Maintenance Planning of Offshore Wind Turbine using Condition Monitoring Information

Ramírez, José G. Rangel; Sørensen, John Dalsgaard

Published in:
Proceedings of the 28th International Conference on Ocean, Offshore and Arctic Engineering

Publication date:
2009

Document Version
Publisher's PDF, also known as Version of record

Proceedings of the 28th International Conference on Ocean, Offshore and Arctic Engineering
OMAE2009
May 31- June 5, 2009, Honolulu, Hawaii, USA

OMAE09-79159

MAINTENANCE PLANNING OF OFFSHORE WIND TURBINE USING CONDITION MONITORING INFORMATION

José G. Rangel-Ramírez
Aalborg University
Sohngaardsholmsvej 57
DK – 9000, Aalborg, Denmark
jr@civil.aau.dk

John D. Sørensen
Aalborg University
Sohngaardsholmsvej 57
DK – 9000, Aalborg, Denmark
jds@civil.aau.dk

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 $g(x_1,x_2,\dots,x_i)$ is formulated as a function of *i* stochastic variables and an event function $h(x_1,x_2,\dots,x_i)$ representing the new information, is considered jointly. The conditional probability of failure is denoted by $P(g(x_1,\dots,x_i)\leq 0\ |h(x_1,\dots,x_i)\leq 0)$. 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: $\hat{x}_i=(\hat{x}_{i,1},\hat{x}_{i,2},\dots,\hat{x}_{i,j})$, the posterior density function is:

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

where

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

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:

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

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.

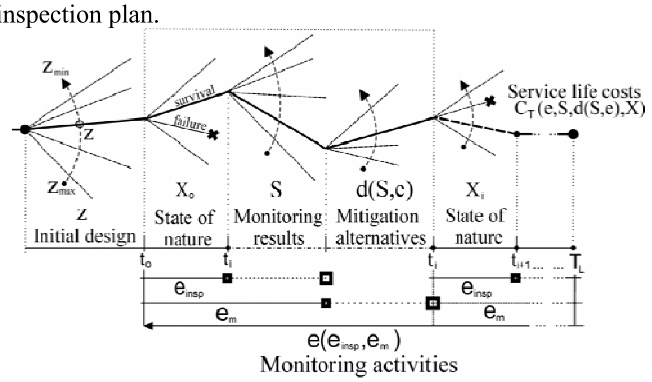

Fig. 1 RBI decision tree

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 $z=(z_1,z_2,z_3\ldots,z_n)$ 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 $c=(c_1,c_2,c_3\ldots,c_n)$ (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:

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

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

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

where $E[C_T]$ is the expected total costs in the service life T_L, C_I is the initial costs, $E\left[C_{Insp}\right]$ is the expected inspection costs, $E\left[C_{Rep}\right]$ 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, $i=1,\ldots,n$ where $t_o \leq t_1, t_2, \ldots, t_n \leq T_L$.

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:

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

where for linear SN-curves:

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

and for bi-linear SN-curves:

$$D_L\left(m_1,m_2,\Delta\sigma_D;\sigma_{\Delta\sigma}(U)\right)= \int_0^{\Delta\sigma_D} s^{m_2}\cdot f_{\Delta\sigma}\left(s|\alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_u(U)}{z}\right)ds + \int_{\Delta\sigma_D}^{\infty} s^{m_1}\cdot f_{\Delta\sigma}\left(s|\alpha_{\Delta\sigma}(U)\frac{\hat{\sigma}_u(U)}{z}\right)ds \tag{7}$$

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

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

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 $f_{\Delta\sigma}\left(s|\sigma_{\Delta\sigma}(U)\right)$ 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:

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

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):

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

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:

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

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

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:

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

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

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

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:

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

and for a wind farm location case:

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

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.

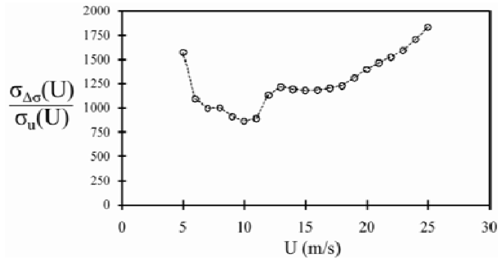

Figure 2. $\sigma_{\Delta\sigma}/\sigma_U$ for mudline bending moment – pitch controlled wind turbine.

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 Cc	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	$1.0\cdot10^{-4}$
$F_U(u)$	$W(\alpha,\beta_U)$	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(μ,σ)	$\mu=I_{ref}\cdot(0.75\cdot U_i+3.6)$, $\sigma=1.4\cdot I_{ref}$
POD(x)	$P_O\cdot(1-\exp(-x/\lambda))$	P_O=1.0, λ=2.67 mm
$N_1(s)$	$K_1\cdot s^{-m_1}$	$s\geq\Delta\sigma_D$
$N_2(s)$	$K_2\cdot s^{-m_2}$	$s<\Delta\sigma_D$

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.

