Risk Based Structural Integrity Management of Marine Platforms Using Bayesian Probabilistic Nets

Roberto Montes-Iturrizaga

Ernesto Heredia-Zavoni

Francisco Vargas-Rodríguez

Instituto Mexicano del Petróleo,
Eje Central Lázaro Cárdenas No. 152,
Mexico, DF 07730, Mexico

Michael Havbro Faber
Swiss Federal Institute of Technology,
ETH Hönggerberg,
CH-8093 Zürich, Switzerland

Daniel Straub
Matrisk GmbH,
CH-8093 Zürich, Switzerland
e-mail: straub@matrisk.com

Juan de Dios de la O
Gerencia de Mantenimiento Integral,
PEMEX Exploración y Producción,
Ciudad del Carmen,
Campeche CP-24180, Mexico

The present paper introduces a general framework for integrity management of offshore steel jacket structures allowing for the risk based planning of inspections and maintenance activities with a joint consideration of various relevant deterioration and damage processes. The suggested approach relates the relevant deterioration and damage processes to damage states, which in turn may be related to the overall integrity of the jacket structural system as measured through the reserve strength ratio. Each state of degradation, irrespective of the cause, can then be assessed in terms of their impact on the annual probability of failure for the structure. Based on data and subjective information regarding the annual probabilities of occurrence of the relevant deterioration and damage processes, together with a probabilistic modeling of the quality of condition control, it is possible to assess the structural effect of each type of deterioration and damage phenomenon. This facilitates the development of a general framework for risk based integrity management. In the present work such a framework is formulated using Bayesian probabilistic networks for evaluating the time varying global structural reliability of jackets subject to progressive deterioration of its members due to the combined effect of different sources of damage. In principle, system effects, i.e., the effect of damage in one element of the structural system on the capacity of other elements, can also be accounted for through a Bayesian probabilistic net; however, this is not considered in this work.
[DOI: 10.1115/1.2979797]

Keywords: risk based inspection, Bayesian networks, jacket platforms, structural reliability, structural damage, corrosion, ship impact, dropped objects

Introduction

Offshore facilities such as fixed steel jacket structures are subject to degradation due to a number of different deterioration and damage processes. Deterioration processes may include fatigue crack growth, corrosion, and scour around the foundation. Damage processes may be due to ship impacts, dropped objects, and overloading due to environmental loads. The objective of structural integrity management is to ensure that structures are maintained in a condition that is acceptable considering the safety of personnel and the economical consequences associated with failures, lost production, and damages to the environment.

Over the past 10–20 years significant developments have been achieved in the area of inspection and maintenance planning for offshore facilities and, in particular, for steel jacket structures subject to fatigue crack growth, e.g., Skjong [1], Madsen et al. [2], Faber et al. [3], Moan et al. [4], and Straub and Faber [5]. Efficient and practically applicable approaches to risk based inspection and maintenance planning for such structures have been formulated and applied in a large number of projects in practice, see, e.g., Refs. [6,4,7]. The main focus on these efforts has been directed toward integrity management in regard to fatigue crack growth. Integrity control regarding degradation due to other deterioration and damage processes has so far been considered separately and less systematically. The reason for this being that a general framework allowing for the integral consideration of all relevant deterioration and damage processes in a risk framework has not yet been formulated in a way allowing for its implementation in the daily practice of offshore operators.

A general framework is introduced here for integrity management of offshore steel jacket structures taking into consideration the combined effect of the relevant deterioration and damage processes. The framework is devised to be used for risk based inspection and maintenance planning and is based on the use of Bayesian probabilistic networks. In this paper, a general introduction to Bayesian probabilistic networks is given first. Models for the estimation of probabilities related with such deterioration and damage processes as corrosion, dents, bends, and loss of members during extreme environmental events are presented and discussed. The combination of damage processes and their effect on member capacity are analyzed next, along with the criterion for the acceptable probability of failure. A case study and an application in the oil industry are then given.

Bayesian Probabilistic Networks

Bayesian probabilistic networks or Bayesian belief networks were developed mainly during the past two decades as a decision support tool originally targeted for purposes of artificial intelligence engineering. Until then artificial intelligence systems were mostly based on "rule based" systems, which suffer significantly from the deficiency that they are not able to handle decision-making subject to uncertainty. In contrast to rule based decision support systems, Bayesian probabilistic networks are so-called normative expert systems, meaning that (1) instead of modeling the expert they model the domain of uncertainty; (2) instead of using inconsistent probability estimations tailored for rules they use rigorous classical probability calculus and decision theory; and (3) instead of replacing the expert they support her/him. The developments of the theory and application areas for Bayesian probabilistic networks have been and are still evolving rapidly.

Contributed by the Ocean Offshore and Arctic Engineering Division of ASME for publication in the JOURNAL OF OFFSHORE MECHANICS AND ARCTIC ENGINEERING. Manuscript received October 10, 2006; final manuscript received November 9, 2007; published online December 11, 2008. Assoc. Editor: Beverley Ronalds. Paper presented at the The 25th International Conference on Offshore Mechanics and Arctic Engineering (OMAE2006), Hamburg, Germany, June 4–9, 2006.

Bayesian probabilistic networks can be used at any stage of a risk analysis, and may readily substitute both fault trees and event trees in a logical tree analysis. Finally, the Bayesian probabilistic networks provide an enormously strong tool for decision analysis, including prior analysis, posterior analysis, and preposterior analysis. A basic introduction to Bayesian networks is given in Ref. [8].

Procedures for risk based inspection (RBI) planning of structures, as an application of Bayesian decision analysis, have been developed since the early 1970s [9]. However, to the best of our knowledge, Bayesian networks have been applied so far for inspection planning of offshore jacket structures subjected to fatigue damage only (see Ref. [10]). In the approach presented in this paper, Bayesian networks are used for risk based structural integrity management of jackets subjected to different sources of damage.

Probabilistic Estimation of Damage

In this study, the types of damage considered are mechanical damages (bends and dents), corrosion in elements above mean sea level, marine growth (local effect), and also complete loss of structural members due to extreme environmental loading. In order to establish the probabilistic relationship between different exposures and types of damage, it is necessary to define models or formulations that predict the amount and/or the extension of damage as a function of exposure time. Such models and formulations are used to estimate the conditional probabilities of elements reaching a damage state given the characteristics of an exposure. These probabilities are needed as input for the Bayesian probabilistic network. Note that the implementation of a Bayesian probabilistic network as a framework for decision-making and integrity management is not limited to the particular models and formulations presented in this paper, but can, in principle, accommodate any probabilistic damage model.

