (SCF) influence. To take into account the mean stress level, a reduced and modified fatigue strength may be calculated by Soderberg, Gerber or Goodman criteria, see [80].

For more than a century where fatigue research have taken place, the presence of fatigue endurance have been consolidated in the S-N Curve or fatigue endurance curve by Wöhler. The SN-curve is typically constructed on either logarithmic or arithmetic scale that indistinctively present the scattered points, having in logarithmic scale the advantage of easily observing the 'knee' part that is present when carbon steels are analyzed, see figure 3.4. The curve can be described with the following equation:

$$N(s) = Ks^{-m} \qquad (15)$$

where N is the number of cycles to fatigue failure, s the stress ranges and K is a material parameters. When there is bilinear consideration, the second part of the SN-curve is typically starting from the fatigue limit $\Delta\sigma_D$ for constant amplitude stress ranges at the number of cycles N_D, see figure 3.4(a). s defines the stress range for simplicity but typically in literature $\Delta\sigma$ is used. In following text both will have the same definition and will be used indistinctively.

When a fatigue design analysis is to be performed, the efforts are usually concentrated in determination of the expected fatigue life through analysis of the loads history. During the load history there are important features that are fundamental to know such as global characteristics (variation of stress amplitude and mean stress) and sequential characteristics (variations of sequences of the load). To obtain the information from these load-histories, cycle counting algorithms are used. These methods may be classified in four groups: rainflow counting, level crossing, range/mean and probability methods.
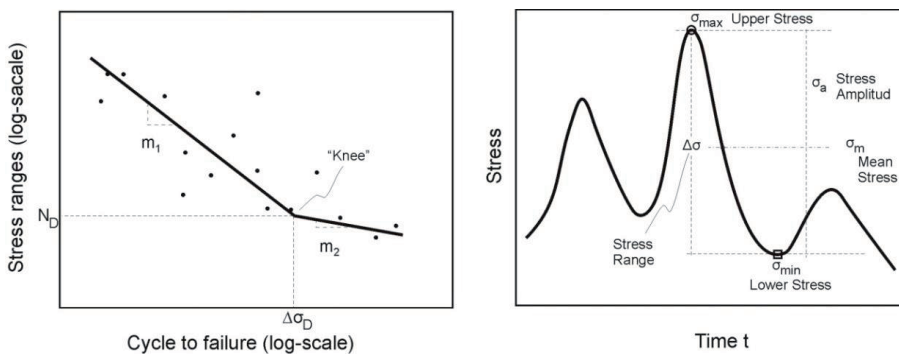
Figure 3.4 – SN curve and basic fatigue load stress history

Using the Palmgren-Miner rule of linear accumulation of damage and the SN-curve the following discrete formula can be used for the accumulated damage:

$$D = \sum_i D_i = \sum_i \frac{n_i}{N_i} = \sum_i \frac{n_i}{K \cdot s_i^{-m}} \qquad (16)$$

and introducing $n_T = \sum_i N_i$

$$D = \sum_i \frac{n_i \cdot n_T}{K \cdot s_i^{-m} \cdot n_T} = \frac{n_T}{K} \sum_i f_{\Delta\sigma} \cdot s^m \qquad (17)$$

where n_T is the total number of cycles of loading and $f_{\Delta\sigma}$ is the probability density function of stress ranges for a variable amplitude loading.
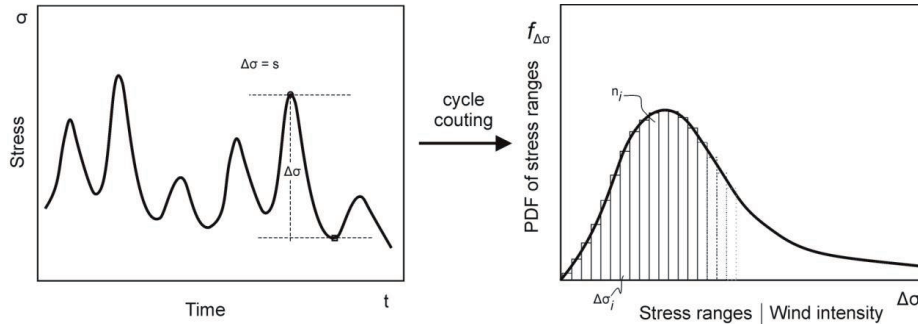
Figure 3.5 – Long-term cycles of loading with fitted density distribution

An important concept in the fatigue analysis and design for OWT is the "equivalence" concept that can be formulated for loads, stress ranges and response conditioned on the type of load (wind), intensity (speed and turbulence) and alternative features (structural component, site, height, recording time, etc).

The formula (17) represents an equivalent stress range approach. In the case of OWT, the distribution function of stress ranges is conditional on the n-minutes wind speed (recordings) considering a specific regime of turbulence (free flow in the simple case) at a definite site, see figure 3.5.

In the equivalent turbulence model in formula (10) from [53], the concept of fatigue damage was used and it includes wake effects when calibrated for offshore (or onshore) conditions. The probability density distribution of stress ranges coupled with the IEC's turbulence model [67] is conditional of the n-minutes (typically, 10 minutes) wind speed at hub height. With this model, it is possible to consider both free flow and in-wind farm wake effects. The Influence function accomplished to include turbulence conditions and characteristics of the simulated wind fields.

The probability density function of stress ranges given n-minutes wind speed (at hub height) can approximately be represented by the Weibull distribution. This typically results in a good fitting when not too high values of the Wöhler exponent are used, see [31].

With respect to the damage equivalent fatigue load concept, there are some remarkable conclusions in [54] about its application:
   a)   When different loading conditions are considered, e.g. wind, wave, etc; the superposition of fatigue loading of the different load should be done carefully considering in- or out-of phase loading and directional misalignment of wind and wave loads.
   b)   For OWT different ways to handle the aerodynamical and structural damping may result in up to 7% errors in the estimation of the equivalent fatigue loading, depending on the component.

Structural components such as tower, support structure and transition node have areas where the fatigue damage is concentrating and are important to identify by a structural analysis. In the context of this work, the 'hot spot' term will be used for those small areas or sectors in the components where damage will appear as cracks. Hot-spots typically appear

in joints with weld seams and local phenomena such as discontinuity of material, stress and geometry can be expected to be significant.

The design codes for OWTs are partially the product of gained knowledge in adjacent areas such as offshore regulations in the O&G industry, marine technology, electrical equipment, material, corrosion, and other topics, see [33]. However, former knowledge could not precisely be matching with what is needed in the OWI, e.g. load cases and load superposition, Inspection and maintenance scheduling based in the O&G industry.

3.5 FATIGUE RELIABILITY FOR OFSHORE WIND TURBINES

A variety of SRM may be applied for OWT structures [44-46]. Fatigue failure in the structures is generally expected at long terms and conditional on the nature of deteriorating factors (load and site conditions) and material properties. Once it is identified as a time-dependent deterioration process, a life cycle analysis can be performed for the discrete chosen interval, e.g. hours, days, months, years; depending on the characteristics of the problem.

In this work, FORM (First Order Reliability Methods) were used to assess the fatigue reliability during the design life. Commonly, SORM (Second Order Reliability Analysis) or Monte Carlo simulation techniques are jointly used but in this work focus is on the accuracy of the proposed models or limit state equations and the SRM are not attempt to be compared. In [114] is described a general view of reliability methods and uncertainty analysis applied to wind turbines.

Several models to assess the reliability can be found in the literature. Tarp-Johansen [49] proposed and used a fatigue limit state function based on the Palmgren-Miner rule for the accumulation of damage which includes uncertainties related with the response, load and material; additionally a probabilistic calibration of design factor is carried out. In the same year and jointly with Sørensen [81] a more elaborated limit state equation is used but uncertainties with the response were not considered. Veldkamp in [48] presented a more elaborated study of uncertainties and a fatigue probabilistic model that take into account an extensive number of uncertainties. Further, Sørensen et al. in [19] and [52] presented a more mature model for assessing the reliability where equivalent fatigue load and damage concept are incorporated. In this model the characteristics of the load, modeling and response are included by an influence function and a code-based model is included. The previous mentioned model is used too in this work for the reasons mentioned in (section 3.2) concerning the IEC-6400-1 turbulence model.

CHAPTER 4
RISK-BASED INSPECTION PLANNING FOR OFFSHORE WIND TURBINES

4.1 INTRODUCTION

When OWT are compared with other offshore structures several notable facts appear. Unlike O&G industry, OWI profits of the site interaction per se. There is no more structural protection than a reliable overall design, damage control and a proper control system managing the load input. Furthermore, in a failure scenario, the economical and energy production loss is not reversible.

In the O&G industry, reliability- or risk-based approaches are applied to manage the deterioration process that certainly is regarded as a highly uncertain process. These methodologies can also assure a proper performance for OWI.

Historically, Risk-based approaches have a qualitative predecessor. The inspection and maintenance (I&M) management was motivated by industrial growth at the past mid-century when it was advocated to reduce failures and unplanned downtime with time-based preventive maintenance programs. These programs and techniques began as research models until the 1960's (RCM-Traditional Reliability Centered Maintenance [82]) with the purpose of optimizing the I&M programs mainly with focus on the Airline industry, see [83] and [84].

From 1960's to middle 1970's several aspects were improved concerning the inspection and condition monitoring techniques providing more information about the state of equipment and posterior failure states; making qualitative failure-based preventive actions more effective than the large time-based preventive maintenance programs used earlier, resulting in better designs with less failures as a result.

With the arrival of computers, more quantitative approaches were used to optimize maintenance qualitative models. Moreover, failure data-bases, measuring technology and theory of reliability made it possible to develop a full quantitative, reliability-based maintenance (RBM) methodology that was motivated mostly by the developments in the mainstream industry (aeronautical, petroleum, marine and nuclear industry). The gain in structural performance provided the data-based feedback to the support decision process and refinement of the numerical and probabilistic models. The decision process in RBM is based theoretically on Bayesian decision theory ([85] and [86]) and the developments during the last almost four decades finally found in *Risk-Based Inspection* (RBI) the rigorous probabilistic tool to manage decisions on damage and risk. RBI can be used to prioritize the minimization of inspection budgets by embracing the suitable life cycle performance and even consider posterior stages.

In offshore and marine engineering, Risk-Centered Maintenance (RCM) could be defined as a process for determining what must be done to ensure that any equipment continue to do whatever its users expect it to do [87]. RCM has hence mainly focus on the system functions and not on the system hardware that can be achieved using the RBI approach as a risk management tool.

RBI methods for O&G installations have been developed during the last 3 decades, see e.g. [88-96]; giving a theoretical guideline based on Bayesian decision theory [97-99] that can be applied also to offshore wind turbines. Based on RBI methods for O&G installations, a framework for optimal inspection and maintenance planning for OWT can be developed.

4.2 RISK BASED INSPECTION AND MAINTENANCE OPTIMIZATION

In contrast to other structures, OWTs usually represent low risk of human injury, allowing the allocation of a minimum reliability level obtained by optimization of the risk-based preventive action costs. The expected costs of the inspection strategy can be optimized by performing time-tabled inspection when reliability level is close to a minimum established by codes and practice recommendations. In work of Faber et al. [100], Sørensen et al. [101] and [102], and Straub [103] a cost- and reliability-based framework is used for inspection planning of steel structures. Application to OWT has been mentioned in Sørensen and Tarp-Johansen [50] and described in the PAPERS [I, II].

There is an important difference with application to OWI that can make that the economical optimization be taken one step further. The condition monitoring and external measurements can provide additional information that may be considered in the RBI approach. In the PAPER [III], it is schematically described how this information affects the process and how through Bayesian statistics this can be integrated into the RBI approach (see the next chapter) by updating the stochastic model. This work is not going further in the economical analysis but in the application of RBI methodology by using the SN fatigue and Fracture Mechanics approaches for the assessment of reliability.

4.2.1 ASSESSMENT OF RELIABILITY WITH IN RBI APPROACH

Typically in the RBI methodology two approaches are used for assessment of the reliability: a SN-fatigue approach based on the fatigue capacity of the component (its material) and a fracture mechanics (FM) approach. In the FM-approach a simulation approach is usually used to estimate the reliability. In codes and standards the minimum reliability level is usually implicitly given though specified SN-curves and partial safety factors. Therefore to obtain the required reliability level the FM approach is usually calibrated to give the same reliability level during the life cycle of the structure as obtained by the SN-approach.

In the SN-approach assessment of the reliability is addressed from a theoretical, physical or code based formulation for the components. The probabilistic model and limit state equations are based on parameters that take into account uncertainty of material, load and structure, not involving an indicator of damage in the real structure [105]. This absence of a damage indicator would make the SN-approach a sort of safe-life approach for fatigue life estimation - making it only possible to integrate information through the stochastic modeling and not though direct measurements of the damage (crack).

The FM-approach (a sort of damage tolerance criterion) uses a fracture mechanics model to formulate a direct relation between the damage estimators and uncertainties. This is important when using the possibility of integration of field-knowledge, e.g. inspection results, measurement and monitoring information. In principle, the FM approach is the link between the SN-approach with no direct damage measure, e.g. crack, wear, denting, and code based reliability requirements.

RBI uses both approaches for assessment of a minimum annual reliability / risk. Although in this work the minimum reliability level is chosen without a direct relation to a risk acceptance criterion (RAC), the minimum reliability level should be attained based on a specific RAC. Straub and Faber in [106] proposed a RAC for offshore structures that can be applied into a RBI framework and further in Straub [103] a generic approach to RBI planning for steel structures was proposed where the RAC also take into account system considerations. Making an analogy with the early methods (section 3.4) to estimate the fatigue endurance, the use of RBI with a RCA can be seen as a fatigue-safe approach. that is shape when are used a damage-tolerance (FM), a safe-life approach (SN) and is regarded

the component contribution to the system failure. In this chapter is briefly describing general aspects of the RBI analysis that were not mentioned in the compilation of technical articles at the end of this work.

4.2.2 RELIABILITY ASSESSMENT USING THE SN-APPROACH

In reliability assessment using the SN-fatigue approach the minimum requirements established by design specifications are followed, playing the role as analysis-indicator of the minimum levels of reliability that should be achieved by the detail. The probabilistic model uses the variables related with the material properties (SN-curve), site conditions (wind, wake and wave condition) and studies of local structural and material properties in certain hot spots (stress concentration). No one of the measurements and indicators are directly related with damage condition in the structure, e.g. crack, wearing and denting. This makes the SN-approach mainly a theoretical approach with the possibility of to require an inspection when reliability is lower than the minimum established level.

In the PAPERS [I-IV] of this work are shown probabilistic models for evaluation of the reliability. An extended explanation can be found in [52]. The First Order Reliability Method (FORM) is used for assessing the reliability with the probabilistic model and the fatigue limit state equations in [52]. This model is a product of the following assumptions:

a) Wind fatigue load dominates the load cases
b) Equivalent load concept conditional on the mean wind speed conditions at the site is used.
c) The response of the structure is considered a narrow-banded Gaussian process [104] implying that the average frequency of crossings of an establish level of the response is proportional to the time interval, e.g. years.
d) Linear accumulation of damage and additional assumptions of the model proposed by Frandsen [53] for wake effects, see the end of section 3.3.1.

4.2.3 RELIABILITY ASSESSMENT USING THE FM-APPROACH

Offshore sites represent highly different sets of events that can be well addressed and described by probabilistic models. The FM-approach is the RBI part that establishes the connection between code-based formulation with field conditions (measurements, inspections and monitoring) through incorporating structural damage indicators in the reliability analysis. For the application of the FM-approach the equivalent stress range concept is used and the methodology is shortly described in the following steps:

a) Simulation of a set of values for the different stochastic parameters that are described in probabilistic manner in the stochastic model.
b) Calculation of parameters in the probabilistic model. These variables include: equivalent stress range, fatigue life, crack size, etc.
c) Statistical analysis of data
d) Updating through the events of no-finding or finding the damage and repairing.

In the simulation of parameters it is intended to obtain set of the outcomes that reflects the probabilistic characteristics of the model when the uncertainties are included. This simulation process can be performed by deriving continuous density functions from the uniform distribution by transformation of variables [107]. Random number generator algorithms should accomplish with six desirable properties, see [108]: randomness, long period of repeating, computational efficiency, repeatability, portability and homogeneity. In this work a congruential quasi-randon number generator is used and to assure a well-spread sample (not depending in the number of generated values) by randomization [109].

The calculations in step *b* are concerned about the application of the formulas shown in the published technical articles jointly with the fracture mechanical model for the accumulation of damage (see section 3.4). Once the simulation is performed, statistical

analysis is performed for the different intervals of the life cycle (yearly basis) and the decision process is started including the decision of repair or not depending on the detected damage, i.e. cracks. In this work, the crack is assumed to be repaired once it is found.

The assessment of the FM-fatigue life results in a FM-reliability curve fitted to the SN-reliability curve during the whole design life or in the most important interval, see figure 4.1. The variables that are iteratively changed in this process are the expected value of the crack growth rate and the initiation period of the crack, see figure 4.1-c. Convergence of the iterations are obtained when the sum of the differences between the cumulative reliability indexes in FM- and SN-approaches for a target period is minimized, see figure 4.1-d.

(a)

(b)

(c)

(d)
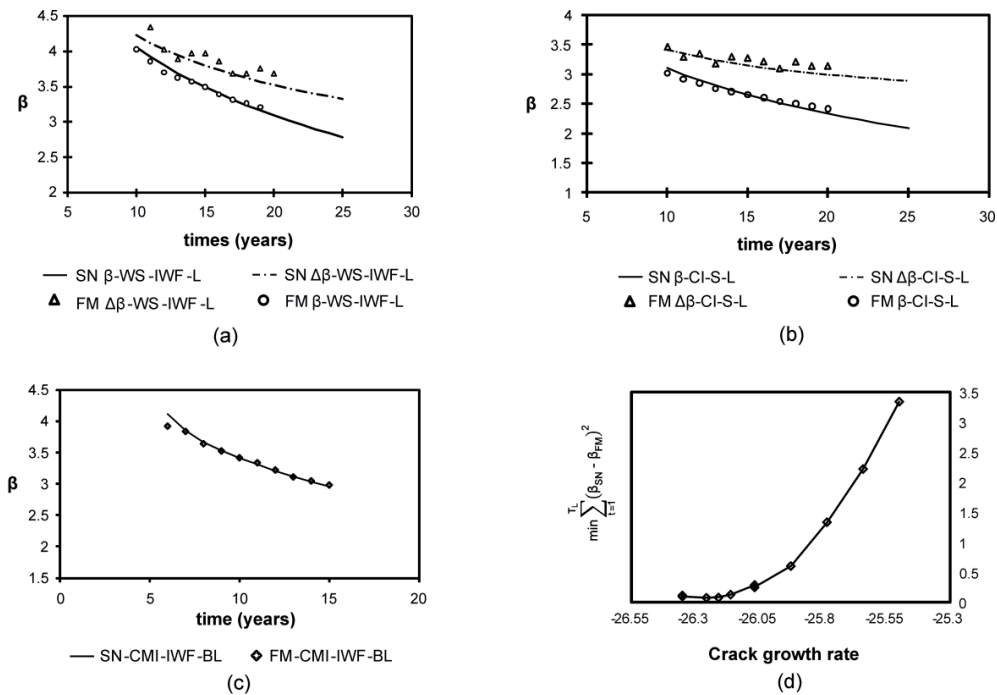
Figure 4.1- (a) SN- and FM- annual and cumulative reliability indexes for a welded steel detail. (b) SN- and FM-annual and cumulative reliability indexes for cast iron steel detail. (c) SN- and FM- cumulative reliability indexes for welded steel detail considering updating. (d) Minimization curve for the crack growth rate.
Δβ-Annual reliability, β-Cumulative reliability, WS – Welded Steel detail, CI – Cast Iron detail, IWF - In-Wind Farm location, S-Single/alone location, L-Linear SN-curve, BL-Bilinear SN-curve and CMI-Condition Monitoring Information.

4.3 INSPECTION AND REPAIR PROCESS

In the FM-modeling process, the inspections can result in detection or no-detection of cracks at hot spots. This is modeled through the probability of detection curve (POD). This probability function takes into account the following:
   a) Inspection method
   b) Inspector experience
   c) Miscellaneous factors depending on the: environment, material, type of defect, number of inspection, location of the defect and characteristic of the defects.

Unsuitable use or modeling of the probability of detection will influence the reliability of updating and the entire RBI of the detail. Straub and Faber in [110] and [111] exemplify the influence of choosing of an inappropriate POD which can result in a non-optimal decision of repair. In PAPER [VII] the influence on the RBI analysis is described by changing the POD-defining parameter (expected minimum detectable crack) within a framework of probabilistic calibration of fatigue design factors (FDF). This can result in lower values of FDF if too small

detectable crack sizes are used. In this work the POD curve was modeled by an exponential model.

4.4 PROBABILISTIC CALIBRATION OF FATIGUE DESIGN FACTOR

This section is dealing specifically with the PAPERS [VI,VII] where a framework for probabilistic calibration of fatigue design factors (FDF) for OWT is proposed. The purpose of this work is to establish the first step in the calibration of fatigue design factor for OWT by using the SN- and FM-approaches resembling the work done in [112] where the calibration of partial safety factor is carried out for a specific code format. The calibration presented in this work is following the steps recommended by the Joint Committee of Structural Safety, JCSS, see [113].

   The probabilistic calibration can be classified in two types: FDF-calibration for a design life without inspections and with inspections. When no inspections are considered the FDF-calibration can be carried out using only the SN-approach and an iterative process to find the corresponding FDF secure that the detail has the acceptable minimum reliability in the life cycle period, see illustration in figure 4.2.

   When inspections are planned to be performed the use of the FM-approach is necessary as explained above. The calibration now consists of two iteration steps: calibration of the FM probabilistic model to the reliability obtained by the SN-approach such as described in section 4.2.3. Unlike RBI, the calibration of FDF has an additional difficulty because it has to be performed iteratively taking into account the whole design life and the inspection times, see figure 4.3. The methodology proposed in PAPER [VII] is influenced by the inspection conditions by the POD-curve where different values or minimum detectable crack sizes are used. This results in important changes in the FDF values.
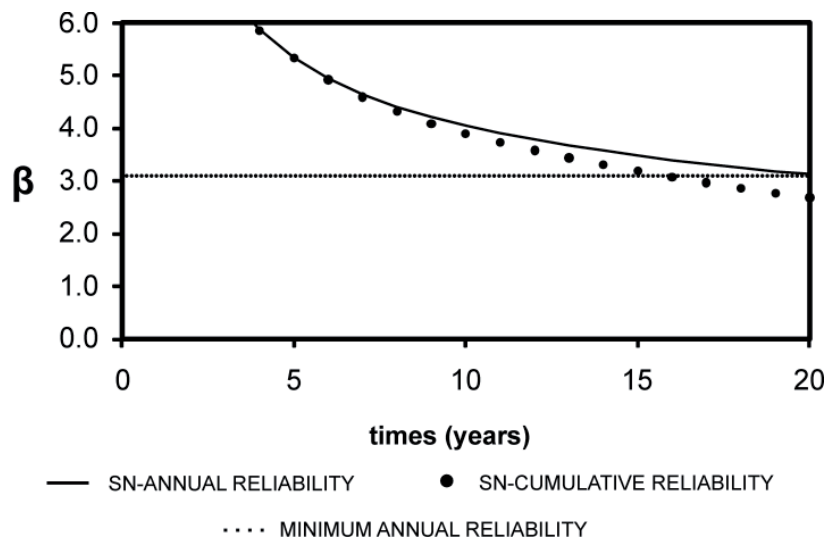
Figure 4.2- Reliability indexes in the probabilistic calibration of FDF for no-inspections during the design life.
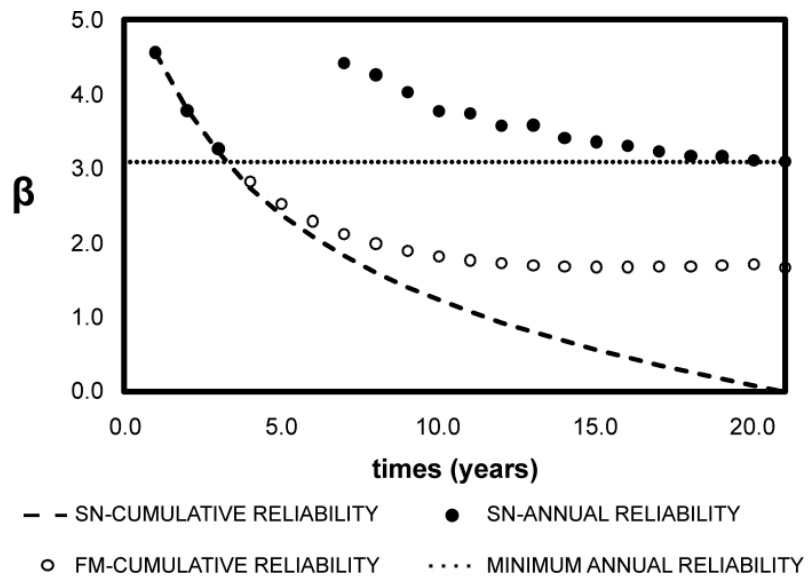
Figure 4.3- Reliability indexes in the probabilistic calibration of FDF, having one inspection during the design life.

CHAPTER 5

RELIABILITY UPDATING FOR OFFSHORE WIND TURBINES

5.1 INTRODUCTION

Uncertainties involved in the structural analysis and design are the reason of the application of a quantitative probabilistic treatment in engineering problems. Before the probabilistic modeling, the first efforts are concentrated in the gain of information from any source with the purpose to reduce the uncertainty.

Nowadays with the advances in measuring technology, recording and inspection techniques, the quality and quantity of information give a good support to the modeling. OWI has many sources of information with variable-time basis, from the infinitesimal (sensors) to long-term lapses of time (inspection results). It is important to mention that external condition monitoring is commonly performed in offshore wind farms, providing information about the climatic condition and medium where the OWT are placed.

In this section is described how to integrate information by updating the stochastic model during life cycle. The updating of information can be carried out in several different manners, attending to the characteristics of the information and condition of the problems. In the following diagram these updating options are shown.
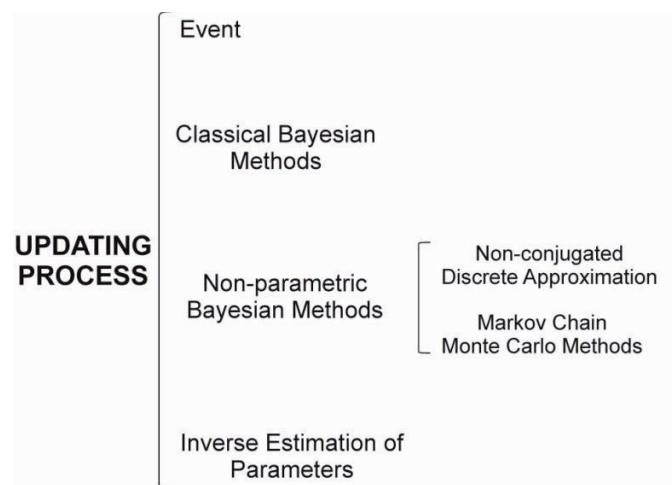
5.1 Updating Process within RBI framework.

In this chapter the process of updating mainly is based on Bayesian statistics. However, there are more techniques for back-estimation of parameters that can be applied in SRM, see [115, 116]. Furthermore, the use of non-parametric Bayesian methods is emphasized due to their importance when the handling of discrete probabilistic functions is contemplated into the SRA.

Non-parametric Bayesian Updating (NPBU) is computationally more efficient and simple when is compared with classical Bayesian updating (CBU). In this work there is no direct comparison between Bayesian updating methodologies since they do not have identical formulations and assumptions. In the PAPER [IX, X], the application of these techniques are described and illustrated.

In this work inverse estimation of the statistical parameter as part of the updating process is not considered. The idea of using the back-estimation as indirect updating of stochastic variables can be carried out when there are realizations of an event $\hat{h}$ available. These realization can be related with the event function $h(x_1, x_2, \ldots, x_i)$ that takes into consideration variables in the SRA. From $\hat{h}$ it is possible to back-estimate the variables x inside the event and subsequently this can be integrated in the SRA. E.g. with information of the crack size $\hat{h}_{crack,j}$, the event function $h_{crack,j}\ x_1, x_2, \ldots, x_i$ can be used to estimate the crack growth rate, initial crack at any specific time j. A detailed review of inverse estimation of parameters is found in [115].

5.2 UPDATING THROUGH EVENT

If the new information can be formulated as an event then in the reliability updating an event function $h(X)$ is formulated and used jointly with the limit state equation $g(X)$ where X are the stochastic variables. The safety margin $M = g(X)$ will be conditional whether the event margin $H = h(x)$ is taking place or not. This event updating can be carried out into the SRA for different set of events and circumstances, see [117] and [118]. For instance, the presence, inspection and measurement of crack sizes in a deteriorated component due to fatigue loading can be modeled by event updating. Additionally and depending on the reparation policy, the damage can be repaired or not, and the reliability can be updated according to this.

RBI is composed by the SN- and FM-approaches. The updating through event into RBI is by the FM-approach and considering that the crack was found (POD curve). However, the updating can be carried out in SN-approach, see [119].

5.3 CLASSICAL BAYESIAN UPDATING

When it is desired to update the stochastic variables of the probabilistic model, Classical Bayesian Statistics can be used. The Bayes' Updating Theorem is defined as:

$$f''_Q(q|\hat{x}) = \frac{f_X(\hat{x}|q) \cdot f'_Q(q)}{f_X(\hat{x}|q) \cdot f'_Q(q)\, dq} \tag{18}$$

where $f(\hat{x}|q)$ is the likelihood density function, $f'_Q(q)$ is the prior density function and $f''_Q(q|\hat{x})$ is the posterior density function. The likelihood function is the density function of the set of realizations $\hat{x}$ of the variable X conditional on the vector Q of statistical parameters q that defines it. The prior distribution represents our beliefs or state of knowledge of the vector of parameters Q. The posterior density distribution is the updated distribution of the vector of parameters Q. The divisor is typically understood as a normalizing constant.

Once the posterior density function is obtained the next step is to calculate the predictive distribution function with the following formula:

$$f_X(x|\hat{x}) = \int f_X(x|q) \cdot f''_Q(q|\hat{x}) \, dq \qquad (19)$$

where $f_X(x|q)$ is the probability density function of the stochastic variable X, $f''_Q(q|\hat{x})$ is the posterior density function and $f_X(x|\hat{x})$ is the predictive, updated distribution of the stochastic variables X. The predictive distribution conditional on the set of realizations $\hat{x}$ of X is the product of the initial assumed probability density function of the set of realizations of X for a given vector of defining parameter Q and the posterior density of the parameters Q integrated over all values of q.

