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Fatigue inspection and maintenance optimization:
A comparison of information value, life cycle cost and reliability based approaches

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Abstract

Fatigue cracks increase structural failure risk and timely maintenance is very important. Maintenance planning is often formulated as a probabilistic optimization problem, considering uncertainties in structural and load modelling, material properties, damage measurements, etc. A decision rule or strategy, e.g. condition based maintenance (CBM), needs to be set up, and then an optimal maintenance criterion or threshold is derived via solving the optimization problem. This paper develops a probabilistic maintenance optimization approach exploiting value of information (VoI) and Bayesian decision optimization. The VoI based approach explicitly quantifies added values from future inspections, and gives an optimal decision (or strategy) by direct modelling decision alternatives and evaluating their expected outcomes, rather than a pre-defined strategy. A comparative study on VoI, life cycle cost (LCC) and reliability based optimization approaches is conducted. It is shown that the VoI based approach takes all available maintenance strategies into account (both with and without inspections), and can reliably yield optimal maintenance strategies, whether the VoI is larger than or equal to zero. When the VoI is equal to zero, LCC and reliability based CBM optimization can result in suboptimal maintenance strategies. The differences in the approaches are illustrated on fatigue-sensitive components in a marine structure.

Key words:

Integrity management; Reliability; Probabilistic modelling; Life cycle cost analysis; Risk analysis; Decision making under uncertainty

1 Introduction

Structural integrity loss as a result of fatigue cracks is a common problem and critical issue in asset management. Fatigue cracks in welded components initially are local problems, but failures of fatigue-sensitive components eventually can lead to rupture of a structural system, posing huge risks to assets, human lives and environment (Frangopol and Soliman 2016). Thus, it is important to control operational risks via timely crack detection and maintenance. Adopting large fatigue design factor is a measure to reduce failure risks at the structural design stage, but too conservative design without operational maintenance is often not economical. Moreover, failure risks need to be re-assessed at operation stage against new inspection data, in consideration of potential human errors in design and fabrication, discrepancies between design and as-built conditions, changes in loading conditions, new hazards, etc. (Biondini and Frangopol 2016). Operational inspections provide additional information on crack damages, which can potentially be utilized to improve the quality of maintenance decisions.

Maintenance methods are usually determined based on engineering experience. For example, maintenance methods for cracks in steel structures usually include: drilling a stop hole, grinding, welding (plus post-weld treatment), hammer peening, metal crack stitching, bonded crack patches, gas tungsten arc melting, splice plate method, partly replacement, etc. (Marazani, Madyira, and Akinlabi 2017, Akyel, Kolstein, and Bijlaard 2017). New methods reported in literature are laser additive crack cladding, self-healing materials, liquid-assist healing, etc. (Marazani, Madyira, and Akinlabi 2017, Fisher et al. 2018).

Maintenance costs often account for a significant part of LCC of large structure assets containing numerous hot-spot areas, e.g. ships and offshore structures (Soliman, Frangopol, and Mondoro 2016). It thus can save costs to develop an efficient maintenance strategy at the beginning of service, specifying the number of interventions in lifetime, inspection times and methods, maintenance criteria and methods, etc. However, maintenance planning and optimization under uncertain crack damage states is challenging, as a result of variabilities and uncertainties in material properties, loads, modelling, inspection detectability, etc. (Zou, Banisoleiman, and Gonzalez Merino 2018). Both the costs and benefits of maintenance are subjected to uncertainties. Probabilistic modelling has been acknowledged as a strong tool to treat uncertainties consistently and widely adopted in structural maintenance optimization (Ang and Tang 2007). Based on probabilistic models, structural reliability methods have been developed to consider the effects of uncertainties in the fatigue and fracture limit state, and reliability has been used as a performance indicator for maintenance optimization (Ayala-Uraga and Moan 2007, Temple and Collette 2015, Lotsberg et al. 2016). Risk analysis methods extend the scope to incorporate failure consequences, in addition to failure probabilities. Using risk as a performance indicator, maintenance priorities are given to structural components associated with high failure risks (Faber et al. 2012, Heredia-Zavoni et al. 2012, Dong and Frangopol 2016). Risk analysis and LCC analysis are theoretical basis for probabilistic maintenance optimization methods and applications (Kim, Soliman, and Frangopol 2013, Zou et al. 2019, Dong and Frangopol 2015). The advantages and limitations of reliability and LCC based maintenance optimization methods have been studied comparatively in (Barone, Frangopol, and Soliman 2013, Zou, Banisoleiman, and González 2018).