Mechanical Damages (Bends and Dents). Mechanical damages are assumed to be produced by dropped objects and ship impacts. In the following only the formulation for dropped objects is presented. For ship impacts the corresponding formulation is similar. The time during which the structural element is exposed to dropped objects, T_{DO}, is divided into an exposure time before the last inspection or repair of the element, $T_{\mathrm{DO},1}$, and the exposure time after the last inspection or repair, $T_{\mathrm{DO},2}$. They are calculated as

$$T_{\mathrm{DO},1} = \max(t_{\mathrm{inst}}, t_R, t_{\mathrm{VI}}, t_{\mathrm{CVI}}, t_{\mathrm{FMD}}, t_{\mathrm{NDE}}) - t_{\mathrm{inst}} \quad (1)$$

$$T_{\mathrm{DO},2} = t - \max(t_{\mathrm{inst}}, t_R, t_{\mathrm{VI}}, t_{\mathrm{CVI}}, t_{\mathrm{FMD}}, t_{\mathrm{NDE}}) \quad (2)$$

where t_{inst} is the year of installation of the platform, t_R is the year of the last repair of the element, t_{VI} is the year of the last visual inspection of the element, t_{CVI} is the year of the last close visual inspection of the element, t_{FMD} is the year of the last flooded member detection (FMD) inspection, t_{NDE} is the year of the last non destructive evaluation (NDE) inspection, and t is the current year where the inspection planning is being performed.

Let Δp_{DO} be the annual rate of dropped objects on an element; Δp_{DO} may be estimated based on the information of previously observed mechanical damages, according to the location (below sea level, splash zone, and above sea level) and orientation (horizontal, diagonal, and vertical) of the elements. The probability of an undiscovered dropped object on a given member, p_{DO}, is then obtained as a function of the exposure time, the quality of the last inspection expressed in terms of the probability of detection, PoD, and Δp_{DO} as

$$p_{\mathrm{DO}} = 1 - [(1 - \Delta p_{\mathrm{DO}})^{T_{\mathrm{DO},2}}\{1 - (1 - \mathrm{PoD})(1 - (1 - \Delta p_{\mathrm{DO}})^{T_{\mathrm{DO},1}})\}] \quad (3)$$

In Eq. (3), $(1-\Delta p_{\mathrm{DO}})^{T_{\mathrm{DO},2}}$ represents the probability that no dropped object has hit the member in the time after the last inspection, and $\{1-(1-\mathrm{PoD})(1-(1-\Delta p_{\mathrm{DO}})^{T_{\mathrm{DO},1}})\}$ is the probability that no dropped object has hit the member before the last inspection. The simplification here is that all previous inspections, except the last one, are neglected.

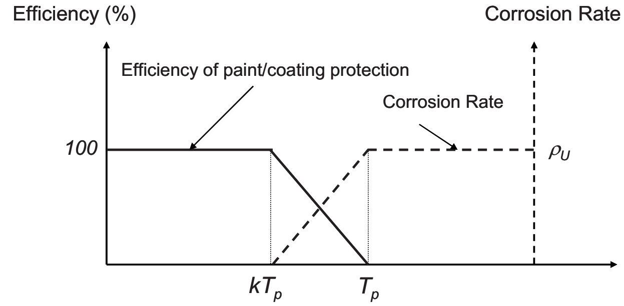

Fig. 1 Model for corrosion degradation

Corrosion. The normal approach to control corrosion damage is twofold. For those parts of the structure that are permanently submerged, it is customary that an anode system be implemented, which is assumed to be an efficient means of corrosion control. For the parts of the structure not permanently submerged, it is normal to implement a coating/paint corrosion protection. As long as the coating/paint is still intact and functional this provides an efficient protection in regard to corrosion. Paint and coating is subject to degradation due to two effects, namely, mechanical damages and time effects. In the following, we address the time evolution of corrosion degradation for members that are not constantly submerged.

In Fig. 1 a model is proposed for the corrosion of such members consisting of three distinct phases. In the first phase, when paint/coating has just been applied, paint/coating is intact and no corrosion takes place. The second phase corresponds to the time interval in which the efficiency of the paint/coating starts to decrease at time kT_P until the efficiency has decreased to 0 at time T_P. The start of the second phase also corresponds to the onset of corrosion. During the second phase, the corrosion rate is assumed to increase linearly from 0 to ρ_U corresponding to the unprotected corrosion rate. During the third phase the paint/coating has no efficiency and the corrosion rate is constant and equal to ρ_U. Figure 1 illustrates corrosion rate as a function of time.

Extreme Environmental Effects. In the following, we address the computation of the probability of complete failure of a member due to extreme hurricane loading. In particular, we are interested in assessing the probability of having lost a member due to the maximum observed hurricane since the last inspection. In the estimation of the probability of damage after a hurricane, it is important to keep in mind that if the design of the member primarily is governed by dead and service loads, then it will be less vulnerable to extreme environmental loads. This is described by a horizontal-to-vertical-load ratio α_L (also termed component-extreme-environmental-load-to-gravity-load ratio, see Ref. [11]). The probability of damage of the member as a function of α_L can be estimated as follows. The limit state function describing the member performance is

$$g_{\mathrm{member}} = R - R_H - S_V \quad (4)$$

where R is the capacity of the element, S_H is the load acting on the member caused by environmental (horizontal) global loading, and S_V is the load acting on the member caused by vertical global loading. With S being the total load, $S=S_H+S_V$, S_H and S_V are evaluated as $S_H=S(\alpha_L/(1+\alpha_L))$ and $S_V=S(\alpha_L/(1+\alpha_L))$. The probabilistic models for R and S are derived from the following basic information: (1) It is assumed that the members fulfill the requirements given by API RP2A-LRFD; (2) it is assumed that both R and S are log-normal distributed; (3) for tubular members,

R is characterized by a mean bias of 1.28 and a coefficient of variation (CoV) of 0.12 when applying API RP2A-LRFD [12]; and (4) S_H is modeled using a characteristic wave height corresponding to a 100 year return period. It is assumed that S_V is characterized by a mean bias of 0.8 and a CoV of 0.10.