By means of the formulae (18) and (19), it is possible to update any of the variables considering the former information and measurements. There are some other considerations for the updating that is important to take into account:

a) How well-supported is the prior knowledge of the variables.
b) The number of parameters defining the prior distribution and the likelihood function.
c) Type of statistical family, and the use of conjugated prior / posterior distributions.
d) Possibility of integration of the predictive distribution in the assessment of reliability.

These considerations are vital for carrying out the updating. When the decision makers disregard them, it may be result in an erroneous estimation of the predictive distribution and the following 'slip-ups' may be occurring:

1) When there is not much information about one or more of the statistical parameters, a vague assumption on the prior can be taken. When this case occurs, the decision maker should pay attention to both the posterior and predictive distributions to be sure that the assumptions are not leading to theoretical and physical wrong statistical descriptions of the parameters and variables. Commonly in the literature prior distribution is taken as an estimator of the beliefs (prior's assumptions), see [120] and [121]. The predictive distribution is estimated for the need of using it in assessment of the reliability.
2) Wrong assumptions can be made when the prior density functions are not well described, e.g. when there is a multi-parameter likelihood function with mixed prior distributions. Another example is to neglect (by a simplicity supposition) a parameter of the likelihood function that could have an important influence on the variable.
3) While the application of conjugacy in Bayesian statistics (see [97]) makes the calculations a straightforward process, it may also bring limitations in the number and parameters.
4) Once a predictive distribution is calculated the next task is to integrate it into reliability analysis in a computational-efficient manner. This is possible for some standard density distributions through their transformation and approximations [122]. However, for complex multi-parameter conjugated predictive distributions, this task is a cumbersome process.

The following sections focus on presenting the updating process with Bayesian Statistical Methods. The non-parametric methods are lying in Bayesian statistics, however other techniques or methods are used from other fields(see [120] and [124]). In this work Markov Chain Monte Carlo techniques (MCMC) are considered within Bayesian statistics how they are generally in the Bayesian literature, see [121] and [123].

There are several approaches for application of Bayesian updating. A formal approach is the standard and ideal case using the classical Bayesian updating process. It is assumed that former information and beliefs are well supporting the decision of choosing certain prior distributions. Moreover conjugation is present to deliver standard distributions for posterior and predictive distributions, e.g. known standard deviation and Normal distributed mean as prior with Normal distributed likelihood, which then results in a Normal distributed posterior and Normal predictive distribution.

There are several drawbacks with this formal approach:

a) Studies related to obtaining the posterior and predictive distributions are limited to a few distributions, see [97]; e.g. the exponential family.
b) When choosing conjugated, multi-parameter prior distributions, the predictive distributions become more complicated and it will be more difficult to integrate to RBI or SRA, e.g. in the simplest case with unknown mean and variance.
c) Unrealistic in some cases when the parameters of the prior distributions are correlated in the conjugated formulation which again affect the posterior.

When there is no previous information supporting the prior beliefs, the non-informative approach can be adopted in CBU. The vague-assumption can be classified as notational and functional. The notational handling refers to the use of certain parameter to choose the prior and functional to the use a particular distribution function as prior. In the literature these procedures have several names: vague, flat, diffuse, non-informative and negligible priors, see [126] and [127]. What is in principle done, is giving more weight to the data and neglecting the beliefs. This vague consideration results in properly weighted posterior and predictive distributions.

In PAPER [III] it is shown how to integrate the classical Bayesian Approach into the RBI format. The influence on the reliability is tangible when the updating is performed on a yearly basis. Meteorological measurements can warn about dispersion of data and change the statistical properties thus integrating the harsher or milder environments into the RBI modeling. Although an increase of reliability is obviously expected, a decrease may be a possibility, [128].

Additional complexity is added when several parameters are considered, see table 5.1 where the case of unknown mean and standard deviation for the Normal distribution is shown.

Table 5.1 Unknown mean and standard deviation for independent and identically Normal distributed samples $\hat{x}$ of X.

Distribution function	Conjugated case	
Prior: variance	$1/\sigma^2 \sim gamma\,(\nu_0/2\,,\nu_0\sigma_0^2/2)$	(20)
Prior: mean conditional on the variance	$\theta|\sigma^2 \sim normal(\mu_0, \sigma^2/\kappa_0)$	(21)
Likelihood function	$X|\theta,\sigma^2 \sim i.i.d.\,normal\,(\theta,\sigma^2)$	(22)
Posterior: mean conditional on the variance	$\theta|X,\sigma^2 \sim normal(\mu_n, \sigma^2/\kappa_n)$	(23)
Posterior: variance	$1/\sigma^2|X \sim gamma\,(\nu_n/2\,,\nu_n\sigma_n^2/2)$	(24)

In prior: $E[1/\sigma^2] = \frac{\nu_0/2}{\nu_0\sigma_0^2/2}$ and $Var[1/\sigma^2] = \frac{\nu_0/2}{{\nu_0\sigma_0^2/2}^2}$ (25)

In posterior: mean $\mu_n = \frac{\kappa_0\mu_0+n\bar{X}}{\kappa_n}$ and $\kappa_n = \kappa_0 + n$ (26)

In posterior: variance $\sigma_n^2 = \frac{1}{\nu_n}\left[\nu_0\sigma_0^2 + (n-1)\frac{\sum_{i=1}^{n}(x_i-\bar{X})^2}{(n-1)} + \frac{n\,\kappa_0}{\kappa_n}(X-\mu_0)^2\right]$ and $\nu_n = \nu_0 + n$ (27)

θ is the mean of the stochastic variable, σ^2 is the variance of the variable, ν_0 is the size of the prior sample, σ_0^2 is the prior sample variance, κ_0 is the size of prior observations, μ_0 is the mean of κ_0 prior observations, n is the number of samples with sample mean X and μ_n is the mean of n prior observations.

5.4 NON-PARAMETRIC BAYESIAN METHODS

Although the application of classical Bayesian updating methods is diverse, it is arguable that there is a lack of 'flexibility' when multi-parameter probabilistic models are considered. The non-parametric Bayesian updating (NPBU) method is an approximate discrete solution of the updating process for multi-parameter models which not necessarily use conjugated or relative distributions. Although these methods can be used in a special accurate formulation, they are approximations that have more flexibility but somehow conditional on the 'computational' resources. In this section the non-parametric methods are grouped in 1) semi- or non-conjugated discrete approximation and 2) MCMC applications.

5.4.1 SEMI OR NON-CONJUGATED DISCRETE APPROXIMATION

The notion of conjugacy is connected to explicit parametric solutions (see [129]) that enable the decision maker to handle probabilistic models on assumptions, e.g. vague prior information, degree of freedom, interdependency of variables, etc. However, drawbacks can appear in the notation. On the other hand, the avoidance of conjugacy turns out to be helpful numerically but not parametrically. From table 5.1 inconveniencies in the conjugating formulations can be exemplified. In formula (21) in the conjugated case, the σ^2/κ_0 term is considered for the case of conjugacy. This means that the prior variance on θ is proportional to the sampling variance and implies the assumption of having the prior variance on θ proportional to the κ_0 prior samples of the population and with small values of that, an unwanted effect can influence the nominal prior uncertainty for θ. Although, there is no need of obtaining the constant divisor in the formula (18), this can require additional numerical efforts when it is calculated. When more than two parameters or any hierarchical sub-dependence is introduced, the classical Bayesian updating approach may be impossible to use in practice, due to the complexity.

The discrete semi-conjugated updating is a discrete approximation. The definition of the posterior distribution $f''_Q(q|\hat{x})$ can be rewritten in its discrete form:

$$p_d\big(q_1, q_2, \dots, q_m | \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n\big) = \frac{p(q_1, q_2, \dots, q_m | \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)}{\sum_{i_1=1}^{G} \sum_{i_2=1}^{H} \cdots \sum_{i_m=1}^{L} p(q_1, q_2, \dots, q_m | \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)} \tag{28}$$

By using the definition of conditional probability:

$$p_d\big(q_1, q_2, \dots, q_m | \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n\big) = \frac{p(q_1, q_2, \dots, q_m, \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)/p(\hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)}{\sum_{i_1=1}^{G} \sum_{i_2=1}^{H} \cdots \sum_{i_m=1}^{L} p(q_1, q_2, \dots, q_m, \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)/p(\hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)} \tag{29}$$

and by simplifying, the discrete formulation of the posterior distribution is obtained:

$$p_d\big(q_1, q_2, \dots, q_m | \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n\big) = \frac{p(q_1, q_2, \dots, q_m, \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)}{\sum_{i_1=1}^{G} \sum_{i_2=1}^{H} \cdots \sum_{i_m=1}^{L} p(q_1, q_2, \dots, q_m, \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)} \tag{30}$$

The marginal (conditional on the samples) posterior distribution for any parameter q can then be obtained by simply summing over the other arrays of parameters, e.g. for calculating the marginal of q_m conditional on the samples $\hat{x}_1, \hat{x}_2, \dots, \hat{x}_n$:

$$p_d\big(q_m | \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n\big) = \sum_{i_1=1}^{G} \sum_{i_2=1}^{H} \cdots \sum_{i_{m-1}=1}^{L} p_d\big(q_1, q_2, \dots, q_{m-1} | \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n\big) \tag{31}$$

In the PAPER [IX] an example is considered for a Lognormal distributed variable $X \sim LN(\mu_X, \sigma_X)$ with a transformation to a Normal distributed variable $Z \sim N(\theta, \sigma)$.

5.4.2 MARKOV CHAIN MONTE CARLO

The MCMC methods were developed in the middle of the last century [130,131] but were not widely used since two decades ago, [132]. In short, these algorithms are based on the Markov property of using sequential sets of sampling that are conditionally independent. Based on that, these algorithms approximate a target distribution when the number of samples tends to infinity just as in Monte Carlo simulations. One of the methods within MCMC is Gibbs sampling (GS). GS represents a rather simple simulation technique to

estimate the posterior probability density function. Unlike CBU and NPBU, GS relies on the full conditional distributions and on a sequential simulation algorithm.

The dependence on the full conditional distribution gives GS its main advantage and strength when a hierarchical arrangement of unknown parameters are constituting the stochastic modeling of a stochastic variable X. In contrast to crude Monte Carlo simulation (MC), the GS algorithm is based on a more elaborated iterative sampling idea but still straightforward. In principle, the simulation of sequences of samples represent state of the parameters $q^{(s)} = \left(q_1^{(s)}, q_2^{(s)}, \dots, q_m^{(s)} \right)$ and with the new set of samples, the new states $q^{(s+1)} = \left(q_1^{(s+1)}, q_2^{(s+1)}, \dots, q_m^{(s+1)} \right)$ will be generated by the following recursive algorithm

1) $q_1^{(s+1)} \sim p(q_1 | q_2^{(s)}, \dots, q_m^{(s)}, \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)$;
2) $q_2^{(s+1)} \sim p(q_2 | q_1^{(s+1)}, \dots, q_m^{(s)}, \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n) \dots$
3) $q_m^{(s+1)} \sim p(q_m | q_1^{(s+1)}, q_2^{(s+1)} \dots, q_{m-1}^{(s)}, \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n) \dots$
4) $q^{(s+1)} = q_1^{(s+1)}, q_2^{(s+1)}, \dots, q_m^{(s+1)}$
5) Initializing $q_1^{(s+2)} \sim p(q_1 | q_2^{(s+1)}, \dots, q_m^{(s+1)}, \hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)$;

A general and detail view to GS can be found in [133-135]. In comparison with CBU and NPBU, GS provides a simulating technique that can handle updating of more parameters or hierarchical definitions of variables, see PAPER [IX].

5.5 POLYNOMIAL CHAOS EXPANSION APPROXIMATION

In this section is described how the updated stochastic modeling described above can be integrated in SRA using a Polynomial Chaos Expansion Approximation (PCEA). This orthogonal approximation is a particular technique to tackle the problem of integration of the uncertainty in structural reliability analysis.

When FORM or SORM is used the non-Normal stochastic variables can usually easily be transformed to a standard Normal variable by the simple transformation $z = F_Z^{-1}\left(\Phi(u) \right)$ and then integrated in the reliability analysis. In the non-parametrical case or in the case of a very intricate distribution the integration to reliability analysis is not simple and could be performed by e.g. a polynomial / rational approximation or by asymptotic expansions, see [136]. In this work a PCEA is used as a generic solution of this problem.

The "Wiener-Hermite chaos" polynomial function is used assuming that the underlying stochastic process is Gaussian, [137]. Although the application of PCEA in this work is mainly concerned with incorporation of uncertainty, in [138] and [139] the use of the Hermit-Chaos expansion is formulated as a framework to account for the randomness and spatial variability of mechanical properties.

Tatang in [140] and Isukapalli in [141] extended the application into chemical engineering. In [141] PCEA is used as a functional approximation for integration of uncertainty into a computational efficient method for propagation. In this way, PCEA can be used to approximate a probabilistic model of a random variable such that it can be expressed as a linear combination of Hermite polynomials having a Gaussian stochastic variable as its argument.

The Homogeneous Chaos expansion was proposed by Wiener [137]. The main advantage of this approximation is its fast exponential convergence rate when Gaussian variables or process are to be represented. However, this rate can be seriously affected in some non-Gaussian cases. A review of the Wiener-Askey scheme for orthogonal polynomial expansion can be found in [142]. The formulation can be adjusted in two manners: the first is by increasing the number of random variables to reduce the random "fluctuations" in the stochastic field and the second is to increase the maximum order of the polynomial chaos for

handling the non-linear behavior of the process. For probabilistic approximations with one stochastic variable, a one-dimensional polynomial chaos approximation is used with an n-order of the homogeneous chaos. The Gaussian stochastic process can be approximated by the following series:

$$X(\omega) = a_0 H_0 + \sum_{i_1=1}^{\infty} a_{i_1} H_1\left(\xi_{i_1}(\omega)\right) + \sum_{i_1=1}^{\infty}\sum_{i_2=1}^{i_1} a_{i_1 i_2} H_2\left(\xi_{i_1}(\omega), \xi_{i_2}(\omega)\right)$$
$$+ \sum_{i_1=1}^{\infty}\sum_{i_2=1}^{i_1}\sum_{i_3=1}^{i_2} a_{i_1 i_2 i_3} H_2\left(\xi_{i_1}(\omega), \xi_{i_2}(\omega), \xi_{i_3}(\omega)\right) + \cdots \tag{32}$$

The term $H_n\left(\xi_{i_1}, \ldots, \xi_{i_n}\right)$ is the Hermite-Chaos term of order n in the standard Gaussian variables $\left(\xi_{i_1}, \ldots, \xi_{i_n}\right)$ with zero mean and unit variance. H_n are Hermite polynomials and a_n are Fourier coefficients of the series. The general polynomial chaos of order n can be obtained with

$$H_n\left(\xi_{i_1}, \ldots, \xi_{i_n}\right) = e^{\frac{1}{2}\xi^T \xi}(-1)^n \frac{\partial^n}{\partial \xi_{i_1} \ldots \partial \xi_{i_n}} \tag{33}$$

Equation (32) is the approximation of the stochastic process. From this process, the probabilistic characteristics can be calculated using the k-central moments equal to $m_{x-k} = E\left[(z - a_0)\right]^k$. From the first moment and k-central moments the parameters a_n can be calculated under an optimization-minimization least-square scheme.

In PAPERS [III, IX and X], these three manners of Bayesian updating are applied for OWT. The application is shown in uni- and multiparametric cases for stochastic variables in the assessment of reliability. The importance of perform the updating of information is found in the decrease of uncertainty not only for a certain variable but within the model. In the PAPERS [IX] and [X] is emphasizing the application of discrete non-conjugated and simulating techniques. The DSCU approach is a approximating tool that is not use commonly for updating because CBU is parametrically easy to carried out. However, CBU is limited. The Gibbs sampling is widely use as MCMC's simulating scheme and common tool within Bayesian network but its application as updating tool in the assessment of reliability have not been emphasize. The application of this NPBU has importance as simple simulating tool and because could be seen as the first step to hierarchically update the variables within the assessment of reliability.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 CONCLUSIONS

This work is addressing the fatigue reliability assessment and reliability-based Inspection and maintenance planning of Offshore Wind Turbines (OWT). The fatigue damage is assumed to occur in details or hot spots where the cracks are potentially initiated. These sectors are found in geometrical and material discontinuities, e.g. in weld seams and casted details. Fatigue damage can influence the performance of the structure significantly; ultimately resulting in failure and collapse.

Nowadays, large clusters of OWT are developed in wind farms. Under these conditions, the fatigue damage increases due to additional turbulence in wakes for wind turbines within the wind farm. This aspect is taken into account by using an equivalent turbulence model [52, 53] which is integrated into the assessment of the reliability.

The inspection and maintenance costs for offshore wind turbines are significantly higher than for onshore locations. The application of a Reliability Based Inspection (RBI) framework for OWT can improve the inspection and maintenance planning and reduce associated costs and thereby decrease the cost of energy. The RBI optimization of inspection and maintenance plans can further assure the fulfillment of required risk acceptance criteria for OWT. Moreover, the RBI can be managed in a generic system approach [103] to be applied as a decision tool to generate inspection and maintenance plans for one wind turbine or the whole cluster of OWT, i.e. the wind farm. The migration of the RBI method from the Oil & Gas industry brings additional challenges such as:

Offshore 'atypical' load cases: The external load conditions and control system generate atypical load scenarios such as an extreme load condition with simultaneous wind and wave loads at the operational stage of OWT (which requires load extrapolation), load situations when there is a voltage fault (variation of electromagnetic torque) during operation, misalignment of wind and wave loads, etc. For the fatigue limit state the different operational stages and external conditions were summarized and merged into a single load situation where damage is accumulating. This is partially allowed by the long-term nature of the fatigue damage phenomenon.

Mechanical, Electrical and Control system components: The influence of the control system is approximately taken into account by using an influence function (see section 3.3.2). This function depends on the type of component considered and on the control system, which can also be influenced by the external load conditions. In the case of offshore platforms in the O&G industry, the wave conditions dominate the wind ones and there is not a control system moduling the wave influence. However, for OWT the control function

represents an additional 'effect' in the normal load situation. Also the configuration of the control system is substantially affecting the forces in the fatigue prone details.

Varying characteristics of exchangeable components: the mechanical and electrical components generally fail at some shorter time intervals than structural members. When failure occurs, the components are changed or repaired. Change of electrical and mechanical components could influence the structural parts.

Structural risk criteria are mainly based on economic losses than possible human injuries: In the oil & gas industry, the failure scenarios and criteria directly consider the consequences of human injuries / deaths and environmental effects. This is not in general the case for the OWI and therefore the RBI optimization can be based on economic criteria directly. The assessment of structural reliability in this work focuses on the following aspects:
   a) Application of RBI for OWT
   b) Formulation of a framework for probabilistic calibration for fatigue design factors (FDF)
   c) Application of Bayesian updating within the assessment of structural reliability and RBI

The **application of RBI planning for OWT** is described in PAPERS [I, II, IV and VIII]. The presented cases deal with welded steel and cast iron details. The stochastic and probabilistic models are evaluated by sensitivity analyses. From the application of RBI planning to OWT, it is concluded that:
   a) RBI can be applied to OWT for single/alone locations and In-wind farm locations. This is accomplished by using the model in [52, 53].
   b) The RBI approach could also be applied as a decision tool for estimating the consequences of a possible service life extension. Also, RBI can be used for strengthening (or reduction) of the programmed inspection & maintenance efforts.
   c) Although the RBI planning was limited to structural components such as support structures or transition nodes, the methodology can also be applied to other structural components. This application can be achieved by using proper influence functions and properties characterizing the considered case.
   d) A particular probabilistic model is used based on [52]. In the work [47-52], it is possible to find other models to carry out the reliability assessment for the fatigue limit state. The main reason for using the model in [52] is the generic application of this to different details, components and the incorporation of an influence function that reflects the characteristics of loads and setup of wind energy converters.
   e) The design and limit state equations and the FM model are represented by improper functions and have multiple integration processes. This makes the process a time and computational consuming process. Due to the use of distribution functions, deviation-limit intervals (instead of improper intervals) can be set up. However, the simulation process counted in thousands can still be a time consuming process. E.g. with up-to-date (dual workstation processor) computational resources, approx. 400 hrs. CPU time is needed for one case of RBI planning for 20 years life time.
   f) According to the equivalent turbulence model in [53], wake conditions have a detrimental influence on the reliability level. As many surrounding OWTs exist, the inner one will have lower reliability if not designed for the higher wake induced loads.
   g) The use of bilinear SN-curves (for design and reliability analysis) decreases the reliability levels in the life cycle. Although the change in slope in the bilinear case is certainly assigning higher number of cycles for low values of the stress ranges, the reliability is affected by the additional larger uncertainty of the bilinear part.
   h) From the obtained reliability values, it can be seen that the life cycle reliability is lower than for oil & gas offshore structures.

The **framework for probabilistic calibration of fatigue design factors (FDF)** presented in the PAPERS [VI and VII] follows the steps recommended by Joint Committee of Structural Safety (JCSS) for general code calibration, see [113, 143]. From the results of the proposed framework for probabilistic calibration for FDF in PAPERS [VI and VII], it can be concluded:

a) The FDF values can be reduced when inspections are performed. The decrease will be reflected in the costs of the OWT support structure. Although a comparison of costs was not carried out, the reductions of the FDF and associated less cost of materials should be further investigated in comparison with the additional life cycle costs to inspection and maintenance / repairs.

b) The influence of the quality of inspections on the FDF is important. When the quality is reduced the FDF values will be higher. Although the examples are illustrative, they basically show the effect of the inspection quality.

c) The framework of reliability-based calibration of FDF values can also be used as a tool to determine a cost-effective fatigue design considering initial design cost and service life costs of a given wind turbine or wind farm.

d) Due to the larger uncertainty associated with the turbulence in a wind farm, the required FDF values for In-wind farm locations are larger than for a single wind turbine.

The **application of Bayesian updating within the assessment of updated reliability and RBI** is addressed in the PAPERS [III, IX and X]. he PAPER [III] presents a straightforward Bayesian inference application with an illustrative example of integration of condition monitoring information using uni-parametric, classical Bayesian updating. Although the examples in PAPER [III] are rather simple, they illustrate the main features of updating process into a RBI framework. The application of classical Bayesian updating allows an effortless integration of the predictive distribution because this is represented by a standard distribution function. However, when classical multi-parametric Bayesian updating is considered, the integration of uncertainty can be a cumbersome task.

In the PAPER [IX] and [X], the application of Non-Parametric Bayesian Updating (NPBU) is shown for the fatigue assessment of reliability. These papers focus on presenting NPBU as a generic updating tool within the assessment of reliability of OWTs. In these papers, the integration of uncertainty is carried out by a Polynomial Chaos Expansion Approximation. This Gaussian-driven generic approximation tackles the problem of integration as described PAPER [III]. Additionally, PAPER [IX] and [X] focus on emphasizing the difference in formulation of classical and non-parametric Bayesian updating approaches. This difference is essential for modeling and solving an updating problem in the suitable manner and not increasing the epistemic uncertainty due to erratic conjugation or parameter-dependence assumptions.

Two approaches are shown in the NPBU methods: Discrete parameter updating and Gibbs Sampling. Both are helpful tools, where discrete parametric updating is an approach for cases with several unknown parameters or hierarchical vectors of unknown parameters. This is generally what is needed for updating stochastic models in the assessment of reliability.

In Monte Carlo Markov Chain, Gibbs Sampling carries out the handling of hierarchical arrangement of stochastic variables. Gibbs Sampling is a suitable method for multi-parametric updating for large hierarchical arrangements. The conclusions for integration of new information and uncertainty to the assessment or reliability and RBI for OWT are:

a) The decision on using any of the shown updating approaches should be made according to the characteristics of the variable(s) or process to be updated. In other words, the notion of conjugacy, mixed prior notation, non-informative assumptions, prior independency and general formulation should be representative for the stochastic variable and type of information considered.

b) The non-informative or vague prior information assumption is to be preferred for engineering problems rather than functional vague prior considerations. This is mainly because predictive distribution is the main target and not only the posterior of

parameters. However, when the target is parameter estimation, the functional non-informative updating can be applied, using the predictive distribution as a right-choice-of-prior estimator (as in general statistical applications).

c) Polynomial Chaos Expansion Approximation can be useful to integrate the updated stochastic variable for reliability assessment using simulation or FORM/SORM methods. Examples indicate that the obtained approximations have less than 2.0% error in the 90% confidence interval. However, it is possible that the PCEA deceive this adjustment criterion and thus it is necessary to check the quantiles in the empirical cumulative density function of the PCEA. It should be mentioned that the stochastic variable is somehow close to a normal / Gaussian process with priors from the exponential family. This can assure in general a good fit of the PCEA, but in cases very different form a normal distribution other polynomials could be relevant [30].

d) The DSCU and GS can result in posterior distributions that are not symmetrical in any of their parameters. In these cases the predictive distribution function is further to be considered from normal distribution family, the least-square minimization of the PCEA becomes more complicated and the percentiles have to be checked in detail.

e) In the assessment of fatigue reliability for OWT, the influence of choosing any of these updating approaches is especially seen in the beginning of the lifetime implying different updated reliabilities, but with 'almost' convergence with time. The updated reliabilities ended (in these particular illustrative cases) in lower life-cycle reliability than if not updating was performed. Commonly, one could suppose that it should be the other way around. However, it should be pointed out that the samples were not from Lognormal distribution. Additionally, the predictive distribution ended in the parametric case as a log-student distribution that is remarkably different than in the initial year.

The **application of RBI planning for OWT** is the first step of application of the RBI methodology in the Offshore Wind Industry. Although the considered examples are based on a particular probabilistic model, it can also be done using different models. The computational resources are important due to the nature of the calculations, which are based on simulations and computation of multiple integrals. In this work risk assessment criteria is not used directly - a minimum reliability level is simply assumed to be given, mainly based on the reliability level implicitly used for calibration of partial safety factors in the IEC 61400-1 standard. As a first approach to OWT, the methodology and examples indicate that RBI can be used for planning and optimization of inspection and maintenance / repair for OWI.

The **framework for probabilistic calibration of FDF values** illustrates the potential of the reliability-based approach for calibration of FDF values or equivalently partial safety factors for fatigue design – and for including the effect of possible inspections during the life time of a wind turbine. This can also be useful in possible lifetime extensions of offshore wind turbines.

The **application of Bayesian updating within the assessment of reliability and RBI** does not only show the application within updating and incorporation of uncertainty in the OWI, it can be used in other applications in civil engineering. The application of Non-parametric Bayesian updating methods is someway the transition between Classical Bayesian statistics and Monte Carlo Markov Chain techniques that could improve the information and integrate the uncertainty for multi-parametric cases and hierarchical arrangements in reliability assessments. The CBU is widely used for engineering purposes in codes, standards and recommendations. This parametrical handling makes it straightforward to integrate the information. Nonetheless, it should be considered according to the characteristics of the problem if full conjugation and mixing notation schemes make sense. The DSCU approach is useful when multivariate updating is considered. It lacks of parametric handling, full conjugating scheme and represent an approximation. These last two characteristics could not entirely be seen as disadvantages due to the fact that the second one possibly makes the easy handling of multivariate updating and the last can be

minimized in error by managing the discrete vector size. In the other hand, the Gibbs sampling is depending on quasi-random processes, a simulation algorithm and discrete considerations. That makes it less exact for updating but unlike DSU and CBU, this MCMC's sampling technique can manage hierarchical arrangement of variables in the stochastic model in the assessment of reliability. The application of DSCU, GS approaches jointly with PCEA can also be applied to other structures and into a risk-based framework for OWT in order to strengthen or reduce the maintenance and inspection efforts in the life cycle of the infrastructure.

6.2 FUTURE WORK

In the RBI application for OWT the following aspects could be considered for further research:

- For future and nowadays clusters of OWTs, a generic approach to RBI planning for OWT could be helpful for decision making on management of I&M efforts for given hot spots, different components and groups of OWT. Generic RBI for planning of oil & gas industry has already been developed [103]. However, offshore wind turbines have additional challenges such as: Clusters of OWT (different structures), different components, different rates of damage affectation (single or in-wind farm location), etc.
- The minimum reliability level to be used for offshore wind turbines should be established by use of risk acceptance criteria. There are different criteria proposed by oil & gas industry but offshore wind turbines have characteristics that would not allow these criteria to suit properly.
- A cost analysis of the application of RBI may be carried out to investigate the cost impacts of a risk-based inspection and maintenance methodology. However, this requires that realistic costs models can be established.
- Several different probabilistic models to assess the fatigue reliability have been proposed, see [47-52]. These models should be compared and evaluated to find their benefits and weaknesses for particular cases using a RBI format.
- The stochastic variables are reflecting the uncertainty in the design and physical models. To assessment and to find the probabilistic distinctiveness of the variables, statistical analysis, measurements, recordings and simulation approaches are carried out. Depending on the source of information, it is possible to devise a hierarchical path or formulation to define the probabilistic model for a stochastic variable X. Instead of just taking the data and assume a distribution function, the hierarchical arrangement will result in a distribution for the variable. Non-parametric updating can be used to update the information through the hierarchical model and PCEA can integrate the uncertainty to the assessment of reliability of the OWT. This methodology should be further investigated.
- Further work is necessary to settle a framework for probabilistic calibration of FDF values. This could be achieved by considering a range of different fatigue critical details, material thicknesses, SN-curves, number of inspections, inspection techniques and repair strategies. Moreover, the sensitivity of the stochastic models should be investigated, especially for Δ, X_w and X_{SCF}.
- Additional to the work with the model in [52], the impact of different influence function for fatigue assessment of reliability should be investigated together with a deeper treatment considering different components, wind condition and characteristics, setup of control system, etc.
- The development of a method for estimation of the probability of failure, considering the extreme load given fatigue failure of one or more components. The extreme load case should include both the stand-still and the operational situations.

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Compilation of Scientific Publications

The technical papers are chronologically ordered, according the publishing order. The following selected papers stand for extended-work covering the overall topics in this thesis.

Paper II

Optimal Risk-Based Inspection Planning for Offshore Wind Turbines

Optimal Risk-Based Inspection Planning for Offshore Wind Turbines

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Abstract

Wind turbines for electricity production have increased significantly the last years both in production capability and size. This development is expected to continue also in the coming years. The support structure for offshore wind turbines is typically a steel structure consisting of a tower and monopile, tripod or jacket type foundation. Monopiles are at present the most typical foundation, but tripods and jackets are expected to be used in the future at larger water depths. The support structures are facing deterioration processes such as fatigue and corrosion. To 'control' this deterioration, inspection and maintenance activities are developed. This paper considers aspects of inspection and maintenance planning of fatigue prone details in jacket and tripod types of wind turbine support structures. Based on risk-based inspection planning methods used for oil & gas installations, a framework for optimal inspection and maintenance planning of offshore wind turbines is presented. Special aspects for offshore wind turbines are considered: usually the wind loading are dominating the wave loading, wake effects in wind farms are important and the reliability level is typically significantly lower than for oil & gas installations. An illustrative example is presented. As part of the results, inspection times are calculated, showing that earlier inspections are needed at in-the-wind farm sites due to the increase of fatigue coming from wake turbulence.