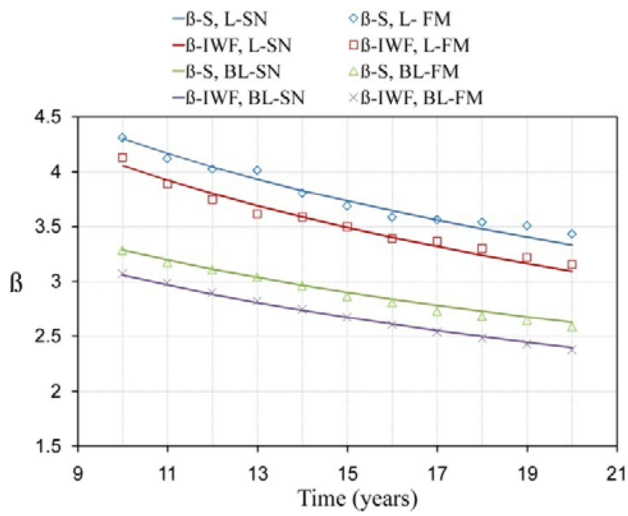

Fig 3. Reliability indices for SN-analysis and calibrated fracture mechanics curve corresponding to the cumulative probability of failure.

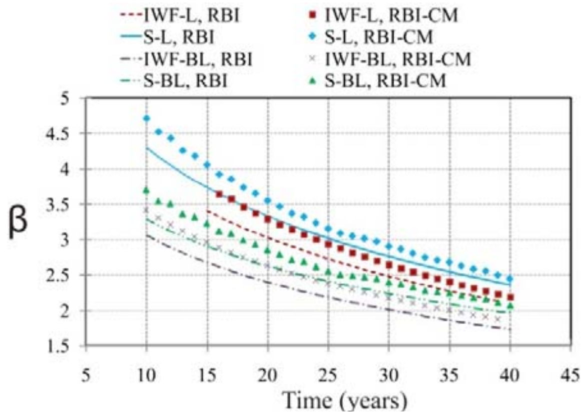

Fig 4. SN-Reliability indices for RBI and RBI with updating (RBI-CM) for corresponding to the cumulative probability of failure.

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

	INSPECTION TIME	
	Maximum Annual $\Delta P_f = 1.0\text{x}10^{-4}$	
CASE	**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.

ACKNOWLEDGMENTS

The financial support from the Mexican National Council of Science and Technology (CONACYT) is greatly appreciated.

REFERENCES

Barthelmie, R., Hansen, O.F., Enevoldsen, Karen, Højstrup J., Frandsen, S., Pryor S., Larsen S., Motta M, Sanderhoff P., 2005. Ten Years of Meteorological Measurements for Offshore Wind Farms. Journal of Solar Energy Division of The American Soceity of Mechanical Engineers. May 2005, Volume 127, pp. 170-176.

Benjamin J.R., Cornell C.A., 1970. Probability, statistics and decision for civil engineering. McGraw Hill, New York.

Faber, M.H., Sørensen, J.D., Rackwitz, R., Thoft-Christensen, P., Bryla P., 1992. Optimal Inspection Strategies for Offshore Structural Systems. Proc. 11th Offshore Mechanics and Arctic Engineering Conference, Calgary, pp. 145-151.

Frandsen S., Chacón L., Crespo A., Enevoldsen P., Gómez-Elvira R., Hernández J., Højstrup J., Manuel F., Thomsen

K. and Sørensen P., 1996. Final Report on Measurements on and Modelling of Offshore Wind Farms, Risø-R-903(EN), Risø National Laboratory, Bonus Energy AS, Universidad Politecnica de Madrid, Elkraft AS, Finish Meteorological Institute.

Frandsen, S., 2005. Turbulence and turbulence-generated structural loading in wind turbine clusters, Risø National Laboratory, Denmark, Report R1188.

Giebel, G. (Ed.), Juhl, A., Hansen, K.G., Giebhardt, J., Phalke, T., Waldl, H., Rebbeck, M., Brady, O., Ruffle, R., Donovan, M.H., Bjerge C., 2004. CleverFarm® -A SuperSCADA system for wind farms. Risø-R-1444(EN) Risø National Laboratory. Roskilde, Denmark. August 2004

Hammed Z., Hong Y.S., Cho Y.M., Ahn S.H. and Kong C.K., 2007. Condition Monitoring and fault detection of wind turbines and related algorithms: A review. Renewable & Sustainable Energy Reviews 13 (2009) 1-39. Elsevier.

IEC 61400-1 (IEC 2005), International Electrotechnical Comission. Wind Turbine generator systems – Part 1: Safety requirements.

Madsen, H.O., Skjong R., Kirkemo F., 1987. Probabilistic Fatigue Analysis of Offshore Structures – Reliability Updating Through Inspection Results. In Integrity of Offshore Structures 3, edited by Faulkner D, Cowling MJ, Incecik A, Elsevier Applied Science.

Raiffa H., Schlaifer R., 1961. Applied Statistical Decision Theory. Cambrige University Press, Cambridge, Mass.

Sørensen, J.D., Frandsen, S. & Tarp-Johansen, N.J., 2007. Fatigue reliability and effective turbulence models in wind farms. Applications of Statistics and Probability in Civil Engineering -Kanda, Takada & Furuta (Eds).

Sørensen, J.D. and Faber, M.H.; 1991. Optimal Inspection and repair strategies for structural systems, Proc. 4th IFIP Conference on Reliability and Optimization of Structural Systems, Rackwitz, R. And Thoft-Christensen, P. (Eds), Springer, Berlin, 383-394.

Thoft-Christensen P., Sørensen J.D., 1987. Optimal strategy for inspection and repair of structural systems. Civil Engineering Systems, 4, 94-100.

Wiggelinkhuizen, E., Verbruggen, T., Braam, H., Rademakers, L., Xiang, J., Watson, S.,2008. Assessment of Condition Monitoring Techniques for Offshore Wind Farms. Journal of Solar Energy Engineering Division of ASME for publication. Paper presented at the European Wind Energy Conference, 2007. August 2008, Vol. 130.