From this information, the (normalized) probabilistic models can be evaluated as follows. The normalized characteristic values of the variables are given by $R_C=1$, $S_{H,C}=\alpha_L/(1+\alpha_L)$, and $S_{V,C}=1/(1+\alpha_L)$. On this basis, it is possible to calculate the member probability of failure for different α_L not considering any observation of hurricanes during the first year of service. Once an extreme environmental load has been observed, the probability that the member has already failed can be calculated by setting S_H equal to the observed load. The uncertainty in the observation is neglected, but S_H is still uncertain because of the inaccuracies in the transfer functions from the environmental load to the member load. It is assumed that this uncertainty is described by a CoV equal to 0.2. Based on this, the probabilistic model for S_H after the observation is $\mu_{S_H}=(\alpha_L/(1+\alpha_L))f$, where f is an exceedance factor defined as the ratio of the observed hurricane load with respect to the design load (1.0, 1.2, etc.); $\mathrm{CoV}_{S_H}=0.2$. The results are based on the simplifying assumption that the environmental loads in the members increase linearly with the global environmental load.

Assessment of Probability of Failure

The reserve strength ratio (RSR) is defined as the ratio of the characteristic values of the base shear capacity of the platform, R_c, and the design load, S_c, as follows [13]:

$$\mathrm{RSR}=\frac{R_C}{S_C} \tag{5}$$

In Eq. (5), R_C is normally taken as the mean base shear capacity and the characteristic design load is taken as the value associated with a 100 year return period sea state. For assessing the platform probability of failure, consider now the following limit state function:

$$g(x)=R-S \tag{6}$$

where R is the base shear capacity of the platform and S is the base shear load. The load S can be expressed in terms of the maximum annual value of wave height, H, as $S=bH^{\delta}$, where b and δ are parameters that can be determined from structural analyses. Once appropriate probability distributions have been assigned to R and H, and to b and δ, the probability of failure can be assessed by structural reliability methods or Monte Carlo simulation using the limit state function in Eq. (6). Furthermore, from the probability distributions, the characteristic values R_c and S_c can be determined, and the corresponding RSR value of the platform is obtained. Hence, a relation can be established between the probability of failure of the platform and its RSR value.

Accounting for the Effect of Damages. In this work, we use the residual influence factor, RIF_i, to measure the effect of full damage, or total loss of functionality, of the ith structural member on the structural capacity. RIF_i is defined as the ratio of the RSR for the structure with the ith member removed (considered to be fully damaged), RSR_{-i}, and the RSR of the undamaged structure as follows:

$$\mathrm{RIF}_i=\frac{\mathrm{RSR}_{-i}}{\mathrm{RSR}} \tag{7}$$

Let us define $\gamma_{D_{i,j}}$ as the damage index for the ith structural member in the jth damage state; $i=1,2,\ldots,N$ and $j=0,1,2,\ldots,M$, where N is the number of structural members and M is the number of possible damage states. For $j=0$, $\gamma_{D_{i,0}}=0$, i.e., no damage or full functionality of the member; for $j=M$, $\gamma_{D_{i,M}}=1$, i.e., full damage or complete loss of member functionality. This index depends on the magnitude of damage accumulated in a member due to the acting deterioration processes. The effect of a given state of damage of the individual structural members on the capacity of the platform is considered as follows:

$$\mathrm{RIF}_{D_{i,j}}=1-\gamma_{D_{i,j}}(1-\mathrm{RIF}_i) \tag{8}$$

where $\mathrm{RIF}_{D_{i,j}}$ is a residual influence factor associated with the state of damage of the ith structural member.

The member capacity is the only member characteristic utilized to indicate the importance for the capacity of the structure as a whole. Different types of damages have a combined influence on member capacity. Therefore, the member capacity node in the Bayesian network must account for the combined effect of several damage types. The overall capacity of the platform is dependent on the damage state of the member through the relationship described by the RIF. Thus, the probability of failure of the structure is a direct function of the probability of being in any one of the different member capacity states (as represented by the value of γ_D). Inspections of the members are then triggered when the platform probability of failure becomes larger than an acceptable value.

Global Probability of Failure and Acceptance Criteria. The probability of platform failure (collapse) and member damage (i.e., without considering $\gamma_{D_{i,0}}$), is

$$P_{\mathrm{COL}\cap\text{member damage}}=\sum_{i=1}^{N}\sum_{j=1}^{M}P_{\mathrm{COL}|\gamma_{D_{i,j}}}P(\gamma_{D_{i,j}}) \tag{9}$$

where $P_{\mathrm{COL}|\gamma_{D_{i,j}}}$ is the conditional probability of platform failure given damage state j in structural member i, and $P(\gamma_{D_{i,j}})$ is the probability of damage state j in structural member i. The conditional probabilities $P_{\mathrm{COL}|\gamma_{D_{i,j}}}$ can be obtained as follows.

- Given a value of $\gamma_{D_{i,j}}$, the corresponding RIF value is obtained from Eq. (8) as follows: $\mathrm{RIF}_{D_{i,j}}=1-\gamma_{D_{i,j}}(1-\mathrm{RIF}_i)$
- Then a RSR associated with damage state j of structural member i, $\mathrm{RSR}_{i,j}$, can be computed following Eq. (7) as follows:

$$\mathrm{RSR}_{i,j}=(\mathrm{RIF}_{D_{i,j}})(\mathrm{RSR})$$

- Once the $\mathrm{RSR}_{i,j}$ value is known, the mean base shear capacity can be obtained and the conditional probabilities of failure, $P_{\mathrm{COL}|\gamma_{D_{i,j}}}$, can be calculated using a reliability method as explained before.

On the other hand, the probabilities of damage state j in structural member i, $P(\gamma_{D_{i,j}})$, are obtained from the Bayesian network as explained in more detail below.

Acceptable Probability of Failure. For the structures considered in the present study it is assumed that the criteria given in PEMEX-NRF-003 [14] are also valid for failures that can be identified through inspections, but with a reduction factor Ψ. This factor accounts for the fact that failure can also occur additionally without previous member failures in a storm event and therefore only part of the risk should be attributed to the failures that occur in combination with member degradation failures (see Ref. [15]). The acceptable probability of failure related to the considered individual member failure mechanisms is then

$$\Delta p_{\mathrm{acc}}=\psi\Phi(-\beta_{\mathrm{NRF}}) \tag{10}$$

β_{NRF} is the minimal annual reliability as specified by PEMEX-NRF-003 [14] and $\Phi(\,)$ is the standard normal cumulative probability distribution function. For the present case, including all types of member damages with the exception of fatigue damages, which are treated separately, a factor of $\Psi=0.4$ is taken. This