Keywords: inspection, reliability, decision analysis, fatigue, wake turbulence

1. Introduction

Risk Based Inspection (RBI) planning is addressed to achieve a suitable life-cycle performance by an optimal inspection, maintenance and reparation strategy. This strategy entails an optimal control of deterioration in the structure, not neglecting important economical, technical and social aspects related with its overall performance.

Operation and maintenance costs for offshore Wind Turbines are much larger than for onshore wind turbines, making RBI an important tool to accomplish substantial improvements in costs that will be considerable, bearing in mind the significant increase of this industry in production capability and size. Attending to this expansion, 5-10 MW wind turbines are developed and going to harsh environments begin to be profitable options. In-place conditions as deep water depths, waves and wind farm location affects significantly the life-cycle performance of offshore wind turbines (OWTs). Depending on the site characteristics, typically, OWTs support structure is made of steel consisting of a tower and monopile, being used at lower water depths; and jacket and tripod support structures used for larger depths due to economical and technical (dynamical behaviour and structural redundancy) advantages over monopile support structures.

RBI for oil & gas installations have been developed during the last two decades, see e.g. Faber *et al.* (2000), Sørensen and Faber (2001) and Moan (2005), giving a theoretical guideline based on Bayesian decision theory that can be applied also to offshore wind turbines.

This paper considers aspects of inspection and maintenance planning of fatigue prone details in jacket and tripod types of OWT support structures. Based on RBI methods for oil & gas installations, a framework for optimal inspection and maintenance planning of OWTs is presented. It is taken into account that for fatigue loading usually the wind load is dominating the wave load. Within wind load, wake effects in wind farms increase the fatigue load significantly.

In contrast to other civil engineering structures and oil & gas installations, OWTs usually represent low risk of human injury, allowing the allocation of a minimum reliability level obtained by minimization of the total expected life-cycle costs. Conditioned and time-tabled maintenance actions (inspection, maintenance and repairing) can be optimized by applying pre-posterior Bayesian decision theory approach permitting use of diverse

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information, e.g. inspection data and load/wind/wave measurements.

In wind farms, which are a viable source of electricity production, additional technical and economical efforts have to be considered related to the interaction of the OWTs. Spatial correlation of OWTs entails turbulence conditions that affect the performance of neighbouring wind turbines. Wake effects, coming from the decrease of wind velocity behind OWT and increase the turbulence, results in a decrease in OWT fatigue life. Other loads from waves and ice represent important aspect also to be considered.

A fatigue failure limit state steel details in OWT is described in this paper. Fatigue failure critical details are located in several structural and mechanical parts (in the nacelle, wind energy converter WEC), being the interaction between structural, mechanical and electrical components a remarkable difference comparing OWTs with other structures. Active control affects considerably the response from wind actions in structural and non-structural parts. Non-structural failure modes are related with start/stop operation and accidental/unusual loads that will affect these specific parts. Within these fatigue critical parts, welded steel details in joints (the support structure and tower) and transition zones (transition node tower-support structure, yaw mechanism, hub) need special careful design concerning the fatigue performance.

RBI optimization of OWT is considered in this paper for fatigue prone details in jacket and tripod type support structures. Probabilistic models and representative limit state equations for ultimate structural fatigue failure are formulated. Examples are described, considering fatigue failure using both linear and bilinear SN-curves and for single and wind farm location.

2. Optimal Planning of Inspection and Maintenance

The time varying fatigue degradation in offshore structures is a highly uncertain process, making a probabilistic approach the best way to deal with the problem. Further, to assess the uncertainties arising from external randomness (external conditions, environmental exposure, etc) and model uncertainties stochastic modelling, is a rational tool. Reliability-based and risk-based approaches for inspection and planning have been developed during the last decades, see Skjong (1985), Madsen *et al.* (1987), Thoft-Christensen and Sørensen (1987) and Fujita *et al.* (1989); and are being applied to outline RBI plans that have as main aim to improve structural reliability and minimize the life cycle overall costs.

The suitable decision plan to improve costs will be carried out in the framework of pre-posterior analysis from classical Bayesian decision theory, see Raiffa and Schlaifer (1961), Benjamin and Cornell (1970) and Ang & Tang (1975), and adapted to the particular case of OWTs.

In Fig. 1 is shown a decision tree for RBI planning for OWTs, The basic steps in the decision process are illustrated. The decisions and random outcomes could be summarized as follows:

- In the *Initial design phase*, the optimal design parameters $z = (z_1, z_2, z_3, .., z_n)$ are determined, having certain limits z_{min}-z_{max}. The interval z_{min}-z_{max} is established according to codes and practice requirements.
- First interaction with external conditions, such as wind and wave climate; triggers a *state of nature X_o* modeled by stochastic variables/process. Random outcomes, due to high-uncertain nature; are part of the process in which reliability and simulation methods attempt to represent numerically time-deterioration process (wear, dent, corrosion, fatigue...). Model uncertainties are included here, and if the statistical basis for evaluation of the uncertainties is limited then also epistemic uncertainties will become important.
- *Monitoring activities e* at the times $t = (t_1, t_2, t_3, .., t_j)$, include inspection, sampling and analyzing actions which result in inspection results S (degree of wear and corrosion, denting level, size of fatigue cracks...) that are obtained depending on inspection quality $q = (q_1, q_2, q_3, .., q_n)$ (inspection techniques, technical expertise of inspectors...).
- Based on the obtained monitoring results, *Mitigation alternatives* will be considered according to a fixed or adapting mitigation policy $d(S)$. Such policies are related to repairing or not repairing activities.
- *State of nature X_i* indicate generation of new random outcomes. Theoretically, these outcomes are based on posterior states of nature which depend on assumptions established to simplify the RBI process, e.g. assuming that repaired components behave like new component (inducated in Fig. 1as the dashed line t_i-t_o).

In Fig. 1, $C_T(e, S, d(S), X_i)$ is the total service life costs. Overall cost optimization will be achieved by minimizing the expected value of C_T:

$$min \ E[C_T(z, e, d(S), X_i)] = C_I(z) + $$
$$E[C_{Insp}(z, e, d(S), X_i)] + $$
$$E[C_{Rep}(z, e, d(S), X_i)] + \qquad (1)$$
$$E[C_F(z, e, d(S), X_i)]$$

$$z_i^{min} \le z_i \le z_i^{max} \ , \ i=1,2, \ ....,n$$

$$\Delta P_{F,i}(t, z, e, d(S)) \le \Delta P_F^{max} \ , \ t=1,2,.....,T_L$$

$E[C_T]$ is the expected total costs in the service life T_L where C_I is the initial costs, $E[C_{Insp}]$ is the expected inspection costs, $E[C_{Rep}]$ is the expected repair costs and $E[C_F]$ is the expected failure costs. Equation (1) is constrained by limits on design parameters and that the annual probability of failure ΔP_{Ft} has to be less than ΔP_F^{max} at all times, assuring a minimum annual risk-state.
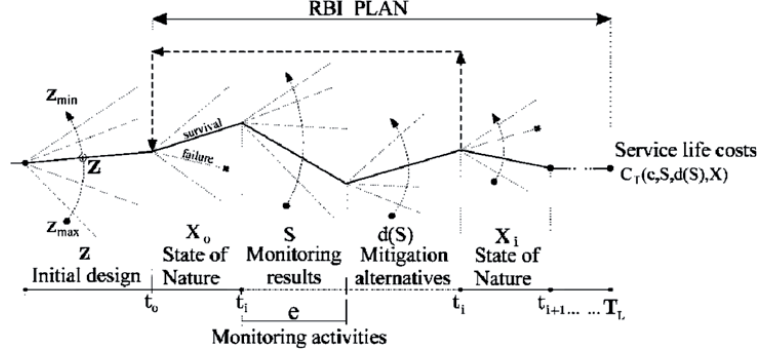
Figure 1. RBI's Decision tree.

The n inspections are performed at times t_j, i=1,2,…,n where $t_0 \leq t_1, t_2, \ldots, t_n \leq T_L$.

The total capitalized expected inspection costs are:

$$C_{Insp}(e,d(S)) = \sum_{i=1}^{n} C_{Insp,i}(q)(1 - P_F(t_i)) \frac{1}{(1+r)^t} \qquad (2)$$

where index i characterizes the capitalized inspection costs at the ith inspection when failure has not occurred earlier, $C_{Insp,i}(q)$ is the inspection cost of the ith inspection, $P_F(t_i)$ is the probability of failure in the time interval $[0,t_i]$ and r is the real rate of interest.

The total capitalized expected maintenance and repair costs are:

$$C_{Rep}(e,d(S)) = \sum_{i=1}^{n} C_{Rep,i}(q) P_{Rep,i}(t_i) \frac{1}{(1+r)^t} \qquad (3)$$

where index i characterize the capitalized reparation costs at the ith inspection when failure has not occurred earlier, $C_{Rep,i}(q)$ is the cost of maintenance and repair (incl. loss of production) at the ith inspection and $P_{R_i}(t_i)$ is the probability of performing a reparation after the ith inspection when failure has not occurred earlier and assuming no earlier repair action has been performed.

The total capitalized expected costs due to failure are:

$$C_F(e,d(S)) = \sum_{t=1}^{t_L} C_F(t) \Delta P_{F,t} P_{COL|FAT} \frac{1}{(1+r)^t} \qquad (4)$$

where index t represent the costs of failure at the time t, $C_F(t)$ is the cost of failure (incl. loss of production), $\Delta P_{F,t}$ is the annual probability of failure and $P_{COL|FAT_i}$ is the conditional probability of collapse or the structures given fatigue failure of the considering component j. It is noted that in this paper fatigue critical components are considered, implying that $P_{COL|FAT_i} = 1$. For less fatigue critical that $P_{COL|FAT_i} < 1$, and the upper limit on the annual fatigue probability of failure, ΔP_F^{max} can be increased.

Considering posterior optimization of the inspection plan, inspection and monitoring data can be use to update RBI plans making this process a recursive activity, see Sørensen et al. (1991). This approach can be used for OWTs' structural and mechanical parts (tower, blades, support structures, gears, shafts…). With inclusion of different types of components, more precise RBI should be carried out, taking into account the refinement in time intervals (years to months or day), structure conditioned-states (active or passive controlled OWTs) and non-usual or extreme external events.

Unlike oil & gas installations, OWTs response is often dominated by wind loading, including wind farm turbulence (wake effects). Wind intensity fluctuations are a significant feature to consider for fatigue failure limit state, causing typical load cycles per year ($v_{wf}=5 \times 10^7$ and $v_{rr}=1 \times 10^7$ cycles per year, wake effects and rotor response dominating case, respectively) that are larger compared with wave dominating cases (typically, $v_{wave}=1 \times 10^6$ cycles per year). Density function of stress ranges, that is obtained from the structural response by different counting methods (Rain-flow counting method, peak counting method…); will differ depending the response dominating cases. Generally, they can be modeled by a Weibull distribution.

3. Wind Load

The wind load at an offshore site is fairly different than at land sites. This variation is principally related with the difference of surface roughness, where sea roughness is typically much smaller than the land one. The wind stability statistics show that sea mean atmospheric stability is slightly on the stable side; whereas over land it is seen slightly unstable conditions on the average, see Frandsen et al. (1996). In addition to the ambient turbulence, OWTs inside of wind farms face certain unfavorable wind variations (see Fig. 2) with increase of wakes behind others OWTs and decrease of their fatigue life.

Wind load stress effects are strongly related with the type of power control (pitch or stall) in the OWT. Moreover, the response is dependent on the OWT mode: standstill or
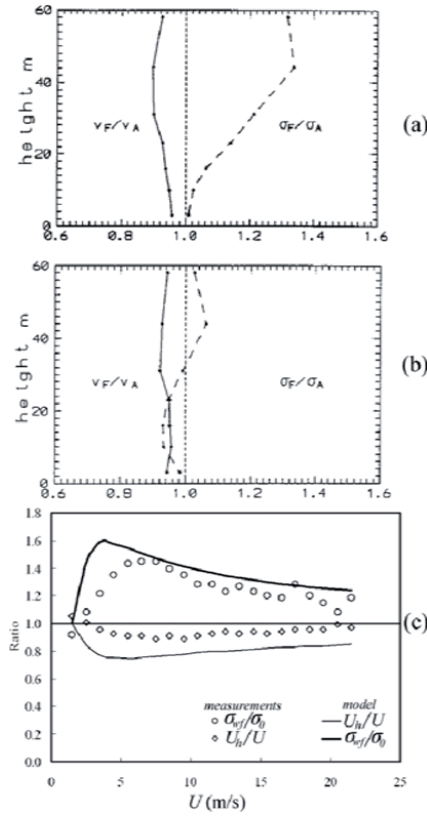
Figure 2. Ratios of wind speed (ν_F/ν_A) and standard deviation of turbulent wind speed fluctuations (σ_F/σ_A) vertical profiles inside and outside the wind farm. The indices "A" and "F" refer to meteorological mast outside of wind farm and inside wind farm, respectively. Ambient wind speed between (a) $8 < U < 12$ m/s and (b) $12 < U < 24$ m/s from Frandsen and Christensen (1994). (c) Ratios of wind speed U at hub height and turbulence σ_u inside (U_h and σ_{wf}) and outside (U and σ_0) the wind farm, as function of wind speed. The full lines are the model predictions, from Frandsen (2005).

operational. Within the operational case there are passive, active or mixed power control, assuring a rational, stable output of electricity and protecting structural and electromechanical parts.

The turbulence intensity, defined as the standard deviation of the wind speed fluctuations divided by the mean (n-minutes) wind speed; represent an important aspect to consider because of its influence on OWT's fatigue life. In this paper is used the following model for the standard deviation of wake turbulence proposed by Frandsen, S. (2005):

$$\sigma = [(1 - N_w p_w)\sigma_0^m + N_w p_w \sigma_w^m]^{1/m} \qquad (5)$$

where σ_0 is the turbulence standard deviation under free flow condition, σ_w is the maximum wake turbulence under wake condition, P_w (=0.06) is the probability of wake condition and N_w is the number of wakes to which the considered wind turbines is exposed to. It is assumed that the standard deviation of the response is proportional to the standard deviation of turbulence; while in certain situations (load, passive or active power control; complex geography, atypical terrain condition…) this simple relation with the response may be inadequate.

The above mentioned turbulence model can be shown to be consistent (with a slightly conservative inaccuracy of 3-4%) when it is used with a superimposed deterministic load component, see Frandsen (2005) and Sørensen et al. (2007).

4. Probabilistic Model for Fatigue Failure

In this section the probabilistic models for assessing the fatigue failure life based on SN-curves and fracture mechanics (FM) model are briefly presented. To evaluate the fatigue life is used the probabilistic model for fatigue failure described in Sørensen et al. (2008).

In the assessment of SN fatigue life, the deterministic design equation for free flow ambient turbulence is written:

$$G(z) = 1 - \frac{\nu \cdot FDF \cdot T_L}{K_c} \int_{U_{in}}^{U_{out}} D\ (m; \sigma_{\Delta\sigma}(U)) \cdot f_U(U) dU = 0 \quad (6)$$

where for linear SN-curve is:

$$D_L(m; \sigma_{\Delta\sigma}(U)) = \int_0^\infty s^m \cdot f_{\Delta\sigma}(s | \sigma_{\Delta\sigma} U) ds \qquad (7)$$

and bi-linear SN-curve is:

$$D\ (m_1, m_2, \Delta\sigma_D; \sigma_{\Delta\sigma}(U)) =$$

$$\int_0^{\Delta\sigma_D} s^{m_2} \cdot f_{\Delta\sigma}\left(s \Big| \alpha_{\Delta\sigma}(U) \frac{\hat{\sigma}_u(U)}{z}\right) ds$$

$$+ \int_{\Delta\sigma_D}^\infty s^{m_1} \cdot f_{\Delta\sigma}\left(s \Big| \alpha_{\Delta\sigma}(U) \frac{\hat{\sigma}_u(U)}{z}\right) ds \qquad (8)$$

$$\sigma_{\Delta\sigma}(U) = \alpha_{\Delta\sigma}(U) \cdot \frac{\sigma_u(U)}{z} \qquad (9a)$$

$$\hat{\sigma}_u(U) = I_{ref}(0.75 \cdot U + b); \qquad b = 5.6 \frac{m}{s} \qquad (9b)$$

ν is the total number of fatigue load cycles per year, FDF is the fatigue design factor ($FDF = T_F/T_L$), K_C is the characteristic value of K (mean log K minus two standard deviation of log K), U_{in} and U_{out} are the cut-in and cut-out wind speed, respectively. $f_U(U)$ is the density function of mean wind speed U, D_L is the expected value of $\Delta\sigma^m$ given standard deviation $\sigma_{\Delta\sigma}$ and mean wind speed U in

which $f_{\Delta\sigma}(s|\sigma_{\Delta\sigma}(U))$ represents the density function for stress ranges given standard deviation $\sigma_{\Delta\sigma}(U)$ at mean wind speed U. This density function and ν can be obtained by counting methods, e.g. Rainflow counting.

In the equation (9a) $\alpha_{\Delta\sigma}(U)$ is the influence coefficient for stress ranges given mean wind speed U ($\sigma_{\Delta\sigma}(U)/\sigma_U(U)$), $\sigma_u(U)$ is the standard deviation of turbulence given mean wind speed U and z is the design parameter (e.g. proportional a cross sectional area). The equation (9b) is the characteristic (90% fractil representative turbulence) ambient turbulence where I_{ref} is the (IEC-) reference turbulence intensity (equal to 0.14 for medium turbulence characteristics).

The corresponding limit state equation is:

$$g(t) = \Delta - \frac{\nu \cdot t}{K} \int_{U_{in}}^{U_{out}} \int_{0}^{\infty} \left[(X_W \cdot X_{SCF})^m \cdot D\left(m; \alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right) \right]$$
$$\cdot f_{\sigma_u}(\sigma_u|U) \cdot f_U \cdot d\sigma_u dU \qquad (10)$$

where Δ is a stochastic variable modeling the uncertainty related to the Miner's rule for linear damage accumulation, t is the life time in years, X_W is the model uncertainty related to wind load effects (exposure, assessment of lift and drag coefficients, dynamic response calculation), X_{SCF} is the model uncertainty related to local stress analysis and $\sigma_u(U)$ is modeled as Lognormal distributed with a representative mean turbulence (90% fractil value-IEC 61400-1) equal to $I_{ref}(0.75 \cdot U + 3.6)$ with a standard deviation equal to 1.4 m/s$\cdot I_{ref}$.

For a wind turbine within a wind farm the design equation based on IEC 61400-1 (IEC 2005) can be written:

$$G(z) = 1 - \frac{\nu \cdot FDF \cdot T_L}{K_C}$$
$$\cdot \int_{U_{in}}^{U_{out}} \begin{bmatrix} (1 - N_w \cdot p_w) \cdot \\ D\left(m; \alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_u(U)}{z}\right) + p_w \\ \cdot \sum_{j=1}^{N_w} D\left(m; \alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_{u,j}(U,j)}{z}\right) \end{bmatrix} \qquad (11)$$
$$\cdot f_U(U)dU = 0$$

where N_w is the number of neighboring wind turbines, p_w is the probability of wake from a neighboring wind turbine (equal to 0.06), $\sigma_{u,i}$ is the standard deviation of turbulence from neighboring wind turbine no. j:

$$\hat{\sigma}_{u,j}(U,j) = \sqrt{\frac{0.9 \cdot U^2}{\left(1.5 + 0.3 \cdot d_j\sqrt{U/c}\right)^2} + \hat{\sigma}_u^2} \qquad (12)$$

where d_j is the distance between OWT normalized by rotor diameter to the neighboring wind turbine j and c is a constant equal to 1 m/s.

The limit state equation corresponding to the above
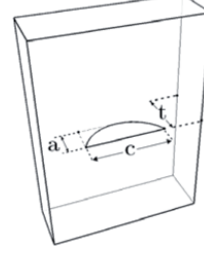
Figure 3. Surface crack idealization in plate under fatigue loads.

equation is written:

$$g(t) = \Delta - \frac{\nu \cdot t}{K} \int_{U_{in}}^{U_{out}} \int_{0}^{\infty} (X_w \cdot X_{SCF})^m$$
$$\cdot \begin{bmatrix} (1 - N_w \cdot p_w) \cdot D\left(m; \alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_u(U)}{z}\right) \\ + p_w \cdot \sum_{j=1}^{N_w} D\left(m; \alpha_{\Delta\sigma}(U)\frac{\sigma_{u,j}(U,j)}{z}\right) \end{bmatrix} \qquad (13)$$
$$\cdot f_U(U) \cdot f_{\sigma_u}(\sigma_u|U) \cdot d\sigma_u dU$$

$$\sigma_{u,j}(U,j) = \sqrt{\frac{X_{wake} \cdot U^2}{\left(1.5 + 0.3 \cdot d_j\sqrt{U/c}\right)^2} + \sigma_u^2} \qquad (14)$$

where X_{wake} is the model uncertainty related with **wake** turbulence model. The design parameter z is calculated using (6) or (11) and then used in limit state equations (10) or (13) to estimate the reliability index or probability for failure corresponding to the reference time t.

For the assessment of fracture mechanics (FM) fatigue life is used a one dimension crack model (see Fig. 3) where the crack length c is for simplicity related with the crack depth a through a constant f_a. A coupled model could also be used, but is computationally much more time-consuming, especially when performing reliability assessments. It is assumed that the fatigue life may be represented by fatigue initiation life and a fatigue propagation life. This is represented as follows:

$$N = N_I + N_P \qquad (15)$$

where N is the number of stress cycles to fatigue failure, N_I the number of stress cycles to crack propagation and N_P is the number of stress cycles from initiation to crack through. The crack growth can be described by the following equations:

$$\frac{da}{dN} = C_A(\Delta K_A)^m, a(N_0) = a_0 \qquad (16)$$

$$\Delta K_A = \Delta\sigma \cdot \sqrt{\pi a} \qquad (17)$$

$$c(f_a \cdot a_0) = c_0 \qquad (18)$$

where C_A and m are the material parameters, a_0 and c_0 describe the initial crack depth a and crack length c, respectively, after N_I cycles and where the stress intensity range is ΔK_A.

The stress range $\Delta\sigma$ is obtained from:

$$\Delta\sigma = Y \cdot \Delta\sigma^e \qquad (19)$$

where Y is the model uncertainty variable related to the geometry function and $\Delta\sigma^e$ is the equivalent stress range. $\Delta\sigma^e$ for a single OWT is calculated with:

$$\Delta\sigma^e = X_W \cdot X_{SCF} \cdot \left[\int_{U_{in}}^{U_{out}} \int_0^\infty D\left(m; \alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right)^m \cdot f_U(U) \cdot f_{\sigma_u}(\sigma_u|U) \cdot d\sigma_u dU \right]^{\frac{1}{m}} \qquad (20)$$

and for a wind farm location case:

$$\Delta\sigma^e = X_W \cdot X_{SCF}$$
$$\cdot \left[\int_{U_{in}}^{U_{out}} \int_0^\infty \begin{array}{c} (1-N_w p_w) \cdot D\left(m; \alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right) \\ + p_w \cdot \sum_{j=1}^{N_w} D\left(m; \alpha_{\Delta\sigma}(U)\frac{\sigma_{u,j}(U,j)}{z}\right) \\ \cdot f_U(U) \cdot f_{\sigma_u}(\sigma_u|U) \cdot d\sigma_u \end{array} dU \right] \qquad (21)$$

The limit state criteria used in the FM analysis is related with the failure when crack exceeds a critical crack size:

$$g(t) = a_c - a(t) \qquad (22)$$

where a_c is the critical crack size and a is crack depth.

For RBI planning the FM model is usually calibrated to result in the same reliability level as the code-based SN model. The RBI planning and maintenance are strongly related with inspection quality (inspection methods, technology, environmental conditions, inspectors' expertise, etc). The incorporation of these influential factors is attained by using a distribution of the smallest detectable crack size by a so-called probability of detection curve (POD). Examples of POD curves are:

$$POD(x) = 1 - 1 \Big/ \left[1 + \left(\frac{x}{x_0}\right)^b \right] \qquad (23)$$

$$POD(x) = P_O \cdot (1 - exp(-x/\lambda)) \qquad (24)$$

where x_0 and λ are the minimum detectable crack size, P_O and b are distribution parameters depending on the inspection methods.

5. Examples

An offshore wind turbine with a steel jacket support structure is considered. The OWT is assumed to have an expected life time equal to 20 years and a design fatigue life time (T_F) equal to 60 years. For the Influence
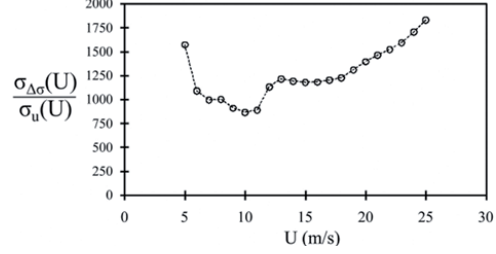
Figure 4. $\sigma_{\Delta\sigma}/\sigma_U$ for mudline bending moment for a representative pitch controlled wind turbine.

coefficient $\alpha_{\Delta\sigma}(U)$ is used the function in Fig. 4 (mudline bending moment-pitch controlled wind turbine) regarding this as a representative function for the stress effects in the support structure. This influence function is highly non-linear due to the control system.

A wind turbine within a wind farm (IWF) and a standalone/single (S) OWT location are considered. For each location is considered linear (L) and bi-linear (BL) SN-curve. In Tables 1-3 are shown the stochastic models used.

The design values z for each case are shown in Table 4 (Equations 6 and 11) and in Fig. 5 is shown the results of the assessment of the reliability with SN approach (Equations 10 and 13). β and $\Delta\beta$ are defined as the cumulative probability of failure (P_F) and the annual probability (ΔP_F) of failure ($\beta = (\Phi^{-1}(P_F(t))$ and $\Delta\beta = (\Phi^{-1}(P_F(t)) - \Phi^{-1}(P_F(t-1)))$), respectively. It is seen that for bilinear SN-curve values of β and z are smaller than for linear cases. The design values for cases in wind farm location (wake turbulence) are larger than the ones exposed to free flow turbulence due to the accumulation of fatigue.

Table 1. SN Stochastic model (welded steel detail)

Variable	Distribution	Expected value	Standard deviation
Δ	N	1.0	0.10
X_W	LN	1.0	0.10
X_{SCF}	LN	1.0	0.10
X_{wale}	LN	1.0	0.15
m_1	D	3	--
m_2	D	5	--
$\Delta_{\sigma D}$	D	71 MPa	--
$\text{Log } K_1$	N	Determined from $\Delta_{\sigma D}$	0.20
$\text{Log } K_2$	N	Determined from $\Delta_{\sigma D}$	0.25
T_F	D	60 years	--
Nw	D	5/--	--
ν	D	$5 \cdot 10^7$	--
U_{in}-U_{out}	D	5-25 m /s	--
p_w	D	0.06/0.0	--
d_j	D	4.0	--

D: Deterministic, N: Normal, LN: LogNormal, W: Weibull.

Table 2. FM Uncertainty modeling (welded steel detail)

Variable	Distribution	Expected value	Standard-deviation
Ln Cc	N	μ_{lncr} (fitted)	0.77
N_I	W	$\mu_0 = T_{inil}$	$0.35 \cdot \mu_0$
Y	LN	1.0	0.10
W_X	LN	1.0	0.10
X_{SCF}	N	1.0	0.10
X_{wale}	LN	1.0	0.15
a_c	D	50 mm	--
a_0	D	0.4 mm	--
f_{cr}	D	4.0	--
Thickness	D	50 mm	--
m	D	3.0	--

Table 3. Distribution parameters and Equations

Variable	Distribution	Parameters
ΔP_F	D	$1.0 \cdot 10^{-3} / 1.0 \cdot 10^{-4}$
$F_U(u)$	$W(\alpha, \beta_U)$	$\alpha = 2.3$, $\beta_U = 10.0$ m/s
$f_{\Delta\sigma D}(\cdot)$	$W(\alpha_{\Delta\sigma D}, \beta_{\Delta\sigma D})$	$\alpha_{\Delta\sigma D} = 0.8$
$f_{\sigma u}(\cdot)$	$LN(\mu, \sigma)$	$\mu = I_{ref}(0.75 \cdot U_j + 3.6)$, $\alpha = 1.4 \cdot I_{ref}$
$POD(x)$	Equation (4.19)	$P_O = 1.0$, $l = 2.67$ mm^{-1}
$N_1(s)$	$K_1 \cdot s^{-m_1}$	$s \geq \Delta\sigma_D$
$N_2(s)$	$K_2 \cdot s^{-m_2}$	$s < \Delta\sigma_D$

Table 4. z-design parameters

IWF-L	S-L	IWF-BL	S-BL
0.5654	0.4934	0.4253	0.3657

Figure 5. Reliability indices for SN-approach corresponding to an cumulative probability of failure

For all the cases the calibration of fracture mechanic reliability curve in the interval 10 to 20 years (see Fig. 6).
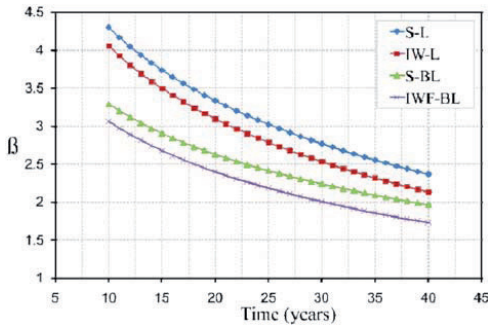
In Figs. 7a-d and Table 5 are shown the resulting life-cycle assessment of reliability and inspection plan
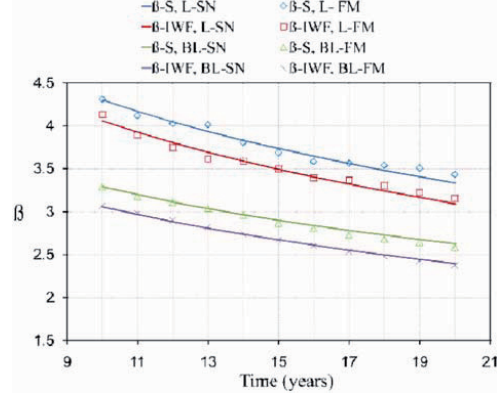
Figure 6. Reliability indices for SN- and calibrated fracture mechanics curve corresponding to the cumulative probability of failure.

obtained with a maximum acceptable annual probability of failure equal to 1.0×10^{-3} and 1.0×10^{-4}. Comparing the first inspection time, slightly earlier inspections are obtained for in-wind farm sites due to the increase of fatigue coming from wake turbulence. It is noted that in all four cases the design parameter z is determined by deterministic design such that the code-based design criteria is exactly satisfied.