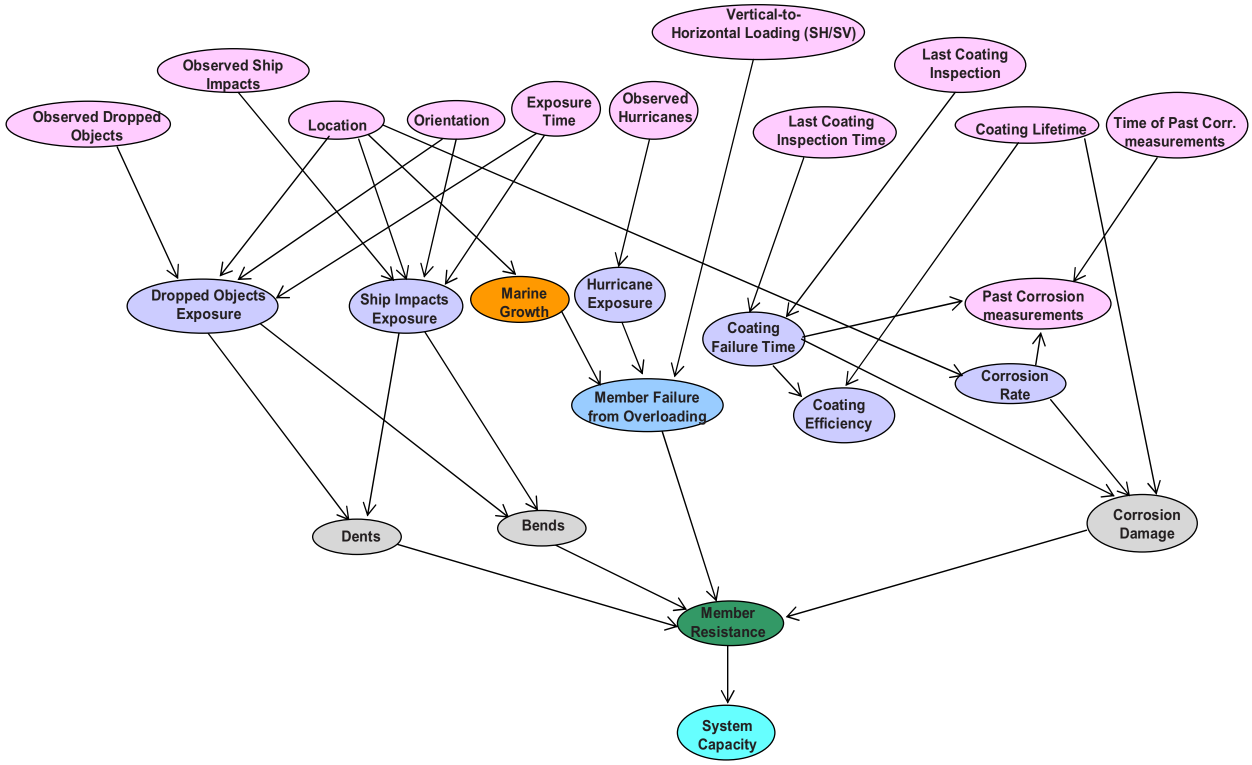

Fig. 2 Bayesian network used for planning inspections

factor is based on consideration of the relative cost of risk reduction for the different risks (risks that are associated with higher cost of risk reduction should have a higher acceptable probability of failure). However, no detailed study has been performed here, and the final choice is based on engineering judgment and is likely to be on the conservative side. For the purpose of determining acceptability of degradation, it is supposed that each element may contribute equally to the platform probability of failure. The total accepted probability of failure of the structure due to degradation, Δp_{acc}, is, thus, divided by the number of elements N. The acceptance criterion is thus

$$\sum_{j=1}^{H_D} (P_{\mathrm{COL}|\gamma_{D_{i,j}}} - P_{\mathrm{COL}|\gamma_{D_i}=0}) P(\gamma_{D_{i,j}}) \leqslant \frac{\Delta p_{\mathrm{acc}}}{N} \tag{11}$$

A minimum probability of failure (local acceptable) criterion is also introduced. This criterion accounts for the following two aspects: serviceability and statistical dependency among individual failure events. This criterion requires that the expected value of γ_{D_i} is less than or equal to 0.01. This criterion has been determined from engineering judgment, taking into account similar criteria applied in the past for inspection planning of joints subject to fatigue [7]. Inspections are required when the acceptance criteria are not satisfied.

Bayesian Network for Structural Integrity Management

The Bayesian network shown in Fig. 2 was developed to define inspection plans for a fixed platform. The individual nodes in the Bayesian network represent variables associated with uncertainties. These uncertainties are represented in the Bayesian networks by assigning (discrete) probabilities to their possible states. In the Bayesian networks these probabilities are input into so-called probability tables. The different variables in the net represent influencing factors, exposures, damage states, member capacity, and overall structural capacity. The structural members' damage index, γ_D, is taken as a discrete variable and may take values equal to 0, 0.25, 0.50, 0.75, and 1.

Mechanical Damages. The dropped objects' exposure distinguishes three states in this work: (a) No dropped object, meaning that no object has hit a member; (b) small dropped object, meaning that a small dropped object has hit a member; and (c) large dropped object, meaning that a large dropped object has hit a member. In order to distinguish between small and large objects in this work it is considered that 90% of dropped objects are small. In case of mechanical damages due to ship impacts, three states are considered for this exposure: no impacts, minor impacts (due to small ships), and large impacts (due to large ships). It is assumed that 80% of impacts are due to small ships.

Corrosion. The node "last coating inspection" has three states: no inspection/no indication/indication. This node has an effect only at the beginning of the calculation of future inspection plans: There is initial corrosion damage if there is "indication." It is assumed that after each future inspection, coating protection is applied and no corrosion damage on the element remains. The probability tables for the coating failure time are obtained by updating the probability of the different time states under the assumption that the inspection is perfect. The "coating efficiency" node distinguishes only three states: "100% efficiency," "reduced efficiency," and "no efficiency."

Extreme Environmental Effects. The hurricane exposure node can take several different states, corresponding to different magnitudes of the largest hurricane that has affected the structure. The following states are considered: (1) $f=1.4$, (2) $f=1.3$, and so on until (9) $f \leqslant 0.7$ (corresponding to no extreme load, since in this case the member probability of failure is considered to be equal to zero). Without an inspection of a given member, the state of the hurricane exposure node, which corresponds to the observed hurricane, has probability 1. In general, observations of hurricanes are reliable and thus no uncertainty in the observed events is considered, i.e., before an inspection, the states in the exposure nodes only take probability values 0 or 1. The probability after an inspection is evaluated taking into account the PoD of the applied inspection technique. Because the damage occurring from a hur-

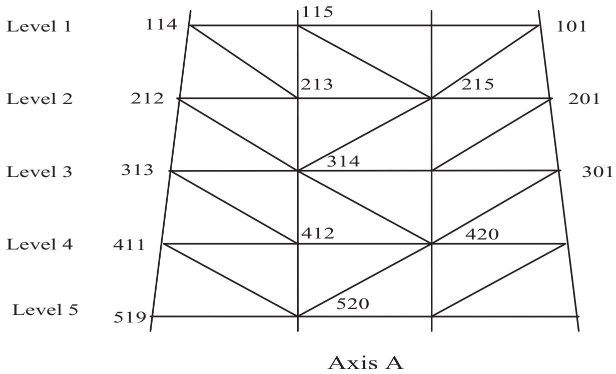

Fig. 3 Location of elements selected for RBI plans

ricane will only lead to damage states 0 or 1, the PoD is generally close to 1 for all inspection levels. For simplicity, only one event is considered in the network, namely, the maximum hurricane that occurred since the last inspection of the member. In the network, the member capacity will become zero if the member failure from the overloading node is in state 1. If the member failure from overloading is zero, the member capacity will be determined by the other damage types.