5. Conclusions

Based on risk-based inspection planning methods for oil & gas installations, a framework for optimal inspection and maintenance planning was applied for offshore wind turbines, addressing the analysis of fatigue prone details (single hot spots in the context of RBI for this work) at the jacket or tripod steel support structures. In wind park location and single offshore wind turbines were considered using a probabilistic model for fatigue failure based on the code used for wind turbine design. This inspection optimization approach represents a viable method to obtain risk-based inspection plans aimed at OWT, regarding its application to large structural systems (steel jacket, tripod and monopile as support structures). Furthermore, it may also be applied to other important components like blades, nacelle, yaw system, etc (see Sørensen *et al.* 2008). Due to the fast growth of wind industry (EWEA 2007) and offshore wind turbine parks, larger and complex clusters of such structural systems may potentially be benefited for optimizing the inspection and maintenance efforts and generate suitable inspection plans ensuring an acceptance criteria with respect to risk. Besides, this RBI approach may also be applied as a decision tool for estimating the consequences of a possible service life extensions and reduction (or strengthening) on the necessary maintenance and inspection efforts.
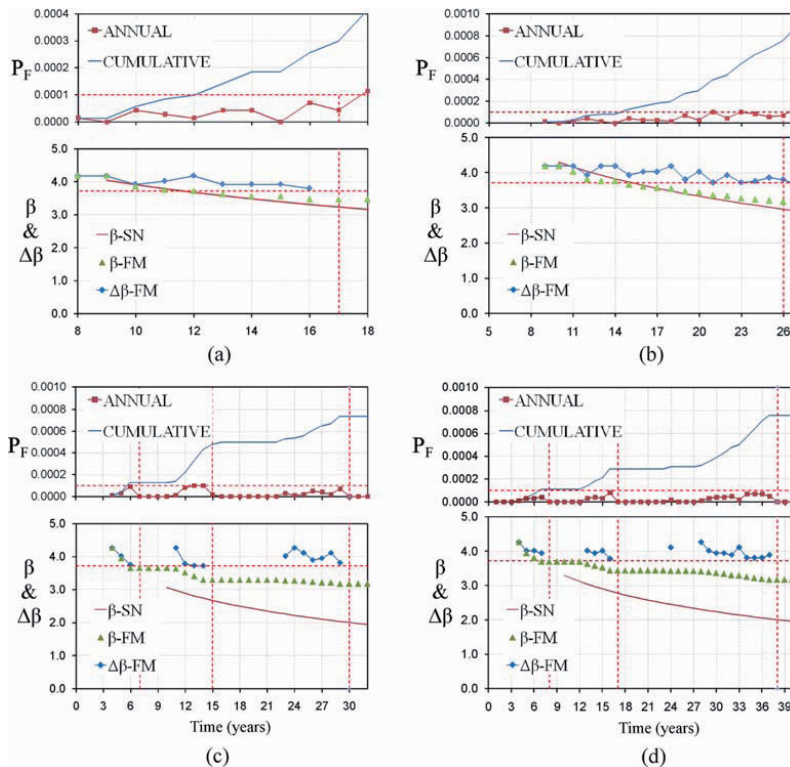
Figure 7. Annual and cumulative probability of failure as a function of time ($\Delta P_F^{max} = 1 \times 10^{-4}$ and reliability indices corresponding to the cumulative and annual probability of failure. (a) In wind farm OWT with linear SN-curve. (b) Single OWT with linear SN-curve. (c) In wind farm OWT with bilinear SN-curve. (d) Single OWT with bilinear SN-curve.

Table 5. Inspections times as a function of the threshold on the maximum annual probability of failure

	INSPECTION TIME	
	Maximum Annual P_f	
CASE	1×10^{-3}	1×10^{-4}
IWF-L	--	17
S-L	--	26
IWF-BL	17	7,15,30
S-BL	23	8,17,38

Acknowledgments

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Paper III

Maintenance Planning of Offshore Wind Turbines Using Condition Monitoring Information

OMAE09-79159

MAINTENANCE PLANNING OF OFFSHORE WIND TURBINE USING CONDITION MONITORING INFORMATION

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ABSTRACT

Deterioration processes such as fatigue and corrosion are typically affecting offshore structures. To "control" this deterioration, inspection and maintenance activities are developed. Probabilistic methodologies represent an important tool to identify the suitable strategy to inspect and control the deterioration in structures such as offshore wind turbines (OWT). Besides these methods, the integration of condition monitoring information (CMI) can optimize the mitigation activities as an updating tool.

In this paper, a framework for risk-based inspection and maintenance planning (RBI) is applied for OWT incorporating CMI, addressing this analysis to fatigue prone details in welded steel joints at jacket or tripod steel support structures for offshore wind turbines. The increase of turbulence in wind farms is taken into account by using a code-based turbulence model. Further, additional modes t integrate CMI in the RBI approach for optimal planning of inspection and maintenance.

As part of the results, the life cycle reliabilities and inspection times are calculated, showing that earlier inspections are needed at in-wind farm sites. This is expected due to the wake turbulence increasing the wind load. With the integration of CMI by means Bayesian inference, a slightly change of first inspection times are coming up, influenced by the reduction of the uncertainty and harsher or milder external agents.

INTRODUCTION

The inspection and maintenance costs for offshore wind farms are in general significantly larger than for onshore structures. Besides economical aspects, the restrictions in time (season) and location (structural part and offshore location) are present, implying more complex inspection and maintenance activities for OWT

During the last decades RBI approaches have been applied to the oil and gas industry (see e.g. Madsen et al. 1987, Thoft-Christensen and Sørensen 1987, Sørensen and Faber 1991, Faber et al. 1992), giving a theoretical background that can also be applied for offshore wind industry considering its particular implications, i.e. wind dominated loading, wind farm locations and internal dependence of different components (mechanical, electrical and structural.

The offshore wind resources have been monitored since the beginning of the 1990's for many purposes such as to investigate the characteristics of prospective wind energy sites in the coastal waters, development and validation of models and monitoring of the performance of the wind turbines in wind farms. This information can be integrated into the RBI approach taking into account the type of information.

The typical support structure for an OWT in shallow water is a monopile, whereas jacket and tripod support structures can be used for larger depths, implying technical improvements as for instance, increased structural redundancy, lighter weight and larger stiffness (influencing the dynamical behavior). For these structures, transition sections 'tower-to-support' and joints are critical design parts, needing special careful design especially with respect to fatigue. Offshore wind farm locations require additional considerations due to the turbulence conditions that affect the performance of neighboring wind turbines decreasing their fatigue life.

In this paper, it is described how CMI can be integrated into a RBI format and applied to OWT addressing fatigue prone structural details.

MONITORING INFORMATION

Due to the desire to increase the efficiency and competitiveness of wind industry in compliance with safety standards and requirements, surveillance systems have been developed. These monitoring systems can be divided in external monitoring information (meteorological measurements) and structural condition monitoring (including mechanical, electrical, structural and electronic parts), having both two aspects: measuring technology (infrastructure, instrumentation and/or measuring devices technology) and data processing (data availability and quality control, processing and diagnostic algorithm, etc).

External measurements for offshore wind farms have been carried out since the beginning of the 1990's (see e.g. Barthelmie et al. 2005, Frandsen et al. 1996), having as main objectives to obtain project-related, long- and short-term data. Within meteorological measurements, the data processing phase will focus on finding the probabilistic properties and characteristics of the external agents (wind, wave, turbulence, geographical influence, etc) and then processing the records with suitable algorithms to maximize the benefit from it.

The components in the OWT may be grouped together considering their reliability against deterioration failure and basically related with their design. High reliabilities are associated with components for which the replacement of the entire component or sub-system is not feasible, neither economically nor technically and their failure will result in a whole system failure, e.g. support structure, transition node and tower. Medium reliabilities for components that are possible to replace or can be replaced but their damage could entail further additional deterioration or direct failure in other components. Finally, low reliability parts are those that are replaced even considering their relative high cost (mainly, parts in wind energy converter, WEC). Monitoring of all three groups of components can be implemented with a condition monitoring system (CMS, see Giebel et al. 2004, Wiggelinkhuizen et al. 2008 and Hameed et al. 2007). It is noted that in the WEC (low and medium reliability components), condition monitoring has become an important issue with a noteworthy increase in conditioning monitoring techniques, deterioration/failure detection algorithms and measuring technology. The high reliability components are only considered in this work within a RBI framework, but in general this probabilistic format based on Structural Reliability Analysis (SRA) and pre-posterior Bayesian decision theory can be implemented for the other types of components.

For jacket and tripod's structural parts such as transition node between the tower and support structure, tower, blades, nacelle, yaw mechanism and hub are important components triggering major consequences in case of failure. For these components, the surveillance activities could be divided in CMS and inspection activities. In CMS monitoring can be carried out as measurements of important spots (stress/strain monitoring), dynamical performance of members (inertial sensing, vibration characteristics) and acoustic emissions. Moreover, the long-term inspection activities are providing data related with the damage (corrosion, cracking, denting, wear and scour condition) through different methods depending on the type of deterioration.

With this real-time information and sequential inspection actions, a gain in information is achieved, making possible the updating of modeling parameters and improvements in accuracy of prediction, e.g. long- and short-term wind intensity distribution, wave conditions, turbulence conditions and damage presence in certain details.

RISK-BASED INSPECTION PLANNING AND CONDITION MONITORING

RBI represents an effective method to deal with structures exposed to deterioration. It has to be linked with a decision tool to identify the most suitable strategy. The decision analysis will accomplish the task of directing the necessary and sufficient mitigation activities, based on information previously collected. The RBI methodology, as an application of Bayesian decision analysis (see Raiffa and Schlaifer, 1961 and Benjamin and Cornell, 1970) and based on SRA; aims at finding the optimal inspection and maintenance strategy that can be updated using e.g. CMI. The inclusion of these data can be achieved through updating and inference of data.

In the updating process variables, parameters and events are updated using new information. The RBI methodology is concerned with updating using events at the moment of finding the suitable inspection and maintenance strategy. The stochastic variables are fixed for the periods when the information is collected in the life-cycle. At updating, a limit state function $g(x_1,x_2,...,x_i)$ is formulated as a function of i stochastic variables and an event function $h(x_1,x_2,...,x_i)$ representing the new information, is considered jointly. The conditional probability of failure is denoted by $P(g(x_1,...,x_i)\leq 0 \,|h(x_1,...,x_i)\leq 0)$. In RBI, the limit state function could be related to fatigue failure and the event function can be the no-detection-of-cracks at the inspection.

Bayesian statistical methods can be used to update the density functions $f_{X_i}(x_i,q_i)$ of stochastic variables x_i considering the vector of the distribution parameters q_i as uncertain. Denoting the prior density function $f'_Q(q_i)$ and assuming that j realizations of the stochastic variable X_i are available: $\hat{x}_i=(\hat{x}_{i,1},\hat{x}_{i,2},...,\hat{x}_{i,j})$, the posterior density function is:

$$f''_Q(q_i|\hat{x}_i)\propto f''(\hat{x}_i|q_i)\cdot f'_Q(q_i) \qquad (1)$$

where

$$f''(\hat{x}_i|q_i)=\prod_{j=1}^{N} f_{X_i}(\hat{x}_{i,j},q_i) \qquad (2)$$

Equation (2) gives the probability of obtaining the given observations assuming that the distribution parameters are q_i. The updated density function of the stochastic variable X_i given the realization $\hat{x}_i$ is obtained by the predictive density function:

$$f_{X_i}(x|\hat{x}_i)=\int f_{X_i}(x_i|q_i)\cdot f''_Q(q_i|\hat{x}_i)dq_i \qquad (3)$$

2

In addition to direct updating of stochastic variables, another way to incorporate CMI consists in using this information as realizations $\hat{h}$ of the event function $h(x_1,x_2,...,x_i)$ that takes into consideration variables involved in the SRA to subsequently infer (for example, through calibration) additional information through it. E.g. once a crack length $\hat{h}_{crack,j}$ is measured, then the function $h_{crack,j}(C_c,a_o,...,t_j)$ related with crack growth ratio, and initial crack length at a specific time j, can be used to estimate these parameters and next to update the inspection plan.
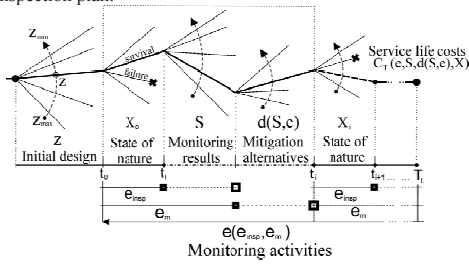

Fig. 1 RBI decision tree

RBI for individual details can be illustrated as shown in figure 1 with the following 'steps':

- *Initial design phase*, in which the optimal design parameters $z=(z_1,z_2,z_3...,z_n)$ are determined, having certain limits z_{min}-z_{max}. These intervals are established according to codes and practical requirements.

- First interaction with external conditions, such as wind, wave and turbulence; cause an initial *state of nature Xo*.

This random outcome, due to high-uncertain nature, is the part of the process in which reliability and simulation methods attempt to represent numerically time-deterioration processes dealing with model uncertainties at the same time.

- *Monitoring activities* "*e*" during the life-cycle are developed, including inspections and condition monitoring. The continuous surveillance can come up with the needing of inspection "e_{insp}" (and next inspection results "S", e.g. corrosion, denting level, size of fatigue cracks...) or directly with unsatisfactory performance records (or meteorological measurement triggering undesirable states of nature) and then a suitable mitigation alternative. The inspection results will depend on inspection quality $c=(c_1,c_2,c_3...,c_n)$ (inspection techniques, technical expertise of inspectors...) and in the case of the condition monitoring will lie in a failure-detection and diagnostic algorithm.

- Based on the obtained monitoring results or unsatisfactory performance records, *mitigation alternatives* will be considered according to the mitigation policy *d(S,e)*. In case of having any unsatisfactory performance recordings or extreme external events, the suitable mitigation alternative will be selected, i.e. based on records and measurements, a failure-detection algorithm can come up with the location of failure, diagnostic and possible mitigation alternatives *d(S,e)*. Such policies are related to repairing or not repairing activities.

- *State of nature Xi* at the *i*th inspection/maintenance represents the beginning of new random outcomes. Theoretically, posterior states of nature depend on assumptions established to simplify the RBI process, e.g. assuming that repaired components behave like new component and repaired parts will have no indication of damage at the inspection.

In Figure 1, $C_T(e,S,d(S,e),X_i)$ is the total service life cost. Overall cost optimization will be achieved by minimizing the expected value of C_T:

$$\min E[C_T(z,e,d(S),X_i)]=$$
$$+C_I(z)+E\left[C_{Insp}(z,e,d(S,e),X_i)\right]$$
$$+E\left[C_{Rep}(z,e,d(S,e),X_i)\right] \quad (4)$$
$$+E\left[C_F(z,e,d(S,e),X_i)\right]$$

$$z_i^{min}\leq z_i\leq z_i^{max} , i=1,2,....,n$$

$$\Delta P_{F,t}\left(t,z,e,d(S)\right)\leq\Delta P_F^{max}, \quad t=1,2,...., T_L$$

where $E[C_T]$ is the expected total costs in the service life T_L, C_I is the initial costs, $E[C_{Insp}]$ is the expected inspection costs, $E[C_{Rep}]$ is the expected reparation costs and $E[C_F]$ is the expected failure costs. Equation (4) is constrained by limits on design parameters and that the annual probability of failure $\Delta P_{F,t}$ has to be less than ΔP_F^{max} at all times, assuring a maximum annual risk-state. The n inspections are performed at times t_i, $i=1,...,n$ where $t_0\leq t_1$, t_2, ...,$t_n\leq T_L$.

PROBABILISTIC FATIGUE FAILURE MODEL

In this section the probabilistic models for assessing the fatigue failure life based on SN-curves (SN) and the fracture mechanics (FM) model are briefly described. To evaluate the fatigue life is used the probabilistic model for fatigue failure described in Sørensen et al. (2007) and using the turbulence model proposed by Frandsen (2005).

In the assessment of the SN fatigue life, the design equations consider the fatigue damage from cut-in and -out wind speed accumulated during the whole life cycle. The deterministic design equation for a wind turbine in free wind flow is written:

$$G(z)=1-\frac{v\cdot FDF\cdot T_L}{K_C}\int_{U_{in}}^{U_{out}} D\left(m;\sigma_{\Delta\sigma}(U)\right)\cdot f_U(U)\ dU=0 \quad (5)$$

where for linear SN-curves:

$$D\left(m;\sigma_{\Delta\sigma}(U)\right)=\int_0^\infty s^m\cdot f_{\Delta\sigma}\left(s|\sigma_{\Delta\sigma}(U)\right) ds \quad (6)$$

and for bi-linear SN-curves:

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$$D\left(m_1,m_2,\Delta\sigma_D\ ;\sigma_{\Delta\sigma}(U)\right)=$$

$$\int_0^{\Delta\sigma_D} s^{m_2}\cdot f_{\Delta\sigma}\left(s\middle|\alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_u(U)}{z}\right)ds \tag{7}$$

$$+\int_{\Delta\sigma_D}^{\infty} s^{m_1}\cdot f_{\Delta\sigma}\left(s\middle|\alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_u(U)}{z}\right)ds$$

$$\sigma_{\Delta\sigma}(U)=\alpha_{\Delta\sigma}(U)\cdot\frac{\sigma_u(U)}{z} \tag{8}$$

$$\hat{\sigma}_u(U)=I_{ref}\cdot(0.75\cdot U+b)\quad,\quad b=5.6\frac{m}{s} \tag{9}$$

ν is the total number of fatigue load cycles per year, FDF is the fatigue design factor (FDF=T_F/T_L), K_C is the characteristic value of K (mean log K minus two standard deviation of log K), U_{in} and U_{out} are the cut-in and cut-out wind speed, respectively; $f_U(U)$ is the density function of mean wind speed U, D_L is the expected value of $\Delta\sigma^m$ given standard deviation $\sigma_{\Delta\sigma}$ and mean wind speed U in which $f_{\Delta\sigma}\left(s\middle|\sigma_{\Delta\sigma}(U)\right)$ represents the density function for stress ranges given standard deviation $\sigma_{\Delta\sigma}(U)$ at mean wind speed U. This density function and ν can be obtained by counting methods, e.g. Rainflow counting.

In the equation (8), $\alpha_{\Delta\sigma}(U)$ is the influence coefficient for stress ranges given mean wind speed U defined as ($\alpha_{\Delta\sigma}(U)=\sigma_{\Delta\sigma}(U)/\sigma_U(U)$), where $\sigma_u(U)$ is the standard deviation of turbulence given mean wind speed U and z is the design parameter (e.g. proportional a cross sectional area). Equation (9) gives the characteristic (90% fractile representative turbulence) ambient turbulence where I_{ref} is the (IEC-61400) reference turbulence intensity (equal to 0.14 for medium turbulence characteristics). The corresponding limit state equation is:

$$g(t)=\Delta-\frac{\nu\cdot t}{K}\int_{U_{in}}^{U_{out}}\int_0^{\infty}\left[(X_W\cdot X_{SCF})^m\cdot D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right)\right]$$
$$\cdot f_{\sigma_u}(\sigma_u|U)\cdot f_U(U)\cdot d\sigma_u\ dU \tag{10}$$

where Δ is a stochastic variable modeling the uncertainty related to the Miner rule for damage accumulation, t is the life time in years, X_W is the model uncertainty related to wind load effects (exposure, assessment of lift and drag coefficients, dynamic response calculation), X_{SCF} is the model uncertainty related to local stress analysis and $\sigma_u(U)$ is modeled as a lognormal distributed stochastic variable with a representative mean turbulence level obtained from a 90% fractile value (see IEC 61400-1) equal to $I_{ref}(0.75\cdot U+3.6)$ and a standard deviation equal to 1.4 m/s $\cdot I_{ref}$.

For a wind farm location the design equation is based on IEC 61400-1 (IEC 2005):

$$G(z)=1-\frac{\nu\cdot FDF\cdot T_L}{K_C}\cdot\int_{U_{in}}^{U_{out}}\left[\begin{array}{c}(1-N_w\cdot p_w)\cdot\\ D\left(m;\alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_u(U)}{z}\right)\\ +p_w\\ \cdot\sum_{j=1}^{N_w}D\left(m;\alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_{u,j}(U,j)}{z}\right)\end{array}\right]$$
$$\cdot f_U(U)\ dU=0 \tag{11}$$

where N_w is the number of neighboring wind turbines, p_w is the probability of wake from a neighboring wind turbine (equal to 0.06), $\hat{\sigma}_{u,j}$ is the standard deviation of turbulence from neighboring wind turbine no. j:

$$\hat{\sigma}_{u,j}(U,j)=\sqrt{\frac{0.9\cdot U^2}{\left(1.5+0.3\cdot d_j\sqrt{U/c}\right)^2}+\hat{\sigma}_u{}^2} \tag{12}$$

d_j is the distance between OWT normalized by rotor diameter to the neighboring wind turbine j and c is a constant equal to 1 m/s.

The limit state equation corresponding to the above design equation is:

$$g(t)=\Delta-\frac{\nu\cdot t}{K}\int_{U_{in}}^{U_{out}}\int_0^{\infty}(X_W\cdot X_{SCF})^m$$
$$\cdot\left[\begin{array}{c}(1-N_w\cdot p_w)\cdot\ D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right)\\ +p_w\sum_{j=1}^{N_w}D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_{u,j}(U,j)}{z}\right)\end{array}\right]$$
$$\cdot f_U(U)\cdot f_{\sigma_u}(\sigma_u|U)\cdot d\sigma_u\ dU \tag{13}$$

$$\sigma_{u,j}(U,j)=\sqrt{\frac{X_{wake}\cdot U^2}{\left(1.5+0.3\cdot d_j\sqrt{U/c}\right)^2}+\sigma_u{}^2} \tag{14}$$

where X_{wake} is the model uncertainty related with the wake turbulence model. The design parameter z is obtained from (5) or (11) and then used in limit state equation (10) or (13) to estimate the reliability index or the probability of failure for the reference time t.

For assessment of the FM fatigue life a one-dimensional crack model is used for illustration. The crack length c is related with the growth crack depth a through a constant f_{cr}. It is assumed that the total fatigue life may be represented by fatigue initiation life and a fatigue propagation life. This is modeled as follows:

$$N=N_I+N_P \tag{15}$$

where N is the number of stress cycles to fatigue failure, N_I is the number of stress cycles to crack propagation and N_P is the number of stress cycles from initiation to crack through. The crack growth can be described by the following equations:

$$\frac{da}{dN}=C_A(\Delta K_A)^m \quad , \qquad a(N_o)=a_o \tag{16}$$

$$\Delta K_A=\Delta\sigma\cdot\sqrt{\pi a} \tag{17}$$

$$c(f_{cr}\cdot a_o)=c_o \tag{18}$$

C_A and m are the material parameters, a_o and c_o describe the initial crack depth a and crack length c, respectively, after N_I cycles and the stress intensity range is denoted ΔK_A. The stress range $\Delta\sigma$ is obtained from:

$$\Delta\sigma=Y\cdot\Delta\sigma^e \tag{19}$$

where Y is the model uncertainty variable related to geometry function and $\Delta\sigma^e$ is the equivalent stress range. $\Delta\sigma^e$ for a single OWT is calculated with:

$$\Delta\sigma^e=X_W\cdot X_{SCF}\cdot\left[\int_{U_{in}}^{U_{out}}\int_0^\infty D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right)^{\frac{1}{m}} \cdot f_U(U)\cdot f_{\sigma_u}(\sigma_u|U)\, d\sigma_u\, dU\right] \tag{20}$$

and for a wind farm location case:

$$\Delta\sigma^e=X_W\cdot X_{SCF}$$

$$\cdot\left[\int_{U_{in}}^{U_{out}}\int_0^\infty \begin{bmatrix}(1-N_w\cdot p_w)\cdot D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right)\\ +p_w\cdot\sum_{j=1}^{N_w} D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_{u,j}(U,j)}{z}\right)\end{bmatrix} dU \cdot f_U(U)\cdot f_{\sigma_u}(\sigma_u|U)\, d\sigma_u\right]^{1/m} \tag{21}$$

The limit state equation used in the FM analysis is modeled by the failure event that the crack depth a(t) exceeds a critical crack size a_c:

$$g(t)=a_c-a(t) \tag{22}$$

For RBI planning the FM model is usually calibrated such that the same reliability level is obtained as using the code-based SN model. The RBI planning is strongly related with inspection quality (inspection methods, technology, environmental conditions, inspectors' expertise, etc). The incorporation of these influential factors is attained by using a stochastic model for the smallest detectable crack size by a probability of detection curve (POD).

EXAMPLES

An offshore wind turbine with a steel jacket support structure is considered as support of an OWT. OWT's have an expected life time typically equal to 20 years and a design fatigue life time (T_F) of 60 years. For the Influence coefficient $\alpha_{\Delta\sigma}(U)$ is used the function shown in figure 2 representing the mud-line bending moment in a pitch controlled wind turbine. It can be considered as a representative function for details in the support structure. This influence function is highly non-linear due to the influence of the control system.
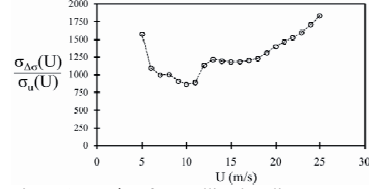
Figure 2. $\sigma_{\Delta\sigma}/\sigma_U$ for mudline bending moment – pitch controlled wind turbine.

Wind turbines in a wind farm (IWF) and standing alone/single (S) are considered. For each location is considered a linear (L) and a bi-linear (BL) SN-curve for a welded steel detail. In tables 1 to 3 are shown the stochastic models and parameters used.

Table 1. SN stochastic models

Variable	Distribution	Expected value	Standard deviation	Comment
Δ	N	1.0	0.10	Damage accumulation
X_W	LN	1.0	0.15	Wind
X_{SCF}	LN	1.0	0.10	Stress concentration factor
X_{wake}	LN	1.0	0.15	Wake
m_1	D	3.0	--	SN-curve. Wöhler Exponent (linear)
m_2	D	5.0	--	SN-curve. Wöhler Exponent (bi-linear)
$\Delta_{\sigma D}$	D	71 MPa	--	Constant amplitude fatigue limit
$Log\ K_1$	N	Determined from $\Delta_{\sigma D}$	0.20	Material parameter
$Log\ K_2$	N	Determined from $\Delta_{\sigma D}$	0.25	Material parameter
T_F	D	60 years	--	Fatigue life
N_w	D	5/--	--	In-wind farm/single OWT
ν	D	$5\cdot10^7$	--	Fatigue cycles per year
U_{in}- U_{out}	D	5 – 25 m/s	--	Cut in – out velocities
p_w	D	0.06/0.0	--	In-wind farm/single OWT
d_j	D	4.0	--	Normalized distance of OWT
$Log\ K_1$ and $Log\ K_2$ are assumed fully correlated				

D: Deterministic, N:Normal, LN:LogNormal, W:Weibull

Table 2. FM stochastic models

Variable	Distribution	Expected value	Standard deviation	Comment
Ln C_c	N	$\mu_{ln\,Cc}$ (fitted)	0.7	Crack growth ratio
N_I	W	$\mu_0 = T_{init} \cdot \nu$	$0.35 \cdot \mu_0$	T_{init}(fitted), Initiation Time
Y	LN	1.0	0.10	Shape factor
X_W	LN	1.0	0.15	Wind
X_{SCF}	N	1.0	0.10	Stress concentration factor
X_{wake}	LN	1.0	0.15	Wake
a_c	D	25 mm	--	Critical crack size
a_o	D	0.4 mm	--	Initial crack size
f_{cr}	D	3.0	--	Crack length/depth ratio
thickness	D	25 mm	--	thickness
m	D	3.0	--	Material parameter
Ln C_c and N_I are correlated with correlation coefficient $\rho_{ln\,Cc,\,N_I} = -0.5$				

Table 3. Distribution parameters and equations

Variable	Distribution	Parameters
P_F	D	$1.0 \cdot 10^{-4}$
$F_U(u)$	$W(\alpha, \beta_U)$	$\alpha=2.3$, $\beta_U=10.0$ m/s
$f_{\Delta\sigma_D}(\cdot)$	$W(\alpha_{\Delta\sigma_D}, \beta_{\Delta\sigma_D})$	$\alpha_{\Delta\sigma_D}=0.8$
$f_{\sigma_u}(\cdot)$	$LN(\mu,\sigma)$	$\mu=I_{ref}\cdot(0.75\cdot U_i+3.6)$, $\sigma=1.4\cdot I_{ref}$
POD(x)	$P_O \cdot (1-exp(-x/\lambda))$	$P_O=1.0$, $\lambda=2.67$ mm
$N_1(s)$	$K_1 \cdot s^{-m_1}$	$s \geq \Delta\sigma_D$
$N_2(s)$	$K_2 \cdot s^{-m_2}$	$s < \Delta\sigma_D$

As a simple illustration of CMI integration, X_W will be updated. It is assumed that the standard deviation is known equal to 0.14. The *prior* density function will be considered normal distributed with mean value equal to 1.0 and standard deviation equal to 0.05. It is assumed that the condition monitoring system allows to estimate X_W each year. The vector of data $\hat{x}_i$, with dimension (t_i-1); will have values around 1.0 and standard deviation equal to 0.05. For the first year, the mean and standard deviation of the stochastic variable X_W are 1.0 and 0.15. The design parameter z will be calculated initially and will be fixed for the remaining life. The updating will be considered from the second year until the last year.

RESULTS
The design values *z* for each case are shown in table 4 (obtained using equations 5 and 11). In figure 3 is shown the

results of the assessment of the reliability with the SN approach (equations 10 and 13) and the calibrated FM model (equations 20 and 21, respectively). The accumulated reliability index β and the annual reliability index Δβ are obtained from cumulative probability of failure (P_F) and the annual probability (ΔP_F) of failure ($\beta=\Phi^{-1}(P_F(t))$ and $\Delta\beta=\left(\Phi^{-1}(P_F(t))-\Phi^{-1}(P_F(t-1))\right)$), respectively. It is seen that for a bilinear SN-curve, values of β and *z* are smaller than for linear cases. The design values for cases in wind farm location are larger than the ones exposed to free flow turbulence due to the larger turbulence level and corresponding accumulation of fatigue.

Table 4. *z*-design parameters

IWF-L	S-L	IWF-BL	S-BL
0.5654	0.4934	0.4253	0.3657

For all the cases a fracture mechanical model is calibrated and the resulting reliability curves are shown in the interval 10 to 20 years, see figure 3.
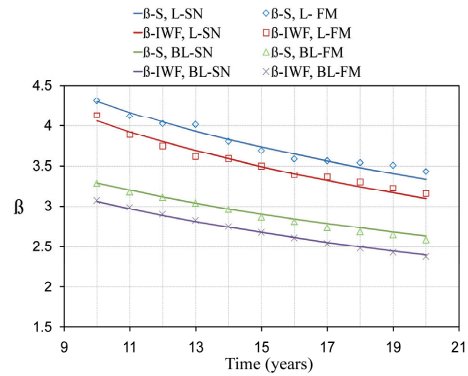

Fig 3. Reliability indices for SN-analysis and calibrated fracture mechanics curve corresponding to the cumulative probability of failure.
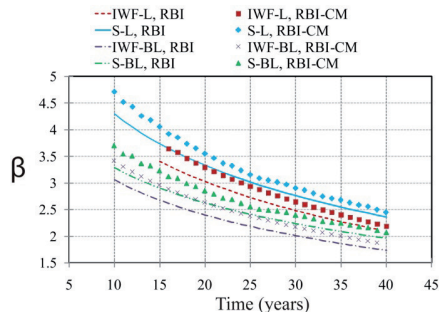
Fig 4. SN-Reliability indices for RBI and RBI with updating (RBI-CM) for corresponding to the cumulative probability of failure.

In the table 6 is shown the resulting inspection plans obtained with a maximum acceptable annual probability of failure equal to 1.0×10^{-4}. Comparing the first inspection time, slightly earlier inspections are obtained for in-wind farm sites due to the increase of fatigue coming from wake turbulence. With the inclusion of CMI by means Bayesian updating, the first inspection times change. It is noted that in all four cases the design parameter z is determined by deterministic design such that the code-based design criteria is exactly satisfied.

The density function for the stochastic parameter (X_W) converges to a standard deviation around 0.09 when more than 10 years of information are incorporated. It is noted that the estimates are assumed to be statistically independent from year to year. Higher reliabilities were therefore obtained for updating cases. Of course, real life information will be for some occasions (years, months, weeks…) harsher (or milder) than in others, showing a different tendency of the predictive density functions used in these examples (see figure 4). For RBI planning the FM model was calibrated to the code-based SN model such that the reliabilities are as close as possible in the vicinity of first inspection time. After the first inspection, the outcome (some information such as no-detection or detection of crack length, crack length, etc) will be obtained in the real life. The inspection planning for the rest of the life-cycle should be conditional on this additional gain of knowledge. The results in table 6 do not integrate this knowledge.

Table 6. Inspections times as a function of the threshold on the maximum annual probability of failure

CASE	INSPECTION TIME	
	Maximum Annual $\Delta P_f = 1.0 \times 10^{-4}$	
	RBI	RBI-Condition Monitoring
IWF-L	17	21
S-L	26	27
IWF-BL	7,15,30	9, 24
S-BL	8,17,38	11

CONCLUSION AND DISCUSSION

Based on RBI methods, a framework for optimal inspection and maintenance planning was applied for OWT, addressing the analysis of fatigue prone details (single hot spots in the context of RBI for this work) at the jacket or tripod steel support structures. In wind farm location and single offshore wind turbines were considered using a probabilistic model for fatigue failure based on the IEC standard used for wind turbine design. The approach represents a viable method to obtain risk-based inspection plans for fatigue critical details in offshore wind turbines, especially details in the tower and the support structure (steel jacket, tripod and monopile). Furthermore, it may also be applied to other important components like blades, nacelle, yaw system, etc (see Sørensen et al. 2007).

The use of the RBI framework for wind farms may potentially be beneficial for optimizing the inspection and maintenance efforts, generating inspection plans assuring fulfillment of acceptance criteria for the whole wind farm. Furthermore, the approach could also be applied as a decision tool for estimating the consequences of a possible service life extension.

The paper presents a straightforward-Bayesian inference case and a simple example is shown of integration of CMI using Bayesian updating, illustrating the main features of updating process into a RBI framework.

Besides of being applied to high reliability components, this approach for updating within a RBI framework may be also used on different components with lower reliability levels (e.g. WEC parts, blades, hub, etc), having the proper limit state equations relating the real-time information coming from the measuring devices for different components.

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8

Paper IV

Risk-Based Inspection and Maintenance Planning Optimization for Offshore Wind Turbines

Risk-Based Inspection and Maintenance Planning Optimization of Offshore Wind Turbines

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ABSTRACT: A risk-based inspection planning (RBI) approach applied to offshore wind turbines (OWT) is presented, based on RBI methodology developed in the last decades in the oil and gas industry. In wind farm (IWF) and single-alone locations are considered using a code-established turbulence models including free flow and in wind farm wake turbulence. Limit state equations for fatigue failure and illustrative examples are presented considering linear and bi-linear SN-curves. As part of the results for each case, inspection times are calculated, showing that earlier inspections are needed in-wind farm sites due to the increase of fatigue coming from wake turbulence.

1 INTRODUCTION

Wind turbine structures, located at offshore sites, face up additional detrimental conditions that decrease their life-cycle performance making inspection, maintenance and repairing activities vital actions for achieving established safety levels. The interaction with harsher environments at offshore location (extreme wave and wind conditions, water depth situation...) imply additional complex and diverse uncertainties that will play an important role in the technical aspects concerning the design life and inspection and maintenance planning policies. These site conditions are highly complex processes that triggers uncertain structural states that can be best modeled in probabilistic terms.

The deterioration processes such as fatigue, corrosion and scour are typically affecting offshore structural systems. The damage decrease the system performance, thus not fulfilling the established safety criteria. To control this deterioration, the inspection/maintenance activities are developed, representing the most relevant and effective means of control.

The RBI methodology, based on Bayesian decision theory, represent an important tool to identify the suitable strategy to inspect and control the deterioration in structures such as wind turbines. During the last decades RBI approach has been applied to the mainstream industry (oil and gas, marine, aeronautical...), giving a theoretical background that can also be applied for OWT.

Unlike other structures, wind turbines have mechanical, electrical and structural components with a close dependence, e.g. blades with pitch control.

This active control affects considerably the response and non-structural failure modes are important in connection to start/stop operation and accidental/unusual loads that will affect these specific parts. Other differences are the low risk of human injury that this kind of structure represents allowing allocation of a lower reliability level and larger operation and maintenance costs.

Offshore Wind farms need additional technical and economical efforts. Spatial correlation of OWTs imply turbulence conditions that affect the performance of neighboring wind turbines. Wake effects, coming from the decrease of wind velocity behind OWT, increase the turbulence resulting in decrease in OWT fatigue life.

In water depths of about 20 m to 50 m, the use of jacket and tripod structures represents a feasible option that improves technical aspects concerning structural redundancy, damage distribution, scour conditions and dynamical behavior. An important OWT part is the transition node between the jacket or tripod and the tubular tower. The transition node is a critical design element, needing special careful design concerning the fatigue performance. In this paper reliability-based inspection and maintenance planning of details in the transition node is considered.

2 WIND LOAD

In addition to the ambient turbulence, OWTs inside of wind farms face certain unfavorable wind variations due to wakes behind other OWT where the

mean wind speed decreases slightly and turbulence intensity increases significantly. The turbulence intensity, defined as the standard deviation of the wind speed fluctuations divided by the mean (n-minutes) wind speed; represent an important aspect to consider because its effects on OWT's fatigue life. In this paper, the following model is used for the efficient standard deviation of wake turbulence proposed by Frandsen, S. (2005):

$$\sigma=\left[(1-N_wp_w)\sigma_0^m+N_wp_w\sigma_w^m\right]^{1/m} \qquad (1)$$

Where σ_0 is the turbulence standard deviation under free flow condition, σ_w is the maximum wake turbulence under wake condition, p_w (=0.06) is the probability of wake condition and N_w is the number of wakes to which the considered wind turbines is exposed to. It is further assumed that the standard deviation of the response is proportional to the standard deviation of turbulence.

Wind load stress effects are strongly related with the type of power control (pitch or stall) in the OWT. Besides, the response is dependent on the OWT mode: standstill or operational.

3 OPTIMAL INSPECTION AND MAINTENANCE PLANNING

Reliability-based and risk-based approaches for inspection and planning have been developed during the last decades, see Skjong (1985), Madsen et al. (1987), Thoft-Christensen and Sørensen (1987) and Fujita et al. (1989); and are being applied to outline RBI plans that have as main aim to improve structural reliability and minimize the life cycle overall costs. The suitable inspection and maintenance plan to improve costs can be carried out in the framework of pre-posterior analysis from classical Bayesian decision theory, see Raiffa and Schlaifer (1961), Benjamin and Cornell (1970) and Ang and Tang (1975), and adapted to the particular case of OWTs.
In figure 3.1 is shown a decision tree for RBI planning for OWTs, The different steps in the decision process are illustrated. The decisions and random outcomes could be summarized as follows:
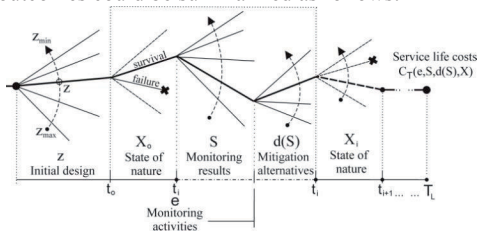
Fig. 3.1 RBI decision tree

• *Initial design phase*, in which the optimal design parameters $z=(z_1,z_2,z_3\ldots,z_n)$ are determinate. They have certain limits z_{min}-z_{max}. This interval is established according codes and practice requirements.
• First interaction with external conditions, such as wind and wave climate; triggers a *state of nature Xo*. This random outcome, due to high-uncertain nature; is the part of the process in which reliability and simulation methods attempt to represent numerically time-deterioration process (wear, dent, corrosion, fatigue…) dealing with model uncertainties at the same time. If the statistical basis for evaluation of the uncertainties is limited then also epistemic uncertainties will become important.
• *Monitoring activities* "*e*" at the times $t=(t_1,t_2,t\ldots,t_i)$, include inspection, sampling and analyzing actions which result in inspection results "*S*" (corrosion, denting level, size of fatigue cracks…) that are obtained depending on inspection quality $q=(q_1,q_2,q_3\ldots,q_n)$ (inspection techniques, technical expertise of inspectors…).
• Based on the obtained monitoring results, *Mitigation alternatives* will be considered according to fixed or adapting mitigation policy *d(S)*. Such policies are related to repairing or not repairing activities.
• *State of nature Xi* at the ith inspection/maintenance represents the beginning of new random outcomes. Theoretically, posterior states of nature depend on assumptions established to simplify the RBI process, e.g. assuming that repaired components behave like new component and repaired parts will have no indication of damage at the inspection.

In Figure 3.1, $C_T(e,S,d(S),X_i)$ is the total service life cost. Overall cost optimization will be achieved by minimizing C_T:

$$\begin{aligned}
\min E[C_T(z,e,d(S),X_i)]= \\
+C_I(z)+E\left[C_{Insp}(z,e,d(S),X_i)\right] \\
+E\left[C_{Rep}(z,e,d(S),X_i)\right] \\
+E\left[C_F(z,e,d(S),X_i)\right]
\end{aligned} \qquad (2)$$

$z_i^{min}{\leq}z_i{\leq}z_i^{max}$, $i=1,2,\ldots,n$
$\Delta P_{F,t}(t,z,e,d(S)){\leq}\Delta P_F^{max}$, $t=1,2,\ldots,T_L$

$E[C_T]$ is the expected (RBI action) costs in the service life T_L where C_I is the initial costs, $E[C_{Insp}]$ is the expected inspection costs, $E[C_{Rep}]$ is the expected reparation costs and $E[C_F]$ is the expected failure costs. Equation (2) is constrained by limits on design parameters and that the annual probability of failure $\Delta P_{F,t}$ has to be less than ΔP_F^{max} at all times, assuring a maximum annual risk-state. The n inspections are performed at times t_i, $i=1,\ldots,n$ where $t_o{\leq}t_1, t_2, \ldots,t_n{\leq}T_L$.

4 PROBABILISTIC MODEL FOR FAILURE

In this section the probabilistic models for assessing the fatigue failure life based on SN-curves (SN) and fracture mechanics (FM) model are briefly mentioned. To evaluate the fatigue life is used the probabilistic model for fatigue failure described in Sørensen et al. (2007).

In the assessment of SN fatigue life, the deterministic design equation for free flow ambient turbulence is:

$$G(z)=1-\frac{v\cdot FDF\cdot T_L}{K_C}\int_{U_{in}}^{U_{out}} D\big(m;\sigma_{\Delta\sigma}(U)\big)\cdot f_U(U)\ dU=0 \qquad (3)$$

where for linear SN-curve:

$$D_L\big(m;\sigma_{\Delta\sigma}(U)\big)=\int_0^\infty s^m\cdot f_{\Delta\sigma}\big(s|\sigma_{\Delta\sigma}(U)\big)\ ds \qquad (4)$$

and bi-linear SN-curve:

$$D_{BL}\big(m_1,m_2,\Delta\sigma_D\ ;\sigma_{\Delta\sigma}(U)\big)=$$
$$\int_0^{\Delta\sigma_D} s^{m_2}\cdot f_{\Delta\sigma}\left(s|\alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_u(U)}{z}\right) ds$$
$$+\int_{\Delta\sigma_D}^\infty s^{m_1}\cdot f_{\Delta\sigma}\left(s|\alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_u(U)}{z}\right) ds \qquad (5)$$

$$\sigma_{\Delta\sigma}(U)=\alpha_{\Delta\sigma}(U)\cdot\frac{\sigma_u(U)}{z} \qquad (6)$$

$$\hat{\sigma}_u(U)=I_{ref}\cdot(0.75\cdot U+b) \quad , \qquad b=5.6\frac{m}{s} \qquad (7)$$

where v is the total number of fatigue load cycles per year, FDF is the fatigue design factor (FDF=T_F/T_L), K_C is the characteristic value of K (mean log K minus two standard deviation of log K), U_{in} and U_{out} are the cut-in and cut-out wind speed, respectively; $f_U(U)$ is the density function of mean wind speed U, D_L is the expected value of $\Delta\sigma^m$ given standard deviation $\sigma_{\Delta\sigma}$ and mean wind speed U in which $f_{\Delta\sigma}\big(s|\sigma_{\Delta\sigma}(U)\big)$ represents the density function for stress ranges given standard deviation $\sigma_{\Delta\sigma}(U)$ at mean wind speed U. This density function and v can be obtained by counting methods, e.g. Rainflow counting.

In the equation (6), $\alpha_{\Delta\sigma}(U)$ is the influence coefficient for stress ranges given mean wind speed U ($\sigma_{\Delta\sigma}(U)/\sigma_U(U)$), $\sigma_u(U)$ is the standard deviation of turbulence given mean wind speed U and z is the design parameter (e.g. proportional a cross sectional area). The equation (7) is the characteristic (90% fractil representative turbulence) ambient turbulence where I_{ref} is the (IEC-) reference turbulence intensity (equal to 0.14 for medium turbulence characteristics). The corresponding limit state equation is:

$$g(t)=\Delta-\frac{v\cdot t}{K}\int_{U_{in}}^{U_{out}}\int_0^\infty \left[(X_W\cdot X_{SCF})^m\cdot D_L\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right)\right]$$
$$\cdot f_{\sigma_u}(\sigma_u|U)\cdot f_U(U)\cdot d\sigma_u\ dU \qquad (8)$$

Where Δ is a stochastic variable modeling the uncertainty related to the Miner rule for damage accumulation, t is the life time in years, X_W is the model uncertainty related to wind load effects (exposure, assessment of lift and drag coefficients, dynamic response calculation), X_{SCF} is the model uncertainty related to local stress analysis and $\sigma_u(U)$ is modeled as lognormal distributed with a representative mean turbulence (90% fractil value-IEC 61400-1) equal to $I_{ref}(0.75\cdot U+3.6)$ with a standard deviation equal to $1.4\,m/s\cdot I_{ref}$.

For a wind farm location the design equation is based on IEC 61400-1 (IEC 2005):

$$G(z)=1-\frac{v\cdot FDF\cdot T_L}{K_C}\cdot\int_{U_{in}}^{U_{out}}\begin{bmatrix}(1-N_w\cdot p_w)\cdot\\ D\left(m;\alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_u(U)}{z}\right)\\ +p_w\\ \cdot\sum_{j=1}^{N_w}D\left(m;\alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_{u,j}(U,j)}{z}\right)\end{bmatrix}$$
$$\cdot f_U(U)\ dU=0 \qquad (9)$$

where N_w is the number of neighboring wind turbines, p_w is the probability of wake from a neighboring wind turbine (equal to 0.06), $\hat{\sigma}_{u,j}$ is the standard deviation of turbulence from neighboring wind turbine no. j:

$$\hat{\sigma}_{u,j}(U,j)=\sqrt{\frac{0.9\cdot U^2}{\left(1.5+0.3\cdot d_j\sqrt{U/c}\right)^2}+\hat{\sigma}_u^2} \qquad (10)$$

where d_j is the distance between OWT normalized by rotor diameter to the neighboring wind turbine j and c is a constant equal to 1 m/s.

The limit state equation corresponding to the above equation is:

$$g(t)=\Delta-\frac{v\cdot t}{K}\int_{U_{in}}^{U_{out}}\int_0^\infty (X_W\cdot X_{SCF})^m$$
$$\cdot\begin{bmatrix}(1-N_w\cdot p_w)\cdot D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right)\\ +p_w\cdot\sum_{j=1}^{N_w}D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_{u,j}(U,j)}{z}\right)\end{bmatrix}$$
$$\cdot f_U(U)\cdot f_{\sigma_u}(\sigma_u|U)\cdot d\sigma_u\ dU \qquad (11)$$

$$\sigma_{u,j}(U,j)=\sqrt{\frac{X_{wake}\cdot U^2}{\left(1.5+0.3\cdot d_j\sqrt{U/c}\right)^2}+\sigma_u^2} \qquad (12)$$

Where X_{wake} is the model uncertainty related with wake turbulence model. The design parameter z is calculated with (3) or (9) and then used in limit state equation (8) or (11) to estimate the reliability index or probability for failure of the reference time t.

For the assessment of FM fatigue life is used for illustration a one dimension crack model (figure

4.1) where the crack length c is related with the growth crack depth "a" through a constant f_{cr}. It is assumed that life may be represented by fatigue initiation life and a fatigue propagation life. This is represented as follows:

$$N=N_I+N_P \tag{13}$$

Where N is the number of stress cycles to fatigue failure, N_I is the number of stress cycles to crack propagation and N_P is the number of stress cycles from initiation to crack through. The crack growth can be described by the following equations:
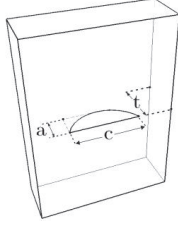
Figure 4.1 surface crack idealization in plate under fatigue loads.

$$\frac{da}{dN}=C_A(\Delta K_A)^m \ , \qquad a(N_o)=a_o \tag{14}$$

$$\Delta K_A=\Delta\sigma\cdot\sqrt{\pi a} \tag{15}$$

$$c(f_{cr}\cdot a_o)=c_o \tag{16}$$

where C_A and m are the material parameters, a_o and c_o describe the initial crack depth a and crack length c, respectively, after N_I cycles and where the stress intensity range is ΔK_A.

The stress range $\Delta\sigma$ is obtained from:

$$\Delta\sigma=Y\cdot\Delta\sigma^e \tag{17}$$

where Y is the model uncertainty variable related to geometry function and $\Delta\sigma^e$ is the equivalent stress range. $\Delta\sigma^e$ for a single OWT is calculated with:

$$\Delta\sigma^e=X_W\cdot X_{SCF}\cdot\left[\int_{U_{in}}^{U_{out}}\int_0^\infty D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right) \\ \cdot f_U(U)\cdot f_{\sigma_u}(\sigma_u|U)\,d\sigma_u\,dU\right]^{\frac{1}{m}} \tag{18}$$

and for a wind farm location case:

$$\Delta\sigma^e=X_W\cdot X_{SCF}$$

$$\cdot\left[\int_{U_{in}}^{U_{out}}\int_0^\infty\left[\begin{array}{l}(1-N_w\cdot p_w)\cdot D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}\right)\\+p_w\cdot\sum_{j=1}^{N_w}D\left(m;\alpha_{\Delta\sigma}(U)\frac{\sigma_{u,j}(U,j)}{z}\right)\end{array}\right]dU \\ \cdot f_U(U)\cdot f_{\sigma_u}(\sigma_u|U)\,d\sigma_u\right]^{1/m} \tag{19}$$

The limit state criteria used in the FM analysis is related with the failure when crack exceeds a critical crack size:

$$g(t)=a_c-a(t) \tag{20}$$

where a_c is the critical crack size and a is crack depth. For RBI planning the FM model is usually calibrated to result in the same reliability level as the code-based SN model. The RBI planning and maintenance is strongly related with inspection quality (inspection methods, technology, environmental conditions, inspectors' expertise, etc). The incorporation of these influential factors is attained by using a distribution of the detectable crack size or probability of detection curve (POD).

5 EXAMPLE

An offshore wind turbine with a steel jacket support structure is considered as support of an OWT. OWT's have an expected life time at 20 years and a design fatigue life time (T_F) of 60 years. For the Influence coefficient $\alpha_{\Delta\sigma}(U)$ is used the function in figure 5.1 (mudline bending moment – pitch controlled wind turbine) regarding this as a representative function in the support structure. This influence function is highly non-linear due to the control system.

Figure 5.1 $\sigma_{\Delta\sigma}/\sigma_U$ for mudline bending moment – pitch controlled wind turbine.

Wind turbine in wind farm (IWF) and alone/single (S) OWT location are considered. For each location is considered linear (L) and bi-linear (BL) SN-curve and cast iron (CI) and welded steel (WS) detail. In tables 5.1–5.3 are shown the stochastic models and parameters used.

Table 5.1 SN stochastic models

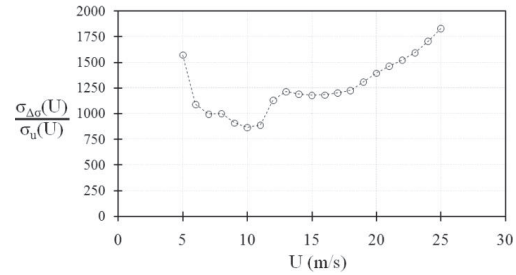| Variable	Distribution	Expected value	Standard deviation
Δ	N	1.0	0.10 , 0.2 (WS) 0.20 , 0.4 (CI)
X_W	LN	1.0	0.10
X_{SCF}	LN	1.0	0.10
X_{wake}	LN	1.0	0.15
m_1	D	3 (WS) 6 (CI)	--
m_2	D	5 (WS) 11 (CI)	--
$\Delta_{\sigma D}$	D	71 MPa (WS) 150 Mpa (CI)	--
Log K_1	N	Determined from $\Delta_{\sigma D}$	0.20 (WS) 0.10 (CI)
Log K_2	N	Determined from $\Delta_{\sigma D}$	0.25 (WS) 0.15 (CI)
T_F	D	60 years	--
N_w	D	5/--	--
ν	D	$5 \cdot 10^7$	--
U_{in} - U_{out}	D	5 – 25 m/s	--
p_w	D	0.06/0.0	--
d_j	D	4.0	--
Log K_1 and Log K_2 are assumed fully correlated			

D: Deterministic, N:Normal, LN:LogNormal, W:Weibull

Table 5.2 FM stochastic models

Variable	Distribution	Expected value	Standard deviation
Ln Cc	N	$\mu_{ln\,Cc}$ (fitted)	0.7
N_I	W	$\mu_0 = T_{init} \cdot \nu$	$0.35 \cdot \mu_0$
Y	LN	1.0	0.10
X_W	LN	1.0	0.10
X_{SCF}	N	1.0	0.10
X_{wake}	LN	1.0	0.15
a_c	D	25 mm	--
a_o	D	0.4 mm	--
f_{cr}	D	3.0	--
thickness	D	25 mm	--
m	D	3.0 (WS) 6.0 (CI)	--
Ln C_c and N_I are correlated with correlation coefficient $\rho_{ln\,Cc,\,N_I} = -0.5$			

Table 5.3 Distribution parameters and equations

Variable	Distribution	Parameters
P_F	D	$1.0 \cdot 10^{-4}$
$F_U(u)$	$W(\alpha, \beta_U)$	α=2.3 , β_U=10.0 m/s
$f_{\Delta\sigma_D}(\cdot)$	$W(\alpha_{\Delta\sigma_D}, \beta_{\Delta\sigma_D})$	$\alpha_{\Delta\sigma_D}$=0.8
$f_{\sigma_u}(\cdot)$	$LN(\mu, \sigma)$	$\mu = I_{ref} \cdot (0.75 \cdot U_i + 3.6)$, $\sigma = 1.4 \cdot I_{ref}$
POD(x)	$P_O \cdot (1 - exp(-x/\lambda))$	P_O=1.0, λ=2.67 mm
$N_1(s)$	$K_1 \cdot s^{-m_1}$	$s \geq \Delta\sigma_D$
$N_2(s)$	$K_2 \cdot s^{-m_2}$	$s < \Delta\sigma_D$

6 RESULTS

The design values z for each case are shown in table 6.1 and 6.2 (equations 3 and 9) and in figures 6.1 and 6.2 are shown the results of the assessment of the reliability with FM approach (equations 18 and 19) calibrated to result in the same reliability level as the code-based SN model (equations 8 and 11). β is defined as the cumulative probability of failure (P_F).

(a)

(b)
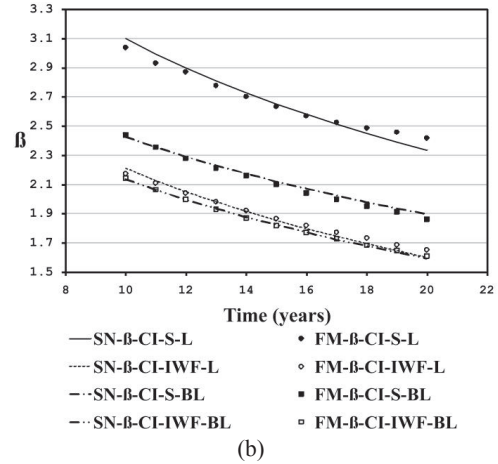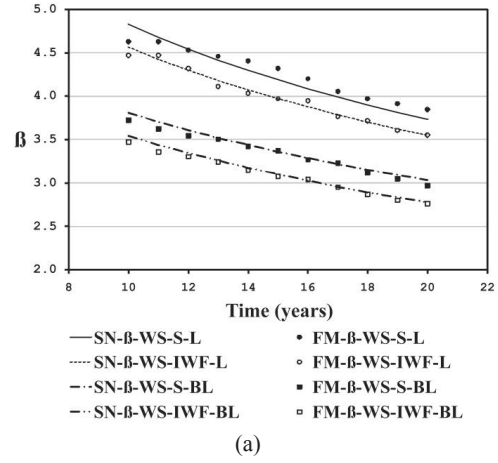
Figure 6.1 SN and FM model for (a) WS detail with S.D.=0.10 and (b) CI detail with S.D.=0.20

It is seen that for bilinear SN-curve values of β and z are smaller than for linear cases. The z design values (table 6.1 and 6.2) for cases in wind farm location (wake turbulence) are larger than the ones exposed to free flow turbulence due to the accumulation of fatigue

Table 6.1 Inspection time and z design parameter

WELDED STEEL DETAIL (WS)				
S.D. = 0.10		S.D.=0.20		
	num. of insp.	insp. time	num. of insp.	insp. time	z
IWF–L	1	19	1	17	0.5654
S–L	0	--	0	--	0.4933
IWF–BL	1	9	1	11	0.4226
S-BL	1	15	1	14	0.3632

Table 6.2 Inspection time and z design parameter

CAST IRON DETAIL (CI)				
S.D. = 0.20		S.D.=0.40		
	num. of insp.	insp. time	num. of insp.	insp. time	z
IWF–L	4	2,4,8,18	4	1,2,5,12	0.1900
S–L	2	5,13	2	3,9	0.1596
IWF–BL	4	1,3,7,16	4	1,2,4,10	0.1864
S-BL	3	2,4,9	3	2,5,11	0.1560

Comparing the inspection times, earlier inspections are coming out in-wind farm sites due to the increase of fatigue coming from wake turbulence. It is noted that in all cases the design parameter z is determined by deterministic design such that the code-based design criteria is exactly satisfied

7 CONCLUSIONS

Based on risk-based inspection planning methods for oil & gas industry, a framework for optimal inspection and maintenance planning was applied for offshore wind turbines, addressing the analysis of fatigue prone details in cast and welded steel detail at the jacket or tripod steel support structures. In wind park location and single OWT were taken into account by using a turbulence model. This inspection optimization approach represents a viable method to outline inspection plans aimed at OWT, regarding its application to large structural systems. Furthermore, it may also be applied to other important components like blades, nacelle, yaw system, etc. Knowingly of the fast growth of wind industry and offshore wind turbine parks, larger and complex cluster of such structural systems may potentially be benefited for optimizing the inspection and maintenance efforts and generate suitable inspection plans ensuring an acceptance criteria with respect to risk. Besides, this RBI approach may also be applied as a decision tool for estimating the consequences of a possible service life extensions and reduction (or strengthening) on the necessary maintenance and inspection efforts.

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Paper VI

Probabilistic Calibration of Fatigue Design Factors for Offshore Wind Turbine Support Structures

Probabilistic Calibration of Fatigue Design Factors for Offshore Wind Turbine Support Structures

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Abstract:

This paper describes a reliability-based approach to determine fatigue design factors (FDF) for offshore wind turbine support structures made of steel. The FDF values are calibrated to a specific reliability level and linked to a specific inspection and maintenance (I&M) strategy used for the considered offshore wind turbines in such a way that the specific uncertainties for the fatigue life are accounted in a rational manner. Similar approaches have been used for offshore oil & gas sub-structures, but the required reliability level for offshore wind turbines is generally lower and the fatigue loading is different. Based on representative stochastic models and response functions a set of FDF values are determined which depend on the degree of accuracy of the fatigue analysis and the consequences of fatigue failure of a critical detail. It is illustrated how the FDF values can be reduced if inspections are planned during the design life, and thereby the basis is available for selecting a cost-effective fatigue design. Further, the results can be used as basis for recommendations in standardization.

1. Introduction

Design for fatigue failure is important for wind turbine components, especially for future very large offshore wind turbines (OWT) where fatigue can be an important design driver for the support structures. Different types of support structures are being developed, most of them made in steel with many fatigue prone details. The estimation of the fatigue life is associated with many uncertainties, e.g. from wave and wind load, wake effects in wind farms, influence of control system and stress analyses to determine stress ranges. Models for the fatigue strength is typically based on experimental tests and used in a SN-approach or a fracture mechanics (FM) method. These models are highly uncertain due to physical, model and statistical uncertainties. Finally, the fatigue damage accumulation rules used in design, e.g. the Miner's rule, are very uncertain if not carefully calibrated together with e.g. the SN curves. Beside of material and load uncertainties, detection and no-detection of fatigue cracks at inspections represent an additional uncertainty that typically is modelled through probability of detection (POD) curves.