Case Study. The example concerns an eight-legged drilling platform, installed in the late 1970s and located in 40 m water-depth in the Gulf of Mexico. The RSR in the longitudinal direction (axis A in Fig. 3) is 2.30; in the transverse direction RSR $=2.35$. Eleven structural elements are selected for the analysis: five horizontal and four diagonal tubular members, as well as two legs. Their characteristics are listed in Table 1 and their location is shown in Fig. 3. Due to the volume of oil production handled by the platform it is classified as being of a "very high consequences of failure" class according to PEMEX-NRF-003 [14]. In using the acceptable probability of failure from PEMEX-NRF-003 [14], it is implied that a risk assessment in terms of economic consequences of failure, as well as cost of mitigation measures such as inspection and maintenance, has been used as a decision tool. This acceptable probability of failure is taken here to determine the acceptance criteria. Thus, the inspection planning using the Bayesian probabilistic net (BPN) is based only on a reliability criteria; no cost-optimization of inspection plans is performed at this stage. Considering the platform acceptable probability of failure [14], the acceptable annual probability of platform failure due to any member failure (Eq. (9)) is equal to 6.15×10^{-7} in this case.

The remaining service life for which inspection plans are to be developed is 20 years. Marine growth is 5 cm at the second bay level, 4 cm at the third one, and 2 cm at the fourth one; there is no marine growth at the fifth one. The last year of coating application is 1997. The values of α_L are based on the longitudinal stresses for each member. The probability of failure as a function of RIF (Eq. (7)) and RSR (Eq. (6)) is calculated supposing that both R and S are log-normal variables ($\sigma_{\ln R}=0.15$, $\sigma_{\ln S}=0.80$; σ denotes standard deviation); hence the computation of the probability of failure using the limit state function in Eq. (5) can be solved analytically. Additionally, median biases in R ($B_R=1.32$) and S ($B_S=0.89$) are assumed. The characteristic load S_C corresponds to a wave height return period of 100 years.

It is considered that the time of the last general visual inspection is the same as that for close visual, nondestructive tests and flooded member inspections. It is also assumed that all elements are undamaged at the time of last inspection. Mean annual rates of dropped objects and ship impacts over elements are presented in Table 2. These rates were calculated based on statistics for eight-legged platforms in the Gulf of Mexico. The value of PoD (Eq. (3)) is taken equal to 0.95. Without previous inspections, the values in the conditional probability table of the node "coating failure time," T_p, are listed in Table 3. After the last coating inspection, the conditional probabilities for T_p are indicated in Tables 4a and 4b. These probabilities are obtained by simply scaling the distribution in Table 3 considering the following: (1) The updated probabilities are equal to zero before the time of last coating inspection if there was no indication of corrosion damage at that time; and

Table 1 Elements' data

Element		Element general data										
Node i	Node j	Element importance	Location (level, bag)	Date of reparation	Axis	Orientation	Design thickness (mm)	Last visual general	RIF$\cdot X$	RIF$\cdot Y$	$\alpha=S_H/S_V$	Ovserved hurricane factor
114	115	Secondary	N1		A	Horizontal	12.7	7/3/2003	0.90	0.90	1	0.6
212	213	Secondary	N2		A	Horizontal	12.7	7/3/2003	0.90	0.90	50	0.6
313	314	Secondary	N3		A	Horizontal	12.7	7/3/2003	0.90	0.90	50	0.6
411	412	Secondary	N4		A	Horizontal	12.7	7/3/2003	0.90	0.90	50	0.6
519	520	Secondary	N5		A	Horizontal	12.7	7/3/2003	0.90	0.90	50	0.6
114	213	Primary	B1		A	Diagonal	15.875	7/3/2003	0.90	0.90	5.0	0.6
215	314	Primary	B2		A	Diagonal	15.875	7/3/2003	0.90	0.90	49.0	0.6
313	412	Primary	B3		A	Diagonal	15.875	7/3/2003	0.90	0.90	50.0	0.6
420	520	Primary	B4		A	Diagonal	15.875	7/3/2003	0.90	0.90	50.0	0.6
101	201	Primary	B1		A	Vertical	31.75	7/3/2003	0.01	0.01	7.0	0.6
201	301	Primary	B2		A	Vertical	31.75	7/3/2003	0.01	0.01	9.0	0.6

Table 2 Mean annual rates of dropped objects and ship impacts over elements

	Mean annual rates of dropped objects and ship impacts, Δp_{DO}					
	Dropped objects			Ship impacts		
Location	Horizontal	Vertical	Diagonal	Horizontal	Vertical	Diagonal
Splash zone	0.0020	0	0.0015	0.0013	0.0012	0.0052
Under water	0.0004	0	0.0001	0	0	0

Table 3 Probability distribution of coating failure time without coating inspections

Time (years)	Coating failure time, T*p* (without coating inspections)
0–2	0.01
2–4	0.05
4–6	0.20
6–8	0.30
8–10	0.25
>10	0.19

Table 5 Probability distribution of corrosion rate

Corrosion rate (mm/year)	Probability of corrosion rate
0	0
1	0.5
2	0.3
3	0.2

(2) the updated probabilities are equal to zero after the time of the last coating inspection if there was indication of corrosion damage at that time. The corrosion rate for elements in atmospheric and splash zones is taken as shown in Table 5. The value of k is taken equal to 0.8.

Eight cases were defined considering different contributions of damage exposure with the purpose of studying their effect on the inspection plans. The cases studied are listed in Table 6. Table 7 shows the exposures (with an "x") corresponding to each of the analyzed elements. The inspection plans for each case studied are shown in Tables 8–13.