FDF values are used in relation to different fatigue assessment requirements (e.g. damage tolerant / safe life design philosophies) and the consequence of failure (fail- or non-fail-safe components). Offshore codes such as [1] and [2] use FDF taking into account component location (i.e. accessible or not for inspection, change and repair).

In the offshore oil & gas industry reliability-based techniques for planning of inspections have been developed during the last 10-20 years and are used as basis for calibration of fatigue design factors and for cost-optimal planning of inspections; see e.g. [3]. The reliability level for oil & gas offshore installations is typically much higher than required for offshore wind turbines. Further, the fatigue loading is quite different. Therefore the results from oil & gas industry cannot be used directly, but the basic principles and approach can be applied for offshore wind turbines. This is described and illustrated in this paper. FDF values are obtained depending on the consequences of fatigue failure and calibrated to a reliability level which is suitable for offshore wind turbines. It is shown how the FDF values can be reduced if inspections are planned to be performed during the design life, and thereby the basis is available for selecting a cost-effective fatigue design with or without inspections (of selected details).

2. Calibration of Fatigue Design factors

Calibration of FDF values (or equivalently partial safety factors to be applied to the fatigue load and the fatigue strength) can be performed on a probabilistic basis through the

steps recommended by [4], see [5] for general code calibration. Basically, it is assumed that a certain number of inspections has to be performed in the design life. Assuming no-inspection within the design life a SN-approach (see appendix A) is used with linear damage accumulation by the Miner's rule. The steps include:

- Definition of code objective: design of fatigue critical details in offshore wind turbine steel substructures
- Stochastic modelling of uncertainties: fatigue load (wind and wave), calculation of fatigue stress effects (stress ranges), SN-curves and model uncertainty (Miner's rule).
- Target reliability level: this should for different classes of fatigue critical details be selected such that the same general reliability level is obtained as for other ultimate failure modes, but taking into account the consequences of failure, see reference [6]. In special cases it can be argued that the reliability level should be increased / decreased if the marginal cost of improving the reliability is low / high, see reference [4].
- Identification of typical fatigue critical details: these have to be selected and used in the calibration to secure that the FDF values can be used in the whole range of typical applications.
- Determination of FDF values: FDF values are calibrated such that the reliability level for the different typical fatigue critical details are as close as possible to the target reliability level.
- The calibrated FDF values have to be verified for use in practical design.

Extension to include the effect of performing inspections during the design life is straightforward if a FM model (see appendix B) is calibrated to the SN-approach and the reliability of possible inspection methods are included though POD-curves (see section 4 and table 1).

3. Probabilistic models

The underlying assumptions of the probabilistic models are briefly described in this section. The turbulence intensity represents an important aspect to consider due to its effects on the OWT's fatigue life. It can be taken into account by specifying a characteristic influence function where the fluctuation of the (n-minutes) wind speed can be related with internal forces (stress ranges) for a specific

component, sector or detail (hot spots) of the OWT support structure.

When an OWT is in wind farm location (IWF) the model should be modified to include additional turbulence due to wake conditions from surrounding turbines. To incorporate this additional IWF turbulence the following code-based [7] model is used:

$$\sigma=\left[\left(1-N_w\cdot p_w\right)\sigma_0^m + N_w\cdot p_w\cdot\sigma_w^m\right]^{1/m} \qquad (1)$$

In equation (1), N_w is for number of wakes affecting the wind turbine, p_w is the probability of wake condition, m is the Wöhler exponent, σ_0 is the turbulence standard deviation under free flow condition and σ_w is the maximum wake turbulence. It is assumed that the standard deviation of response is proportional to the standard deviation of turbulence, see [8]. In the design equation, it is assumed that the response of the structure can be modelled by a narrow-banded stationary Gaussian process and that the failure occurs as a result of the accumulated effect of stress cycles for the given mean wind speed distribution. With these assumptions the frequency of maxima in the response (typical cycles per year, v) are proportional to the time interval t (years).

In the fatigue failure limit state equation, the uncertainties related with the wind, stress concentration factor and Miner rule (see appendix A) are taken into account. In case of IWF, the model in equation (1) is integrated in the design and limit state equations.

4. Reliability-based inspection planning

If inspections are performed during the design life a reliability-based approach can be used to determine the times for the inspections such that the reliability during the whole design life is larger than a minimum reliability level. The reliability of the inspection technique (e.g. visual inspection, Eddy current or MPI) is modelled by a probability of detection (POD) curve, see table 1 and appendix B. Further it is assumed that all detected cracks are perfectly repaired by grinding, welding or replacement.

5. Application examples

A probabilistic calibration of FDF for OWT support structure is presented in this section and illustrative results are presented. A representative influence coefficient function is used where the stress ranges are related to the wind load (wind load is assumed to be

dominating). These functions could be obtained in different manners such as by simulations and/or by measurements.

If measurements or monitoring data are available indirect information about the OWT performance can be obtained. Data from e.g. strain gauges at specific hot spots can provide direct information about stresses at the critical detail.

In the following example is used an influence coefficient function, $\alpha_{\Delta\sigma}(U)$ which is representative for fatigue load effects in a critical welded detail in a steel support structure. The influence function is shown in figure 1. Due to the effect of the control system, the internal stresses will not vary linearly, and thereby the influence function will vary non-linearly as illustrated in figure 1.
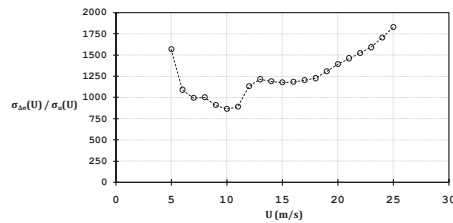

Figure 1. Influence coefficient function $(\sigma_{\Delta\sigma}(U)/\sigma_u(U))$ – pitch controlled wind turbine.

5.1 Example cases

FDF values are obtained for four different cases for welded steel details. These will be the combinations of linear (L) and bilinear (BL) SN-curve cases with in wind farm (IWF) and single (S) location of the wind turbine.

5.2 Stochastic models

Table 1. Distribution parameters and Equations

Variable	Distribution	Parameters	Comment
$f_U(U)$	$W(\alpha,\beta_U)$	$\alpha=2.3$, $\beta_U=10.0m/s$	Mean wind speed
$f_{\Delta\sigma D}(\cdot)$	$W(\alpha_{\Delta\sigma D},\beta_{\Delta\sigma D})$	$\alpha_{\Delta\sigma D}=0.8$	Stress ranges
$f_{\sigma u}(\cdot)$	$LN(\mu,\sigma)$	$\mu=I_{ref}\cdot(0.75\cdot U+3.6)$, $\sigma=1.4m/s\cdot I_{ref}$	Mean turbulence
$POD(x)$	$P_o\cdot(1-exp(-a/\lambda))$	$P_O=1.0$, $\lambda=2.67$ mm	POD curve
$N_1(s)$	$K_1\cdot s^{-m1}$	$s \geq \Delta\sigma_D$	SN curve linear
$N_2(s)$	$K_2\cdot s^{-m2}$	$s < \Delta\sigma_D$	SN curve bi-linear
D: Deterministic, N: Normal, LN: Lognormal, W: Weibull			

An offshore wind turbine with steel jacket / lattice support structure is considered. An expected design life T_L equal to 20 years is assumed. It is noted that for a linear SN-curve,

FDF is related to the partial safety factors on load, γ_f and fatigue resistance, γ_m by FDF = $(\gamma_f\cdot\gamma_m)^m$. In table 1 and 2 representative stochastic models, equations and parameters are shown, based on uncertainty models used for offshore oil & gas installations, see [3] and for offshore wind turbines, see [9] and [10].

Table 2. Stochastic models

Variable	Distr	E[·]	Standard deviation	Comment
Δ	N	1.0	(1) 0.0, (2) 0.2	Damage accumulation
X_W	LN	1.0	V_W	Wind
X_{SCF}	LN	1.0	V_{SCF}	Stress concentration factor
X_{wake}	LN	1.0	(1) 0.10, (2) 0.15	Wake
m_1	D	3.0	--	SN-curve. Wöhler exponent (linear)
m_2	D	5.0	--	SN-curve. Wöhler exponent (bi-linear)
$\Delta\sigma_D$	D	71 MPa	--	Constant amplitude fatigue limit
Log K_1	N	Determined from $\Delta\sigma_D$	0.20	Material parameter
Log K_2	N	Determined from $\Delta\sigma_D$	0.25	Material parameter
N_W	D	5/--	--	In-wind farm/single OWT
N	D	5×10^7	--	Fatigue cycles per year
U_{in} -U_{out}	D	5 – 25 m/s	--	Cut in – out velocities
p_W	D	0.06 / 0.0	--	In-wind farm/single OWT
d_j	D	4.0	--	Normalized distance of OWT
Ln C_C	N	μ_{lnCc} (fitted)	0.77	Crack growth ratio
N_I	W	$\mu_O=T_{init}\cdot v$	$0.35\cdot\mu_O$	T_{init} (fitted), Initiation Time
Y	LN	1.0	0.10	Shape factor
a_C	D	50 mm	--	Critical crack size
a_O	D	0.4 mm	--	Initial crack size
f_{cr}	D	4.0	--	Crack length/depth ratio
thickness	D	50 mm	--	Thickness
m	D	3.0	--	Material parameter
Log K_1 and Log K_2 are assumed fully correlated. Ln C_C and N_I are correlated with correlation coefficient $\rho_{LnCc,NI}$=-0.5				

5.3 Results

Table 3. FDF and T_F (in years) for minimum annual reliability index (Δβ=3.1) and no-inspections during design life.

V_{SCF}		0.05			
V_W	FDF	IWF-L	S-L	IWF-BL	S-BL
	$V_{wake-2},V_{\Delta-2}$	2.00	1.40	2.00	1.60
	$V_{wake-2},V_{\Delta-1}$	1.85	1.30	3.90	1.50
0.10	$V_{wake-1},V_{\Delta-2}$	1.65	1.40	1.95	1.60
	$V_{wake-1},V_{\Delta-1}$	1.55	1.30	1.85	1.50

V_{SCF}		0.05			
V_W	T_F	IWF-L	S-L	IWF-BL	S-BL
	$V_{wake-2},V_{\Delta-2}$	40	28	40	32
	$V_{wake-2},V_{\Delta-1}$	37	26	78	30
0.10	$V_{wake-1},V_{\Delta-2}$	33	28	39	32
	$V_{wake-1},V_{\Delta-1}$	31	26	37	30

Table 4. FDF and T_F (in years) for minimum annual reliability index (Δβ=3.1) and no-inspections during design life.

V_{SCF}		0.1			
V_W	FDF	IWF-L	S-L	IWF-BL	S-BL
	$V_{wake-2},V_{\Delta-2}$	2.15	1.60	2.40	1.90
	$V_{wake-2},V_{\Delta-1}$	2.00	1.45	5.65	4.50
0.10	$V_{wake-1},V_{\Delta-2}$	1.85	1.60	2.35	1.90
	$V_{wake-1},V_{\Delta-1}$	1.70	1.45	5.60	4.50

V_{SCF}		0.1			
V_W	T_F	IWF-L	S-L	IWF-BL	S-BL
	$V_{wake-2},V_{\Delta-2}$	43	32	48	38
	$V_{wake-2},V_{\Delta-1}$	40	29	113	90
0.10	$V_{wake-1},V_{\Delta-2}$	37	32	47	38
	$V_{wake-1},V_{\Delta-1}$	34	29	112	90

In tables 3 and 4 results are shown for one typical fatigue critical detail with the influence coefficient function in figure 1 and without inspections. The minimum target annual reliability index is chosen to $\Delta\beta_{min}$ = 3.1, as used in [11] and [12]. In figure 2 the reliability indices as function of time are shown for IWF-L, V_W=0.1, V_{SCF}=0.05, V_{wake-1} and $V_{\Delta-1}$. Both FDF values and fatigue design lives T_F = FDF · T_L are shown in tables 3 and 4.

Figure 2. Annual reliability indices of SN and FM approach for IWF-L, V_W=0.1, V_{SCF}=0.05, V_{wake-1} and $V_{\Delta-1}$ without inspections during design life.

The results in table 3 and 4 show that the FDF values are generally smaller than those used for fatigue design for oil & gas installations, but are dependent on especially the uncertainty of the stress range calculation (SCF).

In table 5 results are shown for FDF and T_F in the case where one inspection is performed during the design life. In figure 3 the reliability indices as function of time are shown for IWF-L, V_W=0.1, V_{SCF}=0.05,V_{wake-1} and $V_{\Delta-1}$. The effect of the first inspection is seen to be very efficient (with the assumed POD-curve) and results in a significant increase in reliability which has the implication that lower values of FDF and T_F are required to maintain the requirement that the annual reliability has to be larger than $\Delta\beta_{min}$ = 3.1.

Table 5. FDF and T_F (in years) for minimum annual reliability index (Δβ=3.1) and one-inspection during design life.

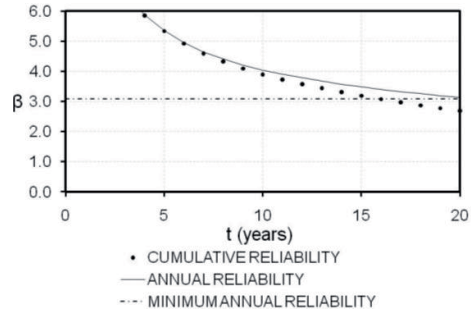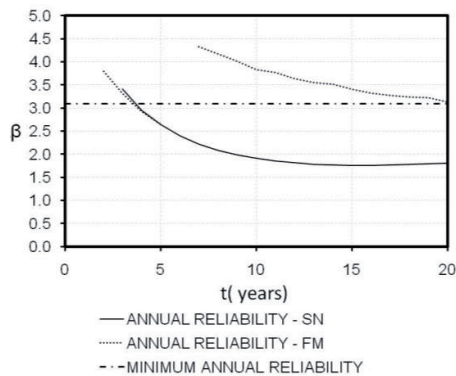| V_{SCF}		0.05			
V_W	FDF / T_F	IWF-L	S-L	IWF-BL	S-BL
0.10	$V_{wake-1},V_{\Delta-1}$	0.35	0.30	0.4	0.30
		7	6	8	6
First inspection time (year)		3	3	3	3

Figure 3. Reliability indices of SN and FM approach for IWF-L, V_W=0.1, V_{SCF}=0.05, V_{wake-1} and $V_{\Delta-1}$ with one-inspection during design life.

The above results illustrate the potential of the reliability-based approach for calibration of FDF values or equivalently partial safety factors for fatigue design – and for including the effect of possible inspections during the life time of the wind turbine. However, more results are needed considering a range of different fatigue critical details, material thicknesses, SN-curves, number of inspections, inspection techniques and repair strategies. Further, the sensitivity of the stochastic models should be investigated, especially for Δ, X_W and X_{SCF}. Finally, for some details where the consequence of failure is less severe, a smaller value of β_{min} can be accepted.

6. Conclusion

A methodology for probabilistic calibration of fatigue design factors for offshore wind turbine support structure is described. Representative stochastic models and influence coefficient functions are presented. For calibration examples single wind turbines and wind turbines within a wind farm are considered for a linear and a bi-linear SN-curve for welded steel details. Representative FDF values are obtained without and with one inspection during the design life.

Using the reliability level used for calibration of partial safety factors for ultimate limit states in the IEC 61400-1 standard lower FDF values are obtained than used for civil engineering structures and offshore oil and gas steel platforms. If an inspection is performed during the design life then the FDF values can be decreased even more. However, the decrease in cost of the substructure due to the lower FDF values should be compared to the cost of

the inspection and possible repair if a crack is detected. It is noted that the results presented are illustrative – more examples (influence coefficients modelling different types of critical details) and different types of inspections should be considered before recommendations for standardization can be formulated.

This framework of reliability-based calibration of FDF values can also be used as a tool to select for a given wind turbine (wind farm) a cost-effective fatigue design considering initial design cost and service life costs.

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Appendices - Probabilistic Models

Appendix A. SN-assessment of reliability

Design equation for free flow condition
Based on the assumptions mentioned in section 3 the design equation for a single/alone OWT can be written:

$$G(z)=1-\frac{v \cdot FDF \cdot T_L}{K_c}\int_{U_{in}}^{U_{out}} D(m;\sigma_{\Delta\sigma}(U,z))\cdot f_U(U) \, dU = 0 \quad (2)$$

where v is the number of stress cycles per year, FDF is the fatigue design factor ($T_F = T_L \cdot$ FDF and FDF$=(\gamma_f \cdot \gamma_m)^m$ for a linear SN-curve using laod and material partial safety factors γ_f and γ_m), T_L is the design life time, K_c is characteristic value of K (material parameter in SN-curve), U_{in} and U_{out} are the cut-in and –out wind speeds, m is the Wöhler exponent in SN-curve, $f_U(U)$ is the probability density function of mean wind speed U, z is the design parameter and D represents the expected value of fatigue for the all stress ranges given a mean wind speed U and standard deviation $\sigma_{\Delta\sigma}$ and considering medium turbulence characteristics [7]. The expected value of $\Delta\sigma$ can be obtained for linear and bilinear SN-curve with the following formulae:

$$D_L= \int_0^\infty s^m \cdot f_{\Delta\sigma}(s|\sigma_{\Delta\sigma}(U,z)) \, ds \quad (3)$$

$$D_{BL}= \int_0^{\Delta\sigma_D} s^{m_1} \cdot f_{\Delta\sigma}(s|\sigma_{\Delta\sigma}(U,z)) \, ds$$
$$\quad (4)$$
$$+ \int_{\Delta\sigma_D}^\infty s^{m_2} \cdot f_{\Delta\sigma}(s|\sigma_{\Delta\sigma}(U,z)) \, ds$$

where $f_{\Delta\sigma}(s|\sigma_{\Delta\sigma})$ represents the probability density function for stress ranges given a standard deviation $\sigma_{\Delta\sigma}$ at the mean wind speed U. $\sigma_{\Delta\sigma}$ and v can be obtained by cycle counting methods, e.g. Rainflow counting and $\sigma_{\Delta\sigma}$ is written:

$$\sigma_{\Delta\sigma}=\alpha_{\Delta\sigma}(U) \cdot \frac{\sigma_u(U)}{z} \quad (5)$$

$$\sigma_u=I_{ref} \cdot (0.75 \cdot U+b) \quad , \quad b=5.6m/s \quad (6)$$

In equation (5), $\alpha_{\Delta\sigma}$ is the influence function referring to an specific detail (hot spot) or sector in the OWT and is a function of the wind speed. σ_U is the (normal) turbulence standard deviation (IEC-) considering class B.

Design equation for in-wind farm location
For wind farm location the turbulence model is integrated at the model, resulting in the following design equation:

$$G(z)=1-\frac{v \cdot FDF \cdot T_L}{K_c} \cdot$$
$$\int_{U_{in}}^{U_{out}} \left[\begin{array}{l} (1-N_w \cdot p_w) \cdot D(m;\sigma_{\Delta\sigma}(U,z)) \\ +p_w \cdot \sum_{j=1}^{N_w} D(m;\sigma_{\Delta\sigma,j}(U,z,j)) \end{array} \right] \cdot f_U(U) \, dU = 0 \quad (7)$$

where $\sigma_{\Delta\sigma,j}$ is the standard deviation of stress ranges considering wake condition from j-neighboring wind turbine and is defined as follows:

$$\sigma_{\Delta\sigma,j}=\alpha_{\Delta\sigma}(U) \cdot \frac{\sigma_{u,j}(U,j)}{z} \quad (8)$$

$$\sigma_{u,j}= \sqrt{\frac{0.9 \cdot U^2}{\left(1.5+0.3 \cdot d_j \sqrt{U/c}\right)^2}+\sigma_u{}^2} \quad (9)$$

d_j is the distance between OWT normalized by the rotor diameter of the neighboring wind turbine j and c is the constant equal to 1 m/s.

Limit state equation for free flow condition
The limit state equation in free flow conditions is written:

$$g(t)=\Delta-\frac{v \cdot t}{K}\int_{U_{in}}^{U_{out}}\int_0^\infty (X_w \cdot X_{SCF})^m$$
$$\cdot \left(\begin{array}{l} D(m;\sigma_{\Delta\sigma}(U,z))\cdot \\ f_{\sigma_u}(\sigma_u|U) \cdot f_U(U) \end{array} \right) \, d\sigma_u \, dU \quad (10)$$

where Δ, X_w and X_{SCF} represent the uncertainties related with the Miner rule of damage accumulation, wind load effects and local stress concentration and analysis. t is the reference time and $f_{\sigma u}$ is the probability density function for free flow turbulence that is modeled as LogNormal distributed with a representative mean turbulence equal to:

$$I_{ref} \cdot (0.75 \cdot U+3.6) \quad (11)$$

and standard deviation equal to 1.4m/s times the I_{ref}.

Limit state equation for in-wind farm location

To assess the reliability in wind farm location the following limit state equation is used:

$$g(t)=\Delta-\frac{v \cdot t}{K}(X_w \cdot X_{SCF})^m \cdot$$

$$\int_{U_{in}}^{U_{out}} \int_0^\infty \left[\begin{array}{c} (1-N_w \cdot p_w) \cdot D(m;\sigma_{\Delta\sigma}(U,z)) \\ +p_w \cdot \sum_{j=1}^{N_w} D(m;\sigma_{\Delta\sigma,j}(U,z,j)) \end{array} \right] \tag{12}$$

$$\cdot f_{\sigma_u}(\sigma_u|U) \cdot f_U(U) \, d\sigma_u \, dU$$

$$\sigma_{u,j}=\sqrt{\frac{X_{wake} \cdot U^2}{\left(1.5+0.3 \cdot d_j\sqrt{U/c}\right)^2}+\sigma_u{}^2} \tag{13}$$

where X_{wake} models the uncertainty related to the wake turbulence conditions coming from surrounding wind turbines. When equation (8) is used with this model, equation (9) will change in order to take into account the wind turbulence with the additional turbulence coming from the wake condition. The formula becomes:

Appendix B. FM-assessment of reliability
Crack model

For the assessment of the FM-fatigue life, a one dimensional representative crack growth model is used with crack length *c* related with the crack depth *a* through a constant factor f_{cr}. The following (Paris- Erdogan) model is used:

$$\frac{da}{dN}=C_a \cdot (\Delta K_a)^m \,, \\ a(N_0)=a_0 \,\,, \,\, c(f_{cr} \cdot a_0)=c_0 \tag{14}$$

where C_a is a material parameter (crack growth rate), ΔK_a is the stress intensity factor range in a stress cycle. a_0 and c_0 represent the initial dimensions of the crack. The fatigue life is represented by two stages: fatigue initiation life (N_I) and fatigue propagation life (N_P). Adding these periods is obtained the number of stress cycles to fatigue failure. The stress intensity factor is written:

$$\Delta K_a=Y \cdot \Delta\sigma_e \cdot \sqrt{a \cdot \pi} \tag{15}$$

Y is a stochastic variable taking into account the uncertainty of the geometry function and $\Delta_{\sigma e}$ is the equivalent stress range that can be calculated as follow for free flow condition:

$$\Delta\sigma_e=X_w \cdot X_{SCF} \cdot$$

$$\left[\int_{U_{in}}^{U_{out}} \int_0^\infty \left(\begin{array}{c} D(m;\sigma_{\Delta\sigma}(U,z)) \cdot \\ f_{\sigma_u}(\sigma_u|U) \cdot f_U(U) \end{array} \right) \, d\sigma_u \, dU \right]^{1/m} \tag{16}$$

In case of wind farm location:

$$\Delta\sigma_e=X_w \cdot X_{SCF}$$

$$\cdot \left[\int_{U_{in}}^{U_{out}} \int_0^\infty \left[\begin{array}{c} (1-N_w \cdot p_w) \cdot D(m;\sigma_{\Delta\sigma}(U,z)) \\ +p_w \cdot \sum_{j=1}^{N_w} D(m;\sigma_{\Delta\sigma,j}(U,z,j)) \\ \cdot f_{\sigma_u}(\sigma_u|U) \cdot f_U(U) \, d\sigma_u \, dU \end{array} \right] \right]^{1/m} \tag{17}$$

Limit state equation

The limit state equation used in the FM-approach is associated with failure that occurs when the crack a(t) at the considered detail exceeds the critical size a_c of the crack (e.g. thickness). The limit state equation is thus written:

$$g(t)=a_c-a(t) \tag{18}$$

The uncertainty related to a chosen inspection technique is modeled by a probability of detection (POD) curve (see table 1).

Paper IX

Bayesian Updating and Integration of Uncertainty in the Assessment of Reliability for Offshore Wind Turbine Support Structures

BAYESIAN UPDATING AND INTEGRATION OF UNCERTAINTY IN THE ASSESSMENT OF RELIABILITY FOR OFFSHORE WIND TURBINE SUPPORT STRUCTURE

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Abstract:

The stochastic models for assessing the life cycle reliability are propped up with the state of knowledge of the considered phenomenon and its variables. Offshore Wind turbines consist of structural, mechanical and electrical parts that are strongly related, influencing each other during operational and standstill states and extreme events. In offshore wind industry the monitoring and inspection activities improve the quality and quantity of information about external phenomena. This information can be used to reduce the uncertainty by updating the stochastic model. Typically, the updating process is carried out through classical Bayesian approach. Although this represents a parametric effortless solution, the limited number of variables, strict conjugation, necessary mixed notation and the problems of integration to the structural reliability analysis represent some drawbacks. The discrete non-conjugated and Gibbs sampling approaches of Bayesian statistics can be used to overcome these disadvantages. Moreover, the integration of uncertainty into the assessment of reliability can be carried out by polynomial chaos expansion approximations. In this paper, these methodologies and updating techniques are applied for stochastic variables in the fatigue assessment of reliability of offshore wind turbines. A short description of their differences and the application of the orthogonal polynomial approximation are described and illustrated in an example.

Keywords: Bayesian Analysis, Structural Reliability, Offshore Wind Turbine, Polynomial Chaos Expansion Approximation

1. INTRODUCTION

In 2030, the European Union (EU) electricity demand is planned to be supplied with 563 TW/year [1] from the Offshore Wind Industry (OWI), which corresponds to 15% of the total electricity demand. One of the main reasons for going offshore is the higher wind speeds at low heights for longer periods than in land. Furthermore, the full-load hours per year are typically 50% larger than at onshore places [2]. On the other hand, offshore structures are exposed to severe deterioration due to the harsh environmental conditions that deteriorates their components.

Unlike offshore structures in the oil and gas (O&G) industry, offshore wind turbines represent much lower direct risk to the society and the personnel due to its location and because personnel is not needed in-situ for the operational phase. This allows having only economical cost included when optimizing the life cycle cost-benefits.

In the OWI, the monitoring, measuring and surveying systems can be compared with the ones for oil & gas industry. The SCADA systems (Systems of Control and Data Acquisition) can provide online data coupled with real-time fault-prediction algorithms, see [4-7]. Currently, there are attempts to integrate this information for structural purpose to predict failures and to assess the influence of the mechanical damage on the structural reliability.

To integrate the new information, a Classical Bayesian Updating (CBU) approach can be used for providing a straightforward solution in case of well-known standard distributions, see [8-10].

However, when there is more than one unknown parameter, the resulting predictive distribution will be intricate and thereby restricts the application of the solution. In case of more than two uncertain/unknown statistical parameters, the CBU approach will not be a viable approach. This is an obstacle that probabilistic updating is facing in its way to be integrated to the Structural Reliability Analysis (SRA).

Within Bayesian statistics, Discrete Semi-Conjugated Updating (DSCU) represents a discrete solution to integrate the information into the probabilistic model, see [11]. This approach can handle updating with either partially or totally discarding the notion of conjugacy that is used in CBU. In addition, it extends the possibility to incorporate multi-parameter probabilistic models. Further, Bayesian simulation techniques can also be applied to update the probabilistic information, i.e. Gibbs sampling. Monte Carlo Markov Chain (MCMC) techniques can use the Bayesian statistical formulation to perform an approximate solution for updating the stochastic models for the SRA, see [12-14].

The Bayesian Updating methods allow integrating new information into the stochastic model and the next challenge comes when the non-parametric multi-parameter distributions are to be used in SRA. In this paper this is accomplished by using a Polynomial Chaos Expansion Approximation (PCEA) of the updated probabilistic model. This application has been used to directly integrate uncertainty into the SRA [15,16] but not formerly applied in a Bayesian updating framework to integrate the updated non-parametric probabilistic model into the SRA.

This paper describes an approach to apply non-parametric Bayesian statistics in SRA by using PCEA. The application is exemplified for fatigue assessment of offshore wind turbine structures but the proposed procedure can also be applied for extreme loads and for other types of structures.

2. UPDATING AND INTEGRATION OF NEW INFORMATION

Due to the desire to increase the efficiency and competitiveness of offshore wind industry, measurement and monitoring technologies have become important for engineering purposes such as failure prediction, damage detection, inspection planning and optimization of design. Bayesian statistics presents a consistent approach to address this integration by updating with new information. The updating process is based on the well know Bayesian updating formula

$$f_\Psi(\psi|z) = \frac{f_Z(z|\psi)\, f_\Psi(\psi)}{\int_\psi f_Z(z|\psi)\, f_\Psi(\psi)\, d\psi} \tag{1}$$

where $f_\Psi(\psi)$ is the prior distribution of the vector or set Ψ of statistical parameters and represents the beliefs concerning the statistical parameters of the probability density function (PDF) $f_Z(z)$ of the stochastic variables Z. The prior distribution is gathering the available information on the parameters at the moment of starting collecting information on Z. $f_Z(z|\psi)$ is the PDF of the stochastic variable Z, defined by the parameters ψ. When this density function is considered as a function of the variables ψ defined for a fixed Z then this PDF is not entirely the same in definition and thus the properties change. This is the reason to call it the likelihood function. The resulting updated PDF is called the posterior density function $f_\Psi(\psi|z)$ of the set Ψ conditional on z. The denominator in the formula (1) is the normalizing constant of the posterior distribution.

When new outcomes $\hat{z} = (\hat{z}_1, \hat{z}_2, \dots, \hat{z}_n)$ of the variable z are available, the density function $f_Z(z|\psi)$ change to its estimating form as $f_Z(\hat{z}|\psi)$ and the posterior to $f_\Psi(\psi|\hat{z})$. The likelihood function uses the samples and is defined by

$$f_Z(\hat{z}|\psi) = \prod_{i=1}^{n} f_Z(\hat{z}_i|\psi) \qquad (2)$$

In this paper, the main reason of calculating the posterior function is the interest *per se* in the predictive density function because it can be used in the assessment of the structural reliability and not as an estimator of good choice of the prior to assure the right beliefs, as in pure statistical cases.

The predictive distribution of Z represents the updated predictions of the probabilistic distribution of Z taking into account both the uncertainty on Ψ and the residual uncertainty on Z conditional on whether parameter ψ is known or not. The assumption of knowing any parameter ψ brings theoretical limitations for the CBU approach and can provide a non-negligible approximation, e.g. for the case with a Normal likelihood with known variance is unlikely to be fully justified in practical cases.

However, the above approach provides a parametric solution for the classical approach and the MCMC technique can be used to obtain the full conditional distributions. The predictive distribution is defined as follows

$$f_Z(z|\hat{z}) = \int_\psi f_Z(z|\psi) \, f_\Psi(\psi|\hat{z}) \, d\psi \qquad (3)$$

where $f_Z(z|\hat{z})$ is the predictive distribution function of z conditional on the new samples $\hat{z}$. The above formulas work together with the notion of conjugacy (see [17]) when the CBU-approach is chosen for simplicity and parametric treatment. However, when the set Ψ has more than one parameter to be updated, the predictive density function is no longer simple to handle. The difficulty is not only in the algebraic handling but also in the incorporation to the SRA. Jointly with the conjugation, mixing of notation is typically used, e.g. normal distribution with unknown mean and standard deviation. When mixed-notation is included in the prior formulation, the decision makers should not generalize for any application case. This can bring either a conservative estimation of the predictive distribution or a wrong estimation. Examples of estimation of distribution with CBU-approach can be found in statistics [18,19] and engineering literature [20,21].

The consideration of "vague" prior information can be done but the decision makers should be aware about the kind of characterization. Although "vague" is commonly interpreted as synonym to "non-informative", "diffuse", "flat" and "negligible" adjectives. This, in a sense, is not entirely correct. The vague-assumption can be classified as notational or functional. For example, in [22] updating with CBU is considered assuming notational-vague considerations when parameters are set to create the non-informative treatment with the purpose of "weighting" the likelihood function and "filter" the right information to the posterior distribution.

When vague functional consideration is taken into account, the "weighting" prior function is a deterministic function such as Jeffrey's and Haldane's prior and arcsine distribution, see [23,24]. This bias filtering of information may affect the predictive distribution and make evident how vague-notational consideration is more suitable for engineering purposes than deterministic vague consideration.

The notion of conjugated, mixed-prior formulation and uni-parametric functions are disadvantages of CBU. Conjugated priors are limited to those existing into the likelihood's family. The DSCU belongs to non-parametric updating techniques and it avoids correlation inherited by mixing the priors' notation for multi-parameter density functions. Moreover, DSCU is more efficient for numerical implementation compared with the entire evaluation of equation (1). The relative posterior discrete density function is calculated by

$$p_d(\psi_m|\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n) = \frac{p(\psi_m, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)}{\sum_{i_l} \cdots \sum_{i_m} p(\psi_{i,m}, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)} \tag{4}$$

where $p(\psi_m, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)$ is the joint probability distribution of the parameters $\psi_m = (\psi_1, \psi_2, \ldots, \psi_m)$ to be updated with the sample $\hat{z} = (\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)$. m refers to the of number of parameters. The denominator is the summation of m-number of finite series of the joint probability distribution $p(\psi_{i,m}, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)$. The complete derivation of formula (4) can be found in the Appendix B.

The DSCU-approach should only be compared with CBU numerically. They produce different results due to their formulations: one is based on conjugation (CBU) and the other on semi- or non-conjugated prior distributions (DSCU). Due to the non-conjugating formulation, DSCU is numerically easier to integrate with more variables. However, the discrete calculation can only be applied for a small number of parameters due to the fact that the chosen discrete vector of every parameter ψ is increasing exponentially with the m-number of updating parameter ψ. The discrete predictive distribution can be obtained by simply multiplying by the discrete probability density distribution $p_{d,Z}(z|\psi)$.

GS (Gibbs Sampling) is a subclass of MCMC algorithms, and represents a simulating technique to estimate the posterior PDF. Unlike CBU and DSCU, GS relies on full conditional distributions and on a sequential simulation algorithm. In contrast to crude Monte Carlo simulation (MC), the GS algorithm uses a more elaborated iterative sampling idea but still rather simple. In essence, the simulation of sequences of samples represent state of the parameters $\psi^{(s)} = \left\{\psi_1^{(s)}, \psi_2^{(s)}, \ldots, \psi_m^{(s)}\right\}$ and with the new set of samples, the new states $\psi^{(s+1)} = \left\{\psi_1^{(s+1)}, \psi_2^{(s+1)}, \ldots, \psi_m^{(s+1)}\right\}$ will start to be generated by the following recursive algorithm

1) $\psi_1^{(s+1)} \sim p(\psi_1|\psi_2^{(s)}, \ldots, \psi_m^{(s)}, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)$;
2) $\psi_2^{(s+1)} \sim p(\psi_2|\psi_1^{(s+1)}, \ldots, \psi_m^{(s)}, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n) \ldots$
3) $\psi_m^{(s+1)} \sim p(\psi_m|\psi_1^{(s+1)}, \psi_2^{(s+1)} \ldots, \psi_{m-1}^{(s)}, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n) \ldots$
4) $\psi^{(s+1)} = \left\{\psi_1^{(s+1)}, \psi_2^{(s+1)}, \ldots, \psi_m^{(s+1)}\right\}$
5) Initializing $\psi_1^{(s+2)} \sim p(\psi_1|\psi_2^{(s+1)}, \ldots, \psi_m^{(s+1)}, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)$;

It is noted that the GS algorithm requires that the full conditional distributions have to be set up for sampling.

In order to illustrate the application of the three approaches, the Normal / Lognormal distribution case is considered. X is assumed to be a Lognormal distributed stochastic variable $X \sim LN(\mu_X, \sigma_X)$. Initially, it is assumed that both μ_X and σ_X are unknown. A transformation of X to a Normal distributed variable $Z \sim N(\theta, \sigma)$ is established. θ and σ are similarly considered to be unknown, i.e. the unknown parameters are $\Psi = \{\theta, \sigma\}$.

For the CBU-approach the prior distributions of the parameters are defined as follows: the mean is assumed to be Normal distributed: $\theta \sim N(\mu_\theta, 1/\mu_\sigma\sqrt{\kappa_0})$ and the standard deviation (in terms of the precision parameter) is assumed to be Gamma distributed: $(1/\sigma^2) \sim Gamma(\nu_0/2, \nu_0\sigma_0^2/2)$. κ_0 and ν_0 can be interpreted as the number of observations from our prior knowledge describing θ and σ. σ_0^2 is the prior sample variance. The joint prior distribution of θ and σ is thus defined by the parameters μ_θ, μ_σ, κ_0, ν_0 and σ_0^2. Using a distribution from the exponential family, the conjugation of the likelihood can be carried out, see appendix A. In figure 2.1, the posterior and predictive distributions are shown for the CBU-approach using the following prior parameters: $\mu_X = 1.0, \sigma_X = 0.15$, $\nu_0\sigma_0^2/2 = 0.045$ and $\nu_0/2 = 2$ (in black).

For case a, 20 log-samples, $\hat{z}$ were simulated from a normal distribution with mean 1 and standard deviation 0.15. If it is assumed that the prior information consists of 10 prior samples that are added to κ_0, the uncertainty decreases (see figure 2.1-a, in gray) for the posterior distribution. However this barely influences the predictive distribution (see figure 2.1-b). E.g. the 5% / 95% probability levels change less than 0.18% in both quantiles. In figure 2.1-c is shown the posterior distribution obtained by Gibbs sampling. This simulating approach allows to fast construction of the posterior distribution due to the dependent sequence of sampling for every parameter.
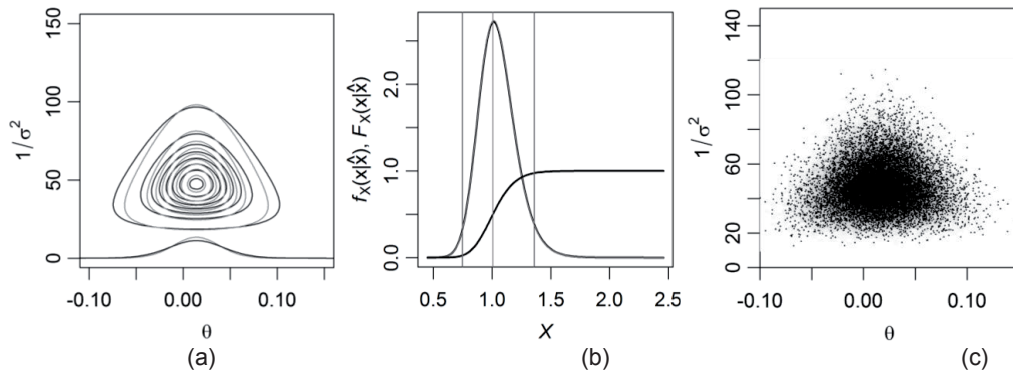

Figure 2.1 – (a) and (b) CBU, (black) the joint posterior of $(\theta, 1/\sigma^2)$ and predictive distribution of X and (gray) joint posterior of $(\theta, 1/\sigma^2)$ and predictive distribution of X with additional 10 prior samples. (c) Gibbs sampling, joint posterior distribution of $(\theta, 1/\sigma^2)$.

For the DSCU and GS approaches, the same basic prior formulation is used. But instead of using the term $1/\mu_\sigma\sqrt{\kappa_0}$ in the θ-prior distribution, σ_θ is simply defined (see appendix B). This definition of the standard deviation originates from the semi-conjugating condition. Obviously, in the Normal case, CBU and DSCU approaches are going to be close in their results when $1/\mu_\sigma\sqrt{\kappa_0}$ is close to σ_θ, e.g. if κ_0 is close to unity and σ_θ is close to μ_σ. The semi-conjugating condition makes the updating formulation of CBU different from the one in DSCU and GS, and thus they should not been compared directly. Although the difference in the central moments is small for this example (see table 2.1, with $\sigma_\theta = 0.075$ for DSCU and GS), the difference becomes larger when the samples $\hat{z}$ fall outside the probable tendency (distribution) of the prior beliefs.

To exemplify the influence of the formulation and the samples, a case b is shown where the samples $\hat{z}$ are taken as 15 log-samples from $N(1.0,0.15)$ and 5 log-samples from $N(1.0,0.25)$. The vector of log-samples is shown in table 2.2. In table 2.1-b is shown the quantitative differences between CBU and DSCU. In case b the CBU mean and standard deviation decrease and increase, respectively while in the DSCU-approach both increase.

Table 2.1 Simulated vector of 20 Log-normal samples, case a and b

case	$\hat{z}$
a	-0.09868 0.02717 -0.13392 0.21454 0.04824 -0.13132 0.07056 0.10503 0.08283 -0.04689
	0.20438 0.05683 -0.09781 -0.40377 0.15592 -0.00676 -0.00243 0.13240 0.11616 0.08533
b	-0.13132 0.07056 0.10503 0.08283 -0.04689 0.20438 0.05683 -0.09781 -0.40377 0.15592
	-0.00676 -0.00243 0.13240 0.11616 0.08533 -0.17032 0.04488 -0.23433 0.33562 0.07915

Table 2.2 1st moment and K-central moments of the predictive distribution of $f_X(x|\hat{x})$ after 20 samples.

	CBU		DSCU		MCMC-GS*	
	(a)	(b)	(a)	(b)	(a)	(b)
Mean	1.0257	1.0183	1.02608	1.02809	1.02552	1.02752
Standard deviation	0.1566	0.1813	0.15922	0.17950	0.15977	0.18018
2nd central moment	0.0245	0.0328	0.02535	0.03222	0.02552	0.03246
3rd central moment	0.0020	0.0037	0.00216	0.00349	0.00220	0.00357
4th central moment	0.0023	0.0043	0.00249	0.00417	0.00255	0.00431
Coefficient of skewness	0.5342	0.6238	0.53581	0.60373	0.54079	0.61163
Coefficient of kurtosis	0.8803	1.0650	0.88711	1.02168	0.91898	1.09117

*500,000 simulations

The values in table 2.2 show the situation when the standard deviation $\sigma_{\theta Z}$ of the mean θ is chosen to result in minimum difference between CBU and both DSCU and GS approaches (see appendix B). The preference of using GS instead of DSCU takes place when a hierarchical modeling of the stochastic model can be used to describe the probabilistic model of Z, see [25-27].

3. INTEGRATION OF UNCERTAINTY

Integration of statistical uncertainty in structural reliability analysis (SRA) is basically not a problem. Generally, when FORM or SORM are used a non-normal distribution can easily be transformed to a standard Normal variable by the simple transformation $z = F_Z^{-1}\big(\Phi(u)\big)$. However, when an intricate or non-parametric distribution function is used, integration of statistical uncertainty can require an additional effort. The integration can be done in different ways, e.g. by a polynomial / rational approximation or by asymptotic expansions, see [28]. Nonetheless, there is a particular necessity for a generic procedure for uncertainty integration in cases where the distribution functions are complex, such as the ones generated in the updating process described above, e.g. In the conjugated case of a normal variable with both statistical parameters unknown.

In this paper, the "Wiener-Hermite chaos" polynomial function is used assuming the underlying stochastic process as Gaussian, [29]. In the context of stochastic processes, the homogeneous chaos expansion converges to any process with finite second-order moments, see [30]. Although the application in this paper is concentrated about the incorporation of uncertainty into the model, Ghanem & Spanos in [31] and Sudret and Der Kiureghian [32] used Hermit-Chaos expansion together with the finite element method for formulating a framework to account for the randomness and spatial variability of mechanical properties.

Besides mechanical and structural application, Tatang in [33], Webster et al. in [34] and Isukapalli in [35] extended the application into chemical engineering. In [35] PCEA is used as a functional approximation for integration of uncertainty into a computational efficient method for propagation. Similarly in this paper PCEA is used to approximate a probabilistic function to a random variable that can be expressed as a linear combination of Hermite polynomials having a Gaussian variable as its argument. The key point in this paper is to integrate the information to decrease uncertainty. Although an increase of reliability is obviously expected, a decrease may be a possibility, [36].

This section presents a brief review of the PCEA techniques for functional approximation. For a deeper description of the theory, reference is made to previous mentioned papers. The Homogeneous Chaos expansion was proposed by Wiener [29]. The main advantage of this approximation is its fast exponential convergence rate when Gaussian variables or process are represented. However, this rate can be seriously affected in some non-Gaussian cases. A review of the Wiener-Askey scheme for orthogonal polynomial expansion can be found in [30].

The formulation can be adjusted in two manners: the first is by increasing the number of random variables to reduce the random "fluctuations" in the stochastic field and the second is to increase the maximum order of the polynomial chaos for handling the non-linear behavior of the process. For probabilistic approximations with one stochastic variable, a one-dimensional polynomial chaos approximation is used with an n-order of the homogeneous chaos. The Gaussian stochastic process can be approximated by the following series:

$$X(\omega) = a_0 H_0 + \sum_{i_1=1}^{\infty} a_{i_1} H_1\big(\xi_{i_1}(\omega)\big) + \sum_{i_1=1}^{\infty} \sum_{i_2=1}^{i_1} a_{i_1 i_2} H_2\big(\xi_{i_1}(\omega), \xi_{i_2}(\omega)\big) + \sum_{i_1=1}^{\infty} \sum_{i_2=1}^{i_1} \sum_{i_3=1}^{i_2} a_{i_1 i_2 i_3} H_2\big(\xi_{i_1}(\omega), \xi_{i_2}(\omega), \xi_{i_3}(\omega)\big) + \cdots \tag{5}$$

The term $H_n\big(\xi_{i_1}, \dots, \xi_{i_n}\big)$ is the Hermite-Chaos term of order n in the standard Gaussian variables $\big(\xi_{i_1}, \dots, \xi_{i_n}\big)$ with zero mean and unit variance. H_n are Hermite polynomials and a_n are Fourier coefficients of the series. The general polynomial chaos of order n can be obtained with

$$H_n\big(\xi_{i_1}, \dots, \xi_{i_n}\big) = e^{\frac{1}{2}\xi^T \xi}(-1)^n \frac{\partial^n}{\partial \xi_{i_1} \dots \partial \xi_{i_n}} \tag{6}$$

In the one dimensional case with a third order chaos expansion the series (5) results in equation (7). This is obtained by constructing the polynomial chaos expansion by the direct approach (see [31]) and using the properties of the orthogonal polynomials:

$$X(\omega) = a_0 + a_1 H_1(\omega) + a_2 H_2(\omega) + a_3 H_3(\omega) \tag{7}$$
$$H_{n=3} = \{1, \xi(\omega), \xi(\omega)^2 - 1, \xi(\omega)^3 - \xi(\omega)\} \tag{8}$$

The parameters a_n can be calculated by an optimization scheme where the least-square error obtained from the k-central moments is minimized. For case a and b in table 2.1 the predictive distributions for the DSCU- and GS-approaches are approximated by PCEA, see table 3.1 and 3.2 and figure 3.1. For case a the error is up to 1.5% for the 97.5% and 2.5% quantile and less than 0.19% for 50% quantile (see table 3.1). In order to add more accuracy, a fourth order chaos PCEA can be used.

Table 3.1 PCEA-parameters and error of the PCEA when is compared with an ECD of the variable X for the case b.

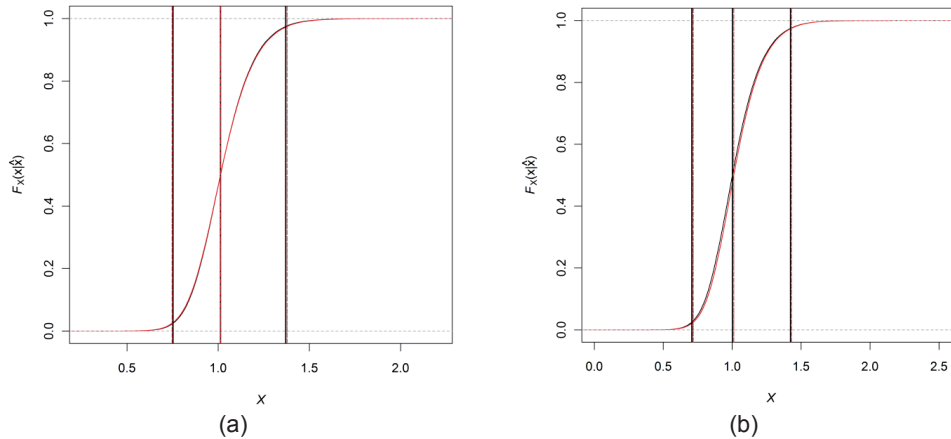|	DSCU	GS
b_0	1.028092	1.027526
b_1	-0.177831	-0.178459
b_2	0.016221	0.016335
b_3	-0.003456	-0.003779
Error for 2.5% quantile	1.23 %	1.47 %
Error for 97.5% quantile	1.31 %	1.27 %
Error for 50.0% quantile	0.1765 %	0.1874 %

Figure 3.1- (a) Comparison of PCEA for the predictive distribution from CBU- (black solid-line), DSCU- (gray) and GS-approaches (red dash-line) for case a. (b) Comparison of PCEA for the predictive distributions from CBU-(black solid-line), DSCU-(gray) and GS-approaches (red dash-line) for case b.

Table 3.2 – Quantiles from the 95% probability interval of case a and b.

	CBU		DSCU		GS	
	A	b	A	B	a	b
2.5% quantile	0.7519	0.7076	0.7479	0.7189	0.7464	0.7168
97.5% quantile	1.3720	1.4232	1.3781	1.4275	1.3791	1.4291

The statistical analysis of the three updating approaches is mainly addressed in this section to compare the different assumptions in the updating techniques. In the following sections the impact on the structural reliability is analyzed for the case of offshore wind turbines (OWT).

4. OFFSHORE WIND TURBINE SUPPORT STRUCTURES

Offshore wind turbines have characteristics that make them different from common structural systems. The reason is their mechanical and electrical systems through a control system influence the internal forces, performances and deterioration processes (e.g. fatigue). Figure 4.1 shows the main components in a wind turbine and the most important degrees of freedom.
The tower transmits the forces to the support structure. The transition zone between the tower and foundation structure is an important part of the wind turbine that is prone to fatigue failure due to changes and discontinuities in geometry and materials. Weld seams can be found in these structural components and cracks can potentially be found there.
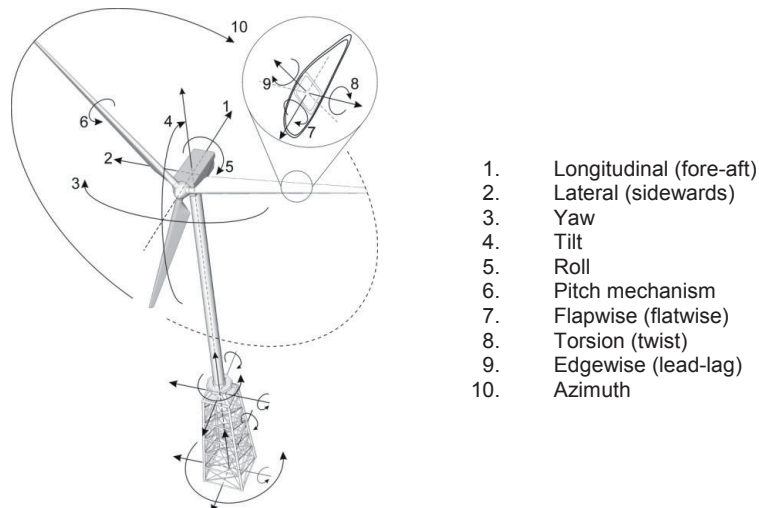
Figure 4.1 - 'Common' degrees of freedom for offshore wind turbines.

1.	Longitudinal (fore-aft)
2.	Lateral (sidewards)
3.	Yaw
4.	Tilt
5.	Roll
6.	Pitch mechanism
7.	Flapwise (flatwise)
8.	Torsion (twist)
9.	Edgewise (lead-lag)
10.	Azimuth

There are different types of support structures. According to EWEA [37], 65.2% of offshore wind turbine support structures at the end of 2009 consist of monopile foundations, 23.1% of gravity foundation, 2% of jackets, 0.8% of tripods and the rest is unknown. The average depth at offshore places is around 9 m (not taking into account Alpha Ventus project with 30 meters depth and using jacket, and the Hywind floating turbine with 220 meters depth). Additionally, the average shore distance is around 14 km. Currently, not all technical solutions have been developed for offshore wind turbines [38]. However, the experience gained in the oil & gas industry may help finding efficient technical solutions especially for tripod and jacket type support structures.

4.1 External and Condition Monitoring

External measuring (EM) and condition monitoring (CM) have been carried out for offshore wind turbines for more than one decade, [39]. The main objective is to gain of information about the external conditions and data related to the wind turbines performance. In EM data on spatial and time/frequency characteristics of the external wave and wind phenomena are collected while in CM data is analyzed mainly to devise failure-detection and diagnostic algorithm to assess the performance of the wind turbines. In [40] and [41] a review of measuring technologies for wind turbines is given.

The monitoring actions can e.g. be real-time measurements and inspection monitoring actions. The SCADA systems are mainly monitoring the nacelle components with the purpose of maximizing its performance and reduce downtime periods. Examples of SCADA system are presented in CONMOW [42], Cleverfarm® [43] and WT-Ω systems [6].

For fatigue assessment in structural components (high-reliability components) information from SCADA systems can be used indirectly for short-term considerations. However, load monitoring algorithms for wind turbines have been developed for components such as blades and rotor components, see [44-46]; where optical and temperature sensors give the information for fatigue load counting. For the high-reliability components, Inspection and supervision actions are only carried out for critical and important components and information of crack growing or mechanical damage can thus be obtained.

For measurements of external conditions different facilities [47], devices and mechanisms for recording, measuring [43] and monitoring [48] are available. Meteorological masts are the main facility to measure the wind speed. However, recent advances in remote sensing technologies, such as SODAR (Sound detection and ranging) and LIDAR (Light Detection and ranging) show promising results, see [49] and [50].

At offshore locations, wind fields behave different than at onshore sites. Sea surface roughness is much smaller than at land locations implying that the wind speeds increase and the free flow turbulence level decrease [51]. Besides higher wind intensity and longer load periods, ocean waves contribute typically to 75% of the horizontal load for support structures. Further, loads from ice, tidal sea level variations and current can be important. According to available statistics, wind and wave load correlation is generally large for sea locations while at offshore location close to the shore, this correlation decrease due to refraction and breaking of the waves [52].

When information from measurements and condition monitoring are available the stochastic model for the assessment of the structural reliability can be updated. This updating typically decreases the uncertainty in the variables and their parameters. CBU-updating has been performed for different situations in structural engineering, see [33], [53-55]. However, the situation of having discrete statistical distributions of the parameters could take place. In such cases, the decision maker can apply a semi-conjugate or non-conjugate discrete updating. In case of many unknown parameters an approximation with GS may be used. The case considered below is about updating of variables related to wind and wake conditions in offshore wind farms for welded details in the support structure that are prone to fatigue failure. The cases exemplify the updating and integration of information due to the measuring, e.g. new devices or measuring facilities.

5. RELIABILITY ASSESSMENT OF FATIGUE
5.1 FATIGUE

The loss of strength as a result of cyclic loading over a period of time is a general phenomenon that takes place for most materials. This failure scenario typically takes place in situations where loads are under the design loads for ultimate, extreme load. The failure phenomenon was modeled by Wöhler [56] for the case of constant amplitude loading. Later, Palmgren [57] and Miner [58] propose a cumulative linear damage summation model that considers variable amplitude loads and may be used to predict the fatigue life.

The fatigue life of a component can be summarized in three phases: crack initiation, crack propagation and final fracture. From an engineering outlook these periods can be defined in two stages: crack initiation life N_I that is defined by the number of loading-straining cycles required to develop a micro-crack and N_P that is the number of cycles required to propagate a crack to a critical size. The last phase may be neglected and the total fatigue life N_T can be expressed as:

$$N_T = N_I + N_P$$
(9)

The approach proposed by Wöhler together with the Palmgren-Miner linear cumulative damage rule represent a simple formulation for estimation of the fatigue life. The fatigue crack propagation is influenced by the micro-structural nature of the material, mean stress level, frequency of load application, the environment and force constrains. There have been many efforts to describe the crack development by different crack growth laws. The Paris-Erdogan law [59] is one of the broadest used:

$$\frac{da}{dN} = C \cdot \Delta K^m$$
(10)

where a is the crack size, N is the number of cycles, ΔK is the stress intensity factor range, C is the crack growth rate and m is the Wöhler exponent. The stress intensity factor range ΔK is a parameter that considers the energy release rate and crack driving force by the following definition:

$$\Delta K = Y \cdot \Delta\sigma \cdot \sqrt{\pi a} \tag{11}$$

where the $\Delta\sigma$ is the stress intensity factor range in a stress cycle and Y is the geometry function that takes into consideration the shape and geometry of the specimen and crack.

Fatigue endurance is an important characteristic for many materials and has been modeled by S-N curves or Wöhler curves, see example in figure 5.1.
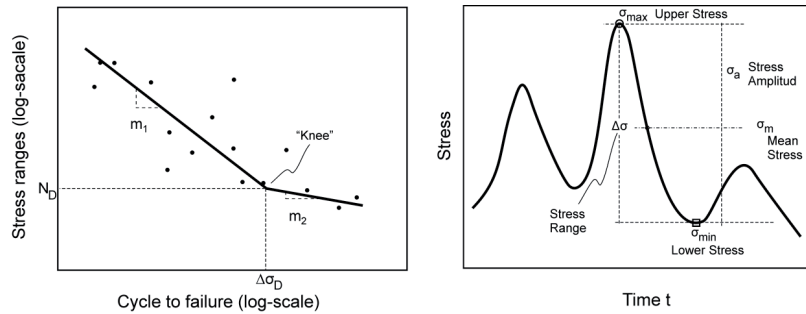

Figure 5.1 – SN curve and basic fatigue load stress history

Using the Palmgren-Miner rule the accumulated damage can be obtained from:

$$D = \sum_i D_i = \sum_i \frac{n_i}{N_i} = \sum_i \frac{n_i}{K \cdot s_i^{-m}}$$

and by introducing $n_T = \sum_i N_i$

$$D = \sum_i \frac{n_i \cdot n_T}{K \cdot s_i^{-m} \cdot n_T} = \frac{n_T}{K} \sum_i f_{\Delta\sigma} \cdot s^m \tag{12}$$

where n_T is the total number of load cycles, K is a material parameter and $f_{\Delta\sigma}$ is the probability density function of stress ranges. An important concept in fatigue analysis for offshore wind turbines is the concept of an equivalent stress range that can be formulated conditioned on the type of load (wind and wave), intensity (e.g. wind speed and turbulence) and other features (structural component, site, height, recording time, etc). Formula (12) represents an equivalent stress range approach. In the case of offshore wind turbines the distribution function of stress ranges is conditional in the n-minutes wind speed (recordings) considering a specific type of turbulence (free flow in the simple case) at a specific site.

The model used in [60] and proposed by Frandsen [61] for wake effects in wind farms is used in this paper. It has the following general characteristics:
  a) Simple implementation of the model.
  b) When the equivalent stress is formulated, the material properties are included in the load calculation (Wöhler exponent of S-N curve).

c) The model should be calibrated to site conditions.
d) The main assumption is the proportionality of turbulence and response.
e) Limitation in maximum number of wind turbines (eight surrounding wind turbines).
f) Uniformity assumption of wake conditions around the offshore wind turbine.
g) The fatigue is assumed to accumulate linearly and a linear SN-curve is used.

The model is described by:

$$\sigma_e = \left[(1 - N_w p_w)\sigma_0{}^m + p_w \sum_{j=1}^{N_w} \sigma_w{}^m \right]^{1/m} \tag{13}$$

$$\sigma_w = \sqrt{\frac{0.9\,U^2}{(1.5 + 0.3 d_j \sqrt{U/c})^2} + \sigma_0{}^2} \tag{14}$$

where σ_e is the effective standard deviation of the turbulence (including wake effects), N_w is the number of neighboring wind turbines, p_w is the probability of wind direction (uniformly distributed), σ_w is the standard deviation of turbulence in a wake and σ_0 is the standard deviation of free flow turbulence, d_j is the distance (normalized by rotor diameter to j^{th} neighboring wind turbine and c is a constant equal to 1 m/s.

In the turbulence model in (13), the concept of linear fatigue damage accumulation is used and offshore wake conditions included. The density function of stress ranges, $f_{\Delta\sigma}$ is coupled with the IEC's turbulence model [60] for n-minutes (typically, 10 minutes) wind speeds at hub height. With this model, it is possible to consider both free flow and in-wind farm wake effects.