From Case 1 (Table 8) it can be observed that for some elements inspections are not required. For instance, element 201-301 has no damage exposures: (1) There is no atmospheric corrosion since it is submerged; (2) for the same reason it is not subjected to ship impacts; and (3) there are no dropped objects as it is a vertical element (leg). The other elements that do not require inspections are only exposed to dropped objects; the results suggest that the rates defined in Table 2 are not high enough for global and local acceptable limits to be exceeded. The three elements that require inspections are exposed to ship impacts and corrosion. Elements 114-115 and 114-213 are additionally exposed to dropped objects. Inspections in element 114-213 are more frequent than for element 114-115 since in the first case the ship impacts' rate is much higher than in the second one (legs and diagonal elements are more likely to be impacted by a ship than horizontal ones), even though the dropped objects' rate is slightly higher for the second case; note also that in both of them the corrosion exposure is the same. On the other hand, inspections of leg element 101-201 are less frequent since the influence of the different kinds of damage considered on the local capacity is considerably less in legs than in horizontal and diagonal elements. This is taken into account in the network by using two conditional probability tables for element capacity: one for legs and another one for diagonal and horizontal elements.

For additional illustration of Case 1, the system probability of failure and the expected value of the member damage index γ_D as a function of time are shown for two of the structural elements: Figure 4 corresponds to the system probability of failure associated with leg element 101-201 and Fig. 5 to the expected value of the member damage index γ_D for diagonal element 114-213. It can be observed that inspections for element 101-201 are required because of exceeding the acceptable probability of platform failure due to member failure (6.15×10^{-7}). In the case of element 114-213 inspections are required because of exceeding the local acceptable criterion ($E[\gamma_D]\leq 0.01$). This is explained by the fact that the influence of damage on the capacity is greater for horizontal and diagonal elements than for legs and that those elements have higher RIF values. Note that after each inspection the platform probability of failure decreases because it was considered that after each future inspection coating protection is applied and thus no corrosion damage remains on the element. Also, note that times $T_{\mathrm{DO},1}$ and $T_{\mathrm{DO},2}$ for mechanical damages and ship impacts (Eq. (3)) change after each future inspection: $T_{\mathrm{DO},1}$ always has an increasing value and the PoD is high (0.95). Thus, the probability

Table 4 Probability distributions of coating failure time: (*a*) inspection with no indication and (*b*) inspection with indication

	Coating failure time, T*p* (coating inspection with no indication)					
	Time of last coating inspection (years)					
Time (years)	0–2	2–4	4–6	6–8	8–10	>10
0–2	0.01	0	0	0	0	0
2–4	0.05	0.051	0	0	0	0
4–6	0.20	0.202	0.213	0	0	0
6–8	0.30	0.303	0.319	0.405	0	0
8–10	0.25	0.252	0.266	0.338	0.568	0
>10	0.19	0.192	0.202	0.257	0.432	1

	Coating failure time, T*p* (coating inspection with indication)					
	Time of last coating inspection (years)					
Time (years)	0–2	2–4	4–6	6–8	8–10	>10
0–2	1	0.167	0.039	0.018	0.012	0.01
2–4	0	0.833	0.192	0.089	0.062	0.05
4–6	0	0	0.769	0.357	0.247	0.20
6–8	0	0	0	0.536	0.370	0.30
8–10	0	0	0	0	0.309	0.25
>10	0	0	0	0	0	0.19

Table 6 Cases analyzed. DO=dropped objects, SI=ship impacts, CO=corrosion, *f*=factor of observed hurricane load (related to the design load), 2DO=dropped objects with rate Δp_{DO} multiplied by 2, 2SI=ship impacts with rate Δp_{DO} multiplied two times, COM(0)=measured corrosion equal to 0 mm, COM(<2 mm)=measured corrosion less than 2 mm, and COM(>2 mm)=measured corrosion greater than 2 mm.

Case	Description	Elements analyzed
1	DO, SI, CO, $f=0.6$	All
2	DO, SI, $f=0.6$	All
3	CO, $f=0.6$	All
4	2DO, 2SI, $f=6$	All
5	DO, SI, CO, $f=0.7$	All
6	COM(0), $f=0.6$	114–115 (horizontal)
	COM(<2 mm), $f=0.6$	114–115 (horizontal)
8	COM(>2 mm), $f=0.6$	114–115 (horizontal)

Table 7 Different exposures for the elements analyzed. DO =dropped objects, SI=ship impacts, and CO=corrosion.

	Exposure		
Element	DO	SI	CO
114–115	x	x	x
212–213	x		
313–314	x		
411–412	x		
519–520	x		
114–213	x	x	x
215–314	x		
313–412	x		
420–520	x		
101–201		x	x
201–301			

of not detecting a damage due to dropped objects or ship impact decreases; given that it is assumed that after each future inspection there are no findings, the probability of damage is consequently reduced.

In Case 2 (only mechanical damages, i.e., exposure to dropped objects and ship impacts) the elements that required inspections are the same as in Case 1 (Table 9). For leg element 101-201, inspection times are the same as in Case 1, which suggests a small influence of corrosion on local and global capacity. On the other hand, fewer inspections are required on elements 114-115 and 114-213 compared to the previous case; hence there is a greater influence of corrosion for these elements.

For Case 3, it is seen that for element 101-201 corrosion is not relevant for inspection planning. Comparing Tables 8–10 it can be observed that in elements 114-115 and 114-213, corrosion is the type of damage that has the largest influence on the required inspection times. For both members the inspection times due to corrosion are the same because their corrosion exposure is the same (Table 10). Note that, comparing Tables 9 and 10 it is confirmed that inspections on element 101-201 are due mainly to the effect of mechanical damages.

Case 4 (Table 11) is similar to Case 2, except that now the ship impacts' and dropped objects' rates are doubled. Note that the elements to be inspected are the same in both Cases 2 and 4, which show that the increment in rates of dropped objects and ship impacts is not enough to require other elements to be inspected. As expected, inspections in this case are more frequent than in Case 2. To check the influence of dropped objects on the required inspection times, the annual rate of dropped objects in Table 2 was modified such that at least one inspection would be required. It was found that for the horizontal elements the rate should be 62 times as high as those in Table 2, and 161 times as high as those for the diagonal elements; in both cases it was the accordance of the acceptable expected element damage, $E[\gamma_D] \leq 0.01$, which controlled the required inspections of the elements.