5.2 STRUCTURAL RELIABILITY

Structural components such as tower, support structure and transition node have areas where the fatigue damage are important. A variety of structural reliability methods may be applied to assess the reliability of offshore wind turbine substructures. In this paper, FORM (First Order Reliability Method) is used to assess the fatigue reliability during the design life.

Several models for reliability analysis of offshore wind turbines can be found in the literature. Tarp-Johansen [62] proposed and used a fatigue limit state function based on the Palmgren-Miner rule which includes uncertainties related with the response, load and material; additionally a probabilistic calibration of design safety factors is carried out. In Sørensen [63] a more elaborated limit state equation is used but uncertainties in the response were not considered. Veldkamp [64] presented a study of the uncertainties and fatigue probabilistic fatigue model that take into account a large number of uncertainties. Further, Sørensen et al. in [65] and [66] presented a more mature model for assessing the reliability where equivalent fatigue loads and damage concepts are incorporated. In this model, the characteristics of the load, modeling and response are included by an influence function and a code-based fatigue model is included. This model is also used in this paper as mentioned in section 3.2 concerning the IEC-6400-1 turbulence model. In the assessment of fatigue reliability, the minimum requirements in design specifications are followed. The probabilistic model includes uncertainties in material (SN-curve), site measurements (wind, wake and wave conditions) and stress concentrations. The limit state and design equations are described in appendix C.

6. EXAMPLE

A welded detail (hot spot) in a wind turbine support structure is considered and the support structure has a T_L design life of 20 years. The fatigue life T_F for the component is 40 years. In tables 6.1 and 6.2 are shown representative stochastic models, equations and parameters (see

explanation of parameters in appendix C). It is only taken the linear case of the limit state equation. The influence function α_{Δ_σ} in figure 6.1 is used.
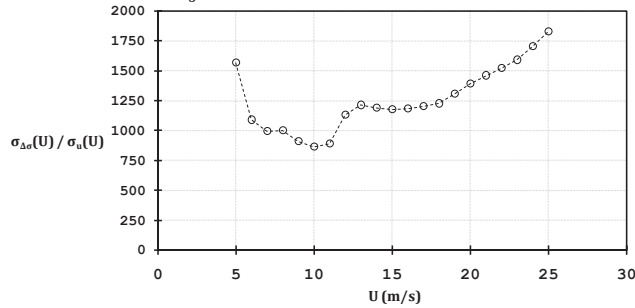

$$\sigma_{\Delta\sigma}(U) \, / \, \sigma_u(U)$$

Figure 6.1 - Influence coefficient function ($\sigma_{\Delta\sigma}(U)/\sigma_u(U)$) – pitch controlled wind turbine.

It is assumed that a meteorological mast provides samples $\hat{x}_w$ of X_W, which can be used for updating of the probabilistic model. X_W is defined as LogNormal distributed X_W. Further, the uncertainty related to the wake model, X_{wake} is updated based on measurements from surrounding wind turbines that can provide samples $\hat{x}_{wake}$. X_{wake} is defined as LogNormal distributed and when is this variable updated, it is assumed that the number of wind turbines is five.

Table 6.1 Distributions and stochastic model

Variable	Distribution	Parameters	Comment
$f_u(U)$	$W(\alpha,\beta_U)$	α=2.3, β_U=10.0m/s	Mean wind speed
$f_{\Delta\sigma_D}(\cdot)$	$W(\alpha_{\Delta\sigma D},\beta_{\Delta\sigma D})$	$\alpha_{\Delta\sigma D}$=0.8	Stress ranges
$f_{\sigma u}(\cdot)$	$LN(\mu,\sigma)$	μ=$I_{ref}\cdot(0.75\cdot U+3.8)$, σ=1.4m/s$\cdot I_{ref.}$	Mean turbulence
$N_1(s)$	$K_1\cdot s^{-m1}$	$s \geq \Delta\sigma_D$	SN curve linear
$N_2(s)$	$K_2\cdot s^{-m2}$	$s < \Delta\sigma_D$	SN curve bi-linear

D: Deterministic, N: Normal, LN: Lognormal, W: Weibull

Table 6.2 Stochastic variables

Variable	Distribution	E[·]	Standard deviation	Comment
Δ	N	1.0	0.1	Damage accumulation
X_w	LN	To be updated	To be updated	Wind
X_{SCF}	LN	1.0	V_{SCF}	Stress concentration factor
X_{wake}	LN	To be updated	To be updated	Wake
m_1	D	3.0	--	SN-curve. Wöhler exponent (linear)
m_2	D	5.0	--	SN-curve. Wöhler exponent (bi-linear)
$\Delta\sigma_D$	D	71 MPa	--	Constant amplitude fatigue limit
Log K$_1$	N	Determined from $\Delta\sigma_D$	0.20	Material parameter
Log K$_2$	N	Determined from $\Delta\sigma_D$	0.25	Material parameter
N_w	D	5/--	--	In-wind farm/single OWT
ν	D	5x10^7	--	Fatigue cycles per year
$U_{in} - U_{out}$	D	5 – 25 m/s	--	Cut in – out velocities
p_w	D	0.06 / 0.0	--	In-wind farm/single OWT
d_j	D	4.0	--	Normalized distance of OWT

Log K$_1$ and Log K$_2$ are assumed fully correlated.

6.1 RESULTS

In figures 6.2 to 6.5 are shown the results of reliability assessment with FORM. It is assumed that the reliability is updated each year sequentially using the information obtained the latest year. The data are assumed statistically independent. β is the reliability index corresponding to the cumulative probability of failure (P_F) and is defined as $\beta = \Phi^{-1}(P_F(t))$. A third order chaos expansion approximation is used in this example.

The variables X_w and X_{wake} are updated to illustrate the impact of updating. Eleven general cases are addressed in this work and shown in the table 6.3.

Table 6.3 – General cases

	General Cases	Updating	Sample vector	Variable	$\sigma_\theta \sim COV_\theta$
1	WITHOUT UPDATING	--	--	$X_w \sim LN(1,0.15)$ $X_{wake} \sim LN(1,0.25)$	--
2	CBU-a	CBU	a	X_w	--
3	DSCU-a	DSCU	a	X_w	0.075
4	GS-a	GS	a	X_w	0.075
5	CBU-b	CBU	b	X_w	--
6	DSCU-b	DSCU	b	X_w	0.075
7	GS-b	GS	b	X_w	0.075
8	CBU-X_w-a, CBU-X_{wake}	CBU	X_w-a / X_{wake}-N(1,0.25)*	X_w and X_{wake}	--
9	DSCU-X_w-a, DSCU-X_{wake}	DSCU	X_w-a / X_{wake}-N(1,0.25)*	X_w and X_{wake}	0.075 / 0.10
10	DSCU-a, COV~0.15	DSCU	a	X_w	0.15
11	DSCU-N(0.9,0.05)*	DSCU	N(0.9,0.05)*	X_w	0.075

*the samples are log-samples of normal distribution

Cases 2-4 were selected to compare the three updating approaches for a consistent sample vector a. It is important to remember that $\sigma_\theta \sim COV_\theta$ is selected such that DSCU and GS to converge by the updating to the results of the CBU case. In the figure 6.2 is shown the initial four cases and case 11 where the samples are obtained with a mean value less than 1 and a small standard deviation. The updated reliability estimates are for case 2-4 below the case without updating and only in case 11 higher updated reliability indices are obtained, as expected. From figure 6.2 is seen an initial difference in the three updating approaches, no matters the identical sample. This is the result of different factors such as the formulation (non-conjugated approach and mixed prior), the limit state equation, PCEA order and the computational algorithms. The basic formulation is the reason for the initial difference (year 5-8) between CBU / DSCU and GS. However, the influence of the updated stochastic variables is also important. In this case X_w and X_{wake} influence the limit state equation (see appendix C) and the choice of PCEA order can be a sensitive step in the calculation of the reliability. For the vector a samples the difference of CBU, DSCU and GS is not significant at the end of the lifetime. It is noted that case 11 converges to a higher reliability level due to the more 'favorable' samples.
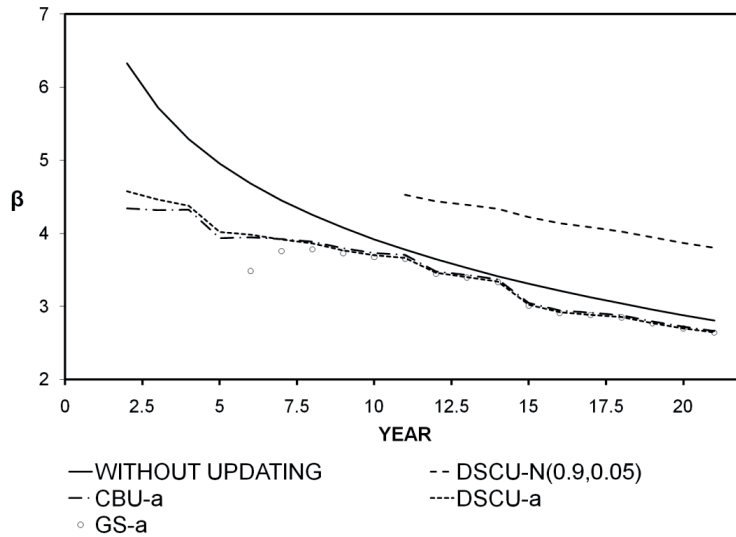
Figure 6.2 – Reliability indices of the assessment of reliability of the general cases 1-4 and 11.

In figure 6.3 the difference between the updated reliability and the reliability without updating is larger than in figure 6.2. The reason is that the vector of samples b has a larger standard deviation. The impact of the sample variation isn't significant when the different approaches are compared, However when a higher σ_θ is used the convergence of this approach takes more samples, see figure 6.5.
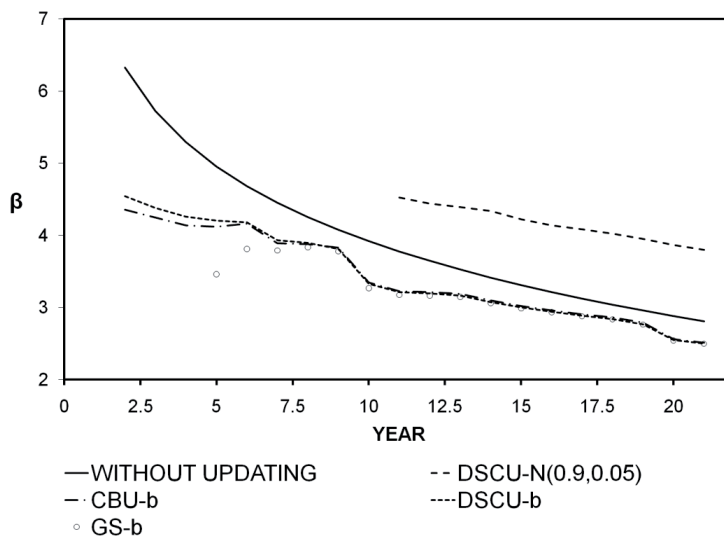

Figure 6.3 – Reliability indices of the assessment of reliability of the general cases 1, 5-7 and 11.

In cases 8 and 9 two variables (X_w and X_{wake}) are updated during the life cycle using samples obtained for each year by measurements or monitoring. The results are shown in figure 6.4. Comparing DSCU and CBU approaches for updating of two variables, The difference is approximately 13% in the beginning of the lifetime. At the end of design life the difference is much smaller but not converging. Also, the impact of number of updated variables is clearly seen at the end of the design life.

—CBU-a − · CBU-Xw-a, CBU-Xwake ----DSCU-Xw-a, DSCU-Xwake
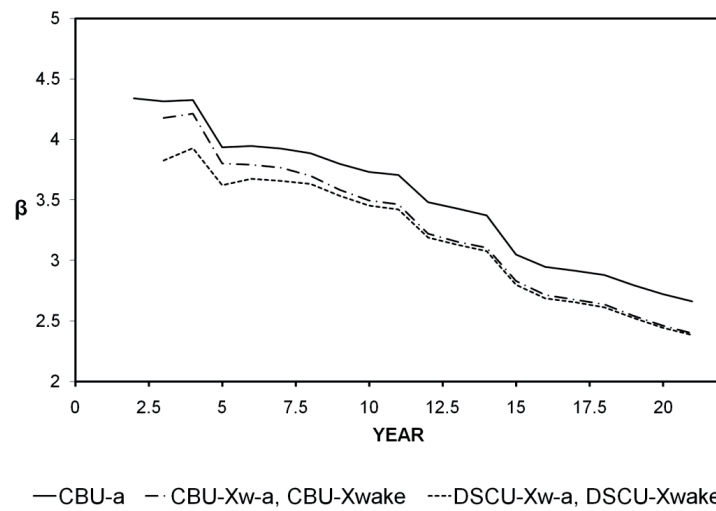
Figure 6.4 - Reliability indices of the assessment of reliability for the cases 2, 8 and 9.

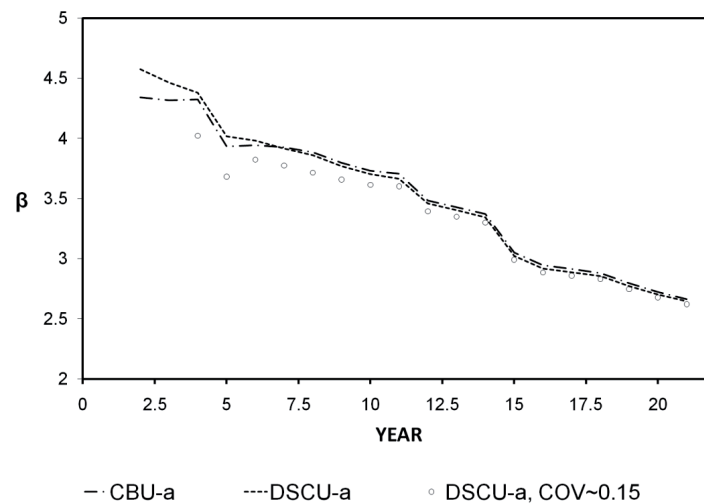− · CBU-a ----DSCU-a ○ DSCU-a, COV~0.15

Figure 6.5 - Reliability indices of the assessment of reliability for the cases 2, 3 and 10.

Figure 6.5 shows a comparison of the CBU and DSCU approaches. Compared to case 3 the prior standard deviation of the mean of X_w is doubled in case 10. It is seen that using the Discrete Semi-Conjugated Updating (DSCU) approach smaller reliabilities (as expected) are obtained in the beginning of the lifetime for case 10, and that the reliabilities are almost converging in the end of the lifetime. The results also show that the choice of updating approach is especially important in the beginning of the lifetime, where only a few data is available and the statistical uncertainty therefore is large. The updated predictive distribution is subjected to statistical uncertainty that will decrease with the integration of new samples. It is important to bear in mind that a strict convergence of the reliability estimates of the CBU and DSCU approaches will not exist due to the different models of the semi-conjugated prior.

7. CONCLUSION AND DISCUSION

Bayesian updating approaches can be applied to model and reduce uncertainty and to integrate new information into the stochastic model in assessment of reliability for OWT support structures. Limit state equations are formulated that allow considering in-wind farm locations with wake effects. In this paper three Bayesian approaches are considered: the classical, a discrete and a technique using simulation for updating. Special emphasis is put on describing the differences in the formulations (conjugation, mixing notation and probability distribution family), algorithm and computational aspects when the approaches are applied for OWT. In particular updating of Lognormal distributed variables is considered in order to illustrate the characteristics, drawbacks and advantages of choosing each of these updating methods.

The Classical Bayesian Updating (CBU) is widely used for engineering purposes in codes and recommendations. It is based on a parametric formulation which allows straightforward to integrate new information. Nevertheless, it should be used carefully since it uses a conjugating and mixing prior that set dependency of parameter. The Discrete Semi-Conjugated Updating (DSCU) approach is useful when multivariate updating is considered. It lacks a parametric handling, a full conjugating scheme and it is an approximate technique. The last two characteristics could not be entirely seen as disadvantages since the second one makes possible the easy handling of multivariate updating and the last can be minimized by managing the discrete vector size. On the other hand, the Gibbs Sampling (GS) technique is based on a quasi-random process model, a simulation algorithm and discrete considerations. This makes it less exact for updating but unlike DSU and CBU, the applied sampling technique can manage hierarchical statistical formulation of the variables in the stochastic model for assessment of the reliability.

Integration of the stochastic models updated by new information in reliability assessment is carried out through a third order Polynomial Chaos Expansion Approximation (PCEA) of the predictive distribution. The PCEA is converging with good accuracy for cases where the predictive distribution is close to a Normal distribution. Values corresponding to a 95% confidence interval and the mean are used for convergence check. However, when the predictive is far from being Normal, different percentiles have to be checked, i.e. in the initial updating stage (with few data) and in cases where the sample is not matching the prior beliefs. It is noted that the least-square optimization-minimization technique used to fit the PCEA can have numerical problems when more local minima are found. Further, reliability methods (e.g. FORM) can be sensitive to small changes of the PCEA.

The examples show that the updated reliabilities by the different techniques converge with time (when many samples are available). However, is should be noted that due to differences in the formulations the three different updating techniques will not have a strict convergence of the reliability estimates in any of the cases. The integration of new information represents the reduction of the phenomenological uncertainty by means of external observations and condition monitoring of OWT. The illustrative examples show the impact of Bayesian updating methods in the assessment of reliability and a clear influence of the chosen prior and updating approach.

The third order PCEA used for approximating the predictive distribution should not be taken as a definitive solution and thus the order should be adapted to the considered case. Finally it is noted, that the application of non-parametric updating techniques together with PCEA can be applied also for reliability assessment of other types of infrastructure systems.

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APPENDICES

A. CLASSICAL BAYESSIAN UDPDATING FORMULATION

Defining X as a Lognormal distributed variable, $X \sim LN(\mu_X, \sigma_X)$ with transformation to a Normal distributed variable denoted $Z \sim N(\theta, \sigma)$. The prior of the mean θ is considered to be Normal distributed $N_\theta \left(\mu_\theta, \mu_\sigma / \sqrt{\kappa_0} \right)$ with an expected value μ_θ and standard deviation $\sigma_\theta = \mu_\sigma / \sqrt{\kappa_0}$ for the CBU-approach. The standard deviation σ_θ is dependent on the mean of σ through its definition. The parameter κ_0 can be interpreted as the number of mean prior samples. The κ_0

term can be taken as the same value of ν_0 or not, depending on our beliefs. In this paper parameter κ_0 is equal to ν_0.

The prior of the standard deviation σ can be modeled by two different conjugating distributions: either in terms of the precision parameter $1/\sigma^2 \sim gamma(\nu_0/2, \nu_0\sigma_0^2/2)$ or in terms of the variance $\sigma^2 \sim inverse-gamma(\nu_0/2, \nu_0\sigma_0^2/2)$. In this paper the model by the precision parameter is used. Regarding the precision notation the definition of the θ is changed to $Z \sim N\left(\mu_\theta, 1/\mu_\sigma\sqrt{\kappa_0}\right)$ and the precision parameter $(1/\sigma^2)$ is defined by the gamma distribution that is defined with expected value $E[\sigma|a,b] = 1/\mu_\sigma^2 = a/b$ and variance $Var[\sigma|a,b] = a/b^2$. The parameters a and b will be adjusted to the value of μ_σ and chosen parameter a or b to adjust the gamma distribution to the beliefs or prior knowledge of the variable. In the table A.1 are shown the formulas for obtaining the posterior distribution.

Table A.1 – Normal distributed case $Z \sim N(\theta, \sigma|\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)$: Unknown mean and standard deviation for conjugating prior with samples $\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n$.

Distribution function	Conjugating case
Prior: variance	$\{1/\sigma^2\} \sim gamma\,(\nu_0/2, \nu_0\sigma_0^2/2)$
Prior: mean conditional in the variance	$\{\theta|\sigma^2\} \sim normal(\mu_\theta, \mu_\sigma/\sqrt{\kappa_0})$
Likelihood function	$\{X|\theta, \sigma^2\} \sim i.i.d.\,normal\,(\theta, \sigma^2)$
Posterior: mean conditional in the variance	$\{\theta|X, \sigma^2\} \sim normal(\mu_n, \sigma^2/\kappa_n)$
Posterior: variance	$\{1/\sigma^2\,|X\} \sim gamma\,(\nu_n/2, \nu_n\sigma_n^2/2)$

In prior gamma: $E[1/\sigma^2] = \frac{\nu_0/2}{\nu_0\sigma_0^2/2}$ and $Var[1/\sigma^2] = \frac{\nu_0/2}{\left(\nu_0\sigma_0^2/2\right)^2}$

In posterior: mean $\mu_n = \frac{\kappa_0\mu_\theta + n\bar{Z}}{\kappa_n}$ and $\kappa_n = \kappa_0 + n$

In posterior: variance $\sigma_n^2 = \frac{1}{\nu_n}\left[\nu_0\sigma_0^2 + (n-1)\frac{\sum_{i=1}^{n}(z_i-\bar{Z})^2}{(n-1)} + \frac{n\,\kappa_0}{\kappa_n}(\bar{Z} - \mu_\theta)^2\right]$ and $\nu_n = \nu_0 + n$

B. DISCRETE SEMI-CONJUGATED UPDATING FORMULATION

The discrete semi-conjugated updating is a discrete numerical 'shortcut'. The definition of the posterior distribution $f_\Psi(\psi|z)$ can be rewritten on its discrete form:

$$p_d(\psi_1, \psi_2, \ldots, \psi_m|\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n) = \frac{p(\psi_1, \psi_2, \ldots, \psi_m|\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)}{\sum_{i_1=1}^{G}\sum_{i_2=1}^{H}\cdots\sum_{i_m=1}^{L} p(\psi_1, \psi_2, \ldots, \psi_m|\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)}$$

B.1

By using the definition of conditional probability:

$$p_d(\psi_1, \psi_2, \ldots, \psi_m|\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)$$
$$= \frac{p(\psi_1, \psi_2, \ldots, \psi_m, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)/p(\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)}{\sum_{i_1=1}^{G}\sum_{i_2=1}^{H}\cdots\sum_{i_m=1}^{L} p(\psi_1, \psi_2, \ldots, \psi_m, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)/p(\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)}$$

B.2

and by simplifying, the discrete formulation of the posterior distribution is obtained:

$$p_d(\psi_1, \psi_2, \ldots, \psi_m|\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n) = \frac{p(\psi_1, \psi_2, \ldots, \psi_m, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)}{\sum_{i_1=1}^{G}\sum_{i_2=1}^{H}\cdots\sum_{i_m=1}^{L} p(\psi_1, \psi_2, \ldots, \psi_m, \hat{z}_1, \hat{z}_2, \ldots, \hat{z}_n)}$$

B.3

The marginal (conditional on the samples) posterior distribution for any parameter ψ can then be obtained by simply summing over the other arrays of parameters, e.g. for calculating the marginal of ψ_m conditional on the samples $\hat{z}_1, \hat{z}_2, \dots, \hat{z}_n$:

$$p_d(\psi_m | \hat{z}_1, \hat{z}_2, \dots, \hat{z}_n) = \sum_{i_1=1}^{G} \sum_{i_2=1}^{H} \dots \sum_{i_{m-1}=1}^{L} p_d(\psi_1, \psi_2, \dots, \psi_{m-1} | \hat{z}_1, \hat{z}_2, \dots, \hat{z}_n) \qquad \text{B.4}$$

For the example considered in this paper, X is defined as Lognormal distributed variable $X \sim LN(\mu_X, \sigma_X)$ with a transformation to normal distributed variable $Z \sim N(\theta, \sigma)$. The prior of the mean is considered to be normally distributed $N_\theta(\mu_\theta, \sigma_\theta)$ for DSCU-approach. Due to the semi-conjugated formulation for DSCU, the value of σ_θ is directly illustrating the difference between CBU and DSCU. In the table B.1 the statistical properties of the posterior are shown for different values of σ_θ.

Table B.1 K-moment and K-central moments of the predictive distribution of $f_X(x|\hat{x})$ for DSCU-approach with different values of $\sigma_\theta \sim COV_\theta$.

$COV_{\theta X}$	0.025	0.05	0.075	0.1	0.15	0.2
Mean	1.01152	1.02165	1.02608	1.02814	1.0298	1.03051
Standard deviation	0.15446	0.15758	0.15922	0.16005	0.1607	0.16106
2nd central moment	0.02386	0.02483	0.02535	0.02561	0.0258	0.02594
3rd central moment	0.00192	0.00206	0.00216	0.00221	0.0022	0.00229
4th central moment	0.00219	0.00238	0.00249	0.00256	0.0026	0.00264
Coefficient of skewness	0.52108	0.52749	0.53581	0.54104	0.5461	0.54830
Coefficient of kurtosis	0.84965	0.86430	0.88711	0.90232	0.9176	0.92431

When $\sigma_{\theta Z}$ is equal to 0.075, the values of the posterior distribution are closed to the values of the CBU-approach in table 2.1. Product of the semi-conjugated prior formulation, the DSCU and GS approach should have an assigned coefficient of variance $COV_\theta \sim \sigma_\theta$. In this example, σ_θ was chosen to be 0.075 to illustrate how CBU is diverging from DSCU and CBU values.

C. LIMIT STATE EQUATIONS
Design equation for free flow condition
Based on the assumptions mentioned in section 3 the design equation for a single offshore wind turbine (not within a wind farm) can be written, see [65,66]:

$$G(z) = 1 - \frac{\nu \, FDF \, T_L}{K_C} \int_{U_{in}}^{U_{out}} D\left(m; \sigma_{\Delta\sigma}(U, z)\right) f_U(U) dU = 0 \qquad \text{C.1}$$

where ν is the number of stress cycles per year, FDF is the fatigue design factor ($T_F = T_L \cdot FDF$) and $FDF = (\gamma_f \cdot \gamma_m)^m$ for a linear SN-curve using load and material partial safety factors γ_f and γ_m, T_L is the design life time, K_C is characteristic value of K (material parameter in SN-curve), U_{in} and U_{out} are the cut-in and –out wind speeds, m is the Wöhler exponent in SN-curve, $f_U(U)$ is the probability density function of mean wind speed U, z is a design parameter and D represents the expected value of fatigue damage for the all stress ranges given a mean wind speed U and standard deviation of stress ranges $\sigma_{\Delta\sigma}$. Medium turbulence characteristics are assumed (IEC-61400). The expected value of the fatigue damage can be obtained for linear and bilinear SN-curve with the following formulae:

$$D_L = \int_0^\infty s^m \, f_{\Delta\sigma}\big(s\big|\sigma_{\Delta\sigma}(U,z)\big)ds \qquad \text{C.2}$$

$$D_{BL} = \int_0^{\Delta\sigma_D} s^{m_1} \, f_{\Delta\sigma}\big(s\big|\sigma_{\Delta\sigma}(U,z)\big)ds + \int_{\Delta\sigma_D}^\infty s^{m_2} \, f_{\Delta\sigma}\big(s\big|\sigma_{\Delta\sigma}(U,z)\big)ds \qquad \text{C.3}$$

where $f_{\Delta\sigma}(s|\sigma_{\Delta\sigma})$ represents the probability density function for stress ranges given a standard deviation $\sigma_{\Delta\sigma}$ at the mean wind speed U. $\sigma_{\Delta\sigma}$ and ν can be obtained by cycle counting methods, e.g. Rainflow counting. $\sigma_{\Delta\sigma}$ is written:

$$\sigma_{\Delta\sigma} = \alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z} \qquad \text{C.4}$$

$$\sigma_u = I_{ref}\,(0.75\,U + b), \;\; b = 5.6\,m/s \qquad \text{C.5}$$

In equation (C.4), $\alpha_{\Delta\sigma}$ is the influence function referring to a specific detail (hot spot) or sector in the OWT and is a function of the wind speed. σ_u is the (normal) turbulence standard deviation (IEC 61400-1).

Design equation for in-wind farm location
For a wind turbine within a wind farm the equivalent turbulence model is integrated at the model resulting in the following design equation:

$$G(z) = 1 - \frac{\nu\,FDF\,T_L}{K_C} \int_{U_{in}}^{U_{out}} \left[(1 - N_w\,p_w)D\big(m;\sigma_{\Delta\sigma}(U,z)\big) + p_w \sum_{j=1}^{N_w} D\big(m;\sigma_{\Delta\sigma,j}(U,z,j)\big)\right] f_U(U)\,dU = 0 \qquad \text{C.6}$$

where $\sigma_{\Delta\sigma,j}$ is the standard deviation of stress ranges considering wake condition from j-neighboring wind turbine and is defined as follows:

$$\sigma_{\Delta\sigma,j} = \alpha_{\Delta\sigma}(U)\frac{\sigma_u(U,j)}{z} \qquad \text{C.7}$$

$$\sigma_{u,j} = \sqrt{\frac{0.9\,U^2}{\left(1.5 + 0.3\,d_j\,\sqrt{U/c}\right)^2} + \sigma_u{}^2} \qquad \text{C.8}$$

d_j is the wind turbine distance to the neighboring wind turbine j normalized by the rotor diameter and c is a constant equal to 1 m/s.

Limit state equation for free flow condition
The limit state equation in free flow conditions is written:

$$g(t) = \Delta - \frac{\nu\,t}{K} \int_{U_{in}}^{U_{out}} \int_0^\infty (X_w X_{SCF})^m\,D\big(m;\sigma_{\Delta\sigma}(U,z)\big)\,f_{\sigma_u}(\sigma_u|U)\,f_U(U)\,d\sigma_u\,dU \qquad \text{C.9}$$

where Δ, X_w and X_{SCF} represent the uncertainties related with the Miner rule of damage accumulation, wind load effects and local stress concentration and analysis. t is the reference time and f_{σ_u} is the probability density function for free flow turbulence that is modeled as LogNormal distributed with a representative mean turbulence equal to I_{ref}·(0.75·U+3.8) and standard deviation equal to 1.4m/s times the I$_{ref}$.

Limit state equation for in-wind farm location

To assess the reliability for wind turbines within a wind farm the following limit state equation is used:

$$g(t) = \Delta - \frac{v\,t}{K}(X_w X_{SCF})^m \int_{U_{in}}^{U_{out}} \int_0^\infty \left[(1 - N_w\, p_w) D\big(m; \sigma_{\Delta\sigma}(U,z)\big) + p_w \sum_{j=1}^{N_w} D\big(m; \sigma_{\Delta\sigma,j}(U,z,j)\big) \right] f_{\sigma_u}(\sigma_u | U)\, f_U(U) d\sigma_u\, dU \qquad \text{C.10}$$

$$\sigma_{u,j} = \sqrt{\frac{X_{wake}\, U^2}{\left(1.5 + 0.3\, d_j\, \sqrt{U/c}\right)^2} + \sigma_u{}^2} \qquad \text{C.11}$$

where X_{wake} models the uncertainty related to the wake turbulence conditions coming from surrounding wind turbines.