Table 8 Results: Case 1

Element		Times of inspection (years)																			
Node i	Node j	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
114	115		XX					XX					XX					XX			
212	213																				
313	314																				
411	412																				
519	520																				
114	213	XX			XX			XX			XX			XX			XX			XX	
215	314																				
313	412																				
420	520																				
101	201							XX								XX					
201	301																				

Table 9 Results: Case 2

Element		Times of inspection (years)																			
Node i	Node j	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
114	115											XX									
212	213																				
313	314																				
411	412																				
519	520																				
114	213				XX					XX				XX				XX			
215	314																				
313	412																				
420	520																				
101	201							XX								XX					
201	301																				

Table 10 Results: Case 3

Element		Times of inspection (years)																			
Node i	Node j	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
114	115		XX					XX					XX					XX			
212	213																				
313	314																				
411	412																				
519	520																				
114	213		XX					XX					XX					XX			
215	314																				
313	412																				
420	520																				
101	201																				
201	301																				

Hence, dropped objects alone are damage exposure unlikely to trigger by itself inspections of the elements; and, as shown in this example, if it did it would be because of the local serviceability criterion.

In Case 5 (Table 12) the effect of observed hurricanes is evaluated. It is important to remember that $f=0.6$ is associated with zero probability of lost elements during a hurricane. The results show that the effect of an observed hurricane with $f=0.7$ is not enough to modify the inspection plans for elements 114-115 and 114-213. In the case of leg elements, due to the corresponding RIF values, an inspection is required in the first year of the remaining service life; after that, as already discussed, the effect of observed hurricanes vanishes and the frequencies (not the times) of inspection are the same as for Case 1.

Cases 6–8 assess the effect of having (or not) corrosion evidence before the start of the remaining life. Results show that only when measured corrosion is greater than 2 mm the updated prob-

Table 11 Results: Case 4

Element		Times of inspection (years)																			
Node i	Node j	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
114	115				XX					XX					XX					XX	
212	213																				
313	314																				
411	412																				
519	520																				
114	213	XX		XX		XX		XX		XX		XX		XX	XX	XX	XX	XX	XX	XX	XX
215	314																				
313	412																				
420	520																				
101	201			XX				XX			XX			XX			XX			XX	
201	301																				

Table 12 Results: Case 5

Element		Times of inspection (years)																			
Node i	Node j	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
114	115		XX					XX					XX					XX			
212	213																				
313	314																				
411	412																				
519	520																				
114	213	XX			XX			XX			XX			XX			XX			XX	
215	314																				
313	412																				
420	520																				
101	201	XX								XX								XX			
201	301	XX																			

Table 13 Results for corrosion for element 114–115 (horizontal)

Case	Times of inspection (years)																			
	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
3																				
6																				
7																				
8																				

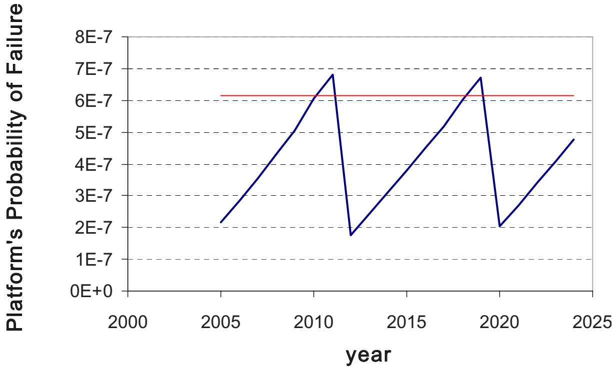

Fig. 4 Probability of platform failure caused by failure of element 101-201 (Case 1)

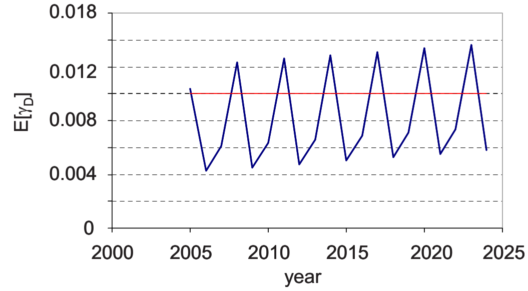

Fig. 5 Expected value of γ_D for element 114-213 (Case 1)

ability distributions for coating failure time, T_p, and "corrosion rate," ρ_U, cause inspection frequencies to increase in element 114-115 (Table 13).

Application in the Oil Industry. The methodology presented in this paper is already being applied in the Mexican oil industry with significant economical savings. During 2005, risk-based inspection planning for 35 fixed platforms in the Gulf of Mexico were calculated using the Bayesian network presented here. As an illustration, the inspection plans for one of these platforms are

Table 14 Inspection plans for a fixed platform in the Gulf of Mexico

Element		Times of Inspection (years)																			
Node i	Node j	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
101	117			XX					XX					XX					XX		
101	209			XX				XX				XX				XX				XX	
110	209			XX					XX					XX					XX		
117	209			XX				XX				XX				XX				XX	
101	201											XX									
117	217											XX									
102	118	XX					XX					XX					XX				
102	210			XX				XX				XX				XX				XX	
118	210	XX				XX				XX				XX				XX			
111	210			XX					XX					XX					XX		
102	202											XX									
118	218									XX											XX
104	120	XX					XX					XX					XX				
104	212			XX				XX				XX				XX				XX	
120	212			XX				XX				XX				XX				XX	
104	203											XX									
120	219									XX											XX
106	122			XX					XX					XX					XX		
106	213			XX				XX				XX				XX				XX	
122	213			XX				XX				XX				XX				XX	
106	205											XX									
122	221											XX									
117	118			XX					XX					XX					XX		
118	120	XX					XX					XX					XX				
120	122	XX					XX					XX					XX				
117	218			XX				XX				XX				XX				XX	
118	219			XX				XX				XX				XX				XX	
120	218			XX				XX				XX				XX				XX	
122	219			XX				XX				XX				XX				XX	
101	102			XX					XX					XX					XX		
102	104			XX					XX					XX					XX		
104	106			XX					XX					XX					XX		
101	202			XX				XX				XX				XX				XX	
102	203	XX				XX				XX				XX				XX			
104	202			XX				XX				XX				XX				XX	
106	203			XX				XX				XX				XX				XX	
101	108			XX					XX					XX					XX		
102	108			XX					XX					XX					XX		
107	109			XX					XX					XX					XX		
108	115			XX					XX					XX					XX		
114	116			XX					XX					XX					XX		
115	117			XX					XX					XX					XX		
115	118			XX					XX					XX					XX		
103	109	XX					XX					XX					XX				
103	112	XX					XX					XX					XX				
111	112			XX					XX					XX					XX		
112	119	XX					XX					XX					XX				
116	119			XX					XX					XX					XX		
105	112			XX					XX					XX					XX		
105	113	XX					XX					XX					XX				
112	121			XX					XX					XX					XX		
113	121	XX					XX					XX					XX				

listed in Table 14. The platform was installed in 1980 at 49 m water-depth and is categorized as a "very high consequences of failure" facility in accordance with PEMEX-NRF-003 [14]. The remaining service life for which inspection plans are to be developed is 30 years, though Table 14 shows results only for the next 20 years. The last year of coating application is 2002. The platform has 220 elements, but only 52 require inspections at the times listed in Table 14. The results in Table 14 can be compared to those obtained using other inspection planning strategies, such as inspecting different elements every year in a way that after some time span, for instance, 5 years, all of the elements have been inspected once. Under such inspection strategy, it is clear that the total number of inspections would be greater than that shown in Table 14 using the BPN formulation. Comparative analyses were carried out for the 35 platforms mentioned above, and it was found that the number of elements to be inspected is reduced using Bayesian networks. This represents significant savings in inspection costs.

Conclusions

A general framework has been introduced for integrity management of offshore steel jacket structures, allowing for the risk based planning of inspections and maintenance activities and accounting for the combined effect of different deterioration and damage processes. The approach applied in the paper relies on the use of Bayesian probabilistic networks as an efficient tool for the representation of the causal relationships between exposure events, damage states, and the effects on the overall structural capacity.

A Bayesian network is formulated generically such that it is generally applicable for any given platform. Platform specific information is accounted for through the assignment of node probability tables, which are relevant for the individual platforms. Inspection results or information about extreme events for the individual platforms is easily introduced by conditioning of the relevant states in the nodes of the Bayesian network. The approach has been illustrated through an application on a steel jacket structure from the Gulf of Mexico. It has been shown that inspection times depend on many factors, including location, orientation, and relative importance of the structural elements. It was also shown that inspection plans can be very sensitive to changes in parameters, which define exposures, such as rates of ship impacts, dropped objects, and corrosion.

In general, the method can be said to be relatively robust with respect to errors in the execution of the inspection (e.g., inspection of the wrong details). Most risks increase linear with time, in which case a missed inspection implies a risk two times the acceptable risk. Because most considered structures are highly redundant, this is not critical, as long as it can be ensured that there are systematic errors in the execution of the inspections. The methodology may be seen as providing a systematization of engineering knowledge, experience, and available data. As such it seems that the procedure cannot be verified as a whole, however, the individual constituents of the procedure as outlined within the present paper provide the basis for the procedure; these may be improved over time as more information on inspection results becomes available. This is particularly facilitated by the fact that the BN model is transparent, i.e., it allows determining the influence of the individual assumptions on the inspection outcomes. Future efforts should now be directed toward refining the model with additional experiences and information collected from future inspections. Because the BN also allows identifying the most relevant parameters in the model, focus can be directed toward collecting information on these. In this context, the BN can be used to demonstrate to the operator the benefit of systematically collecting additional information to improve the model.

Acknowledgment

The authors are thankful to Mr. Enrique Marcial from IMP for his support on implementing the software for the Bayesian network analysis and for his collaboration in generating the results for the inspection plans.

References

[1] Skjong, R., 1985, "Reliability Based Optimization of Inspection Strategies," *Proceedings of ICOSSAR 85*, Kobe, Japan, May 27–29, Vol. III, pp. 614–618.
[2] Madsen, H. O., Sørensen, J. D., and Olesen, R., 1989, "Optimal Inspection Planning for Fatigue Damage of Offshore Structures," *Proceedings of ICOSSAR 89*, San Francisco, CA, August 8–11, Vol. 3, pp. 2099–2106.
[3] Faber, M. H., Engelund, S., Sørensen, J. D., and Bloch, A., 2000, "Simplified and Generic Risk Based Inspection Planning," *Proceedings of the 19th Offshore Mechanics and Arctic Engineering Conference*, New Orleans, LA, February 14–17.
[4] Moan, T., Vårdal, O. T., and Johannesen, J. M., 1999, "Probabilistic Inspection Planning of Fixed Offshore Structures," *Proceedings of ICASP8*, Sydney, Australia, December 12–15, pp. 191–200.
[5] Straub, D., and Faber, M. H., 2006, "Computational Aspects of Risk Based Inspection Planning," Comput. Aided Civ. Infrastruct. Eng., **21**(3), pp. 179–192.
[6] Pedersen, C., Madsen, H. O., Nielsen, J. A., Riber, J. P., and Krenk, S., 1992, "Reliability Based Inspection Planning for the Tyra Field," *Proceedings of the 11th Offshore Mechanics and Arctic Engineering Conference*, Calgary, Canada, June 7–11, Vol. 2, pp. 255–263.
[7] Faber, M. H., Sørensen, J. D., Tychsen, J., and Straub, D., 2005, "Field Implementation of RBI for Jacket Structures," ASME J. Offshore Mech. Arct. Eng., **127**(3), pp. 220–226.
[8] Faber, M. H., 2006, *Risk and Safety in Civil, Surveying and Environmental Engineering* (Lecture notes), Swiss Federal Institute of Technology, Zurich, Switzerland. http://www.ibk.ethz.ch/fa/education/lecture_notes.
[9] Straub, D., and Faber, M. H., 2005, "Risk Based Inspection Planning for Structural Systems," Struct. Safety, **27**, pp. 335–355.
[10] Friis-Hansen, A., 2000, "Bayesian Networks as a Decision Support Tool in Marine Applications," Ph.D. thesis, Department of Naval Architecture and Offshore Engineering. Technical University of Denmark, Kongens Lyngby.
[11] Turner, R. C., Ellinias, C. P., and Thomas, G. A. N., 1994, "Worldwide Calibration of API RP2A-LRFD," J. Waterway, Port, Coastal, Ocean Eng., **120**(5), pp. 423–433.
[12] HSE, 2001, "Load factor Calibration for ISO 13819—Regional Annex: Component Resistance," Offshore Technology Report, No. 2000/072, Health & Safety Executive, UK. www.hse.gov.uk/research.
[13] Stahl, B., Aune, S., Gebara, J. M., and Cornell, C. A., 1998, "Acceptance Criteria for Offshore Platforms," *Proceedings of the 17th Offshore Mechanics and Arctic Engineering Conference*, Lisbon, Portugal.
[14] PEMEX, 2000, "Diseño y Evaluación de Plataformas Marinas Fijas en la Sonda de Campeche," NRF-003-PEMEX-2000, Mexico DF, Mexico.
[15] Straub, D., 2004, "Generic Approaches to Risk Based Inspection Planning of Steel Structures," Ph.D. thesis, Swiss Federal Institute of Technology (ETH), Zurich, Switzerland.