Development in sensors, non-destructive evaluation and data analytics makes it earlier to collect more condition information to support maintenance decision making and attracts growing interest of researchers and engineers in CBM. Additional information reduces the uncertainty affecting decision making, leading to improved decisions (if available). Over the past few years, VoI algorithms and decision analysis have been applied to quantifying the expected values of inspection or monitoring activities for deteriorating structures (Straub 2014, Haladuick and Dann 2018, Thöns 2018), to optimising maintenance decisions (Zou et al. 2019, Zitrou, Bedford, and Daneshkhah 2013, Huynh, Barros, and Bérenguer 2012), to scheduling inspections (Memarzadeh and Pozzi 2016, Irman, Thöns, and Leira 2017) and to optimising sensor placement (Malings and Pozzi 2016), etc. There is however a lack of a comparative study on VoI, LCC and reliability based maintenance optimization approaches, which would contribute to better understanding of the differences between these approaches.

This paper presents, for the first time, a detailed comparative study on VoI, LCC and reliability based fatigue inspection & maintenance optimization approaches in structural engineering. The objective is to develop a probabilistic inspection & maintenance optimization approach exploiting VoI computation, and reveal strengths and limitations of the VoI based approach, in comparison to LCC and reliability based approaches. Fatigue inspection and maintenance optimization problem is solved, employing Bayesian decision optimization and taking into account the effects of uncertainty and uncertainty reduction via condition inspections. Section 2 describes the optimal maintenance decision problem. Section 3 gives methodology to the problem. Reliability, LCC and VoI based maintenance optimization approaches are formulated respectively, by integration of probabilistic modelling of crack propagation, inspection and maintenance effect. In Section 4, the three approaches are applied to a numerical example, and results obtained by the three approaches are analyzed and discussed comparatively. In Section 5, some important conclusions from the study are drawn.

2. Optimal Maintenance Decision Problem

Fatigue cracks are commonly found in metallic structures. Macrocracks usually occur as result of initial flaws or cracks induced during fabrication, residual stresses, geometry discontinuity and stress concentrations (in the vicinity of structural connections or openings), etc., and propagate under repetitive loading (Schijve 2003). Ship and offshore structures are typical structures prone to fatigue under wave loading, with numerous welded structural components, hot-spot areas and fatigue-sensitive details.

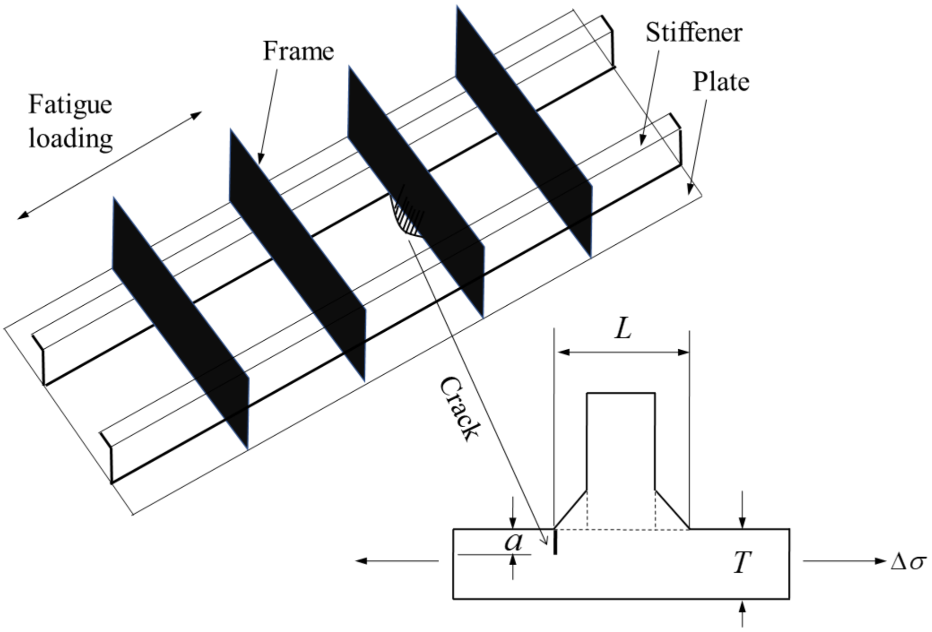

Figure 1 An illustration of typical fatigue-sensitive details in marine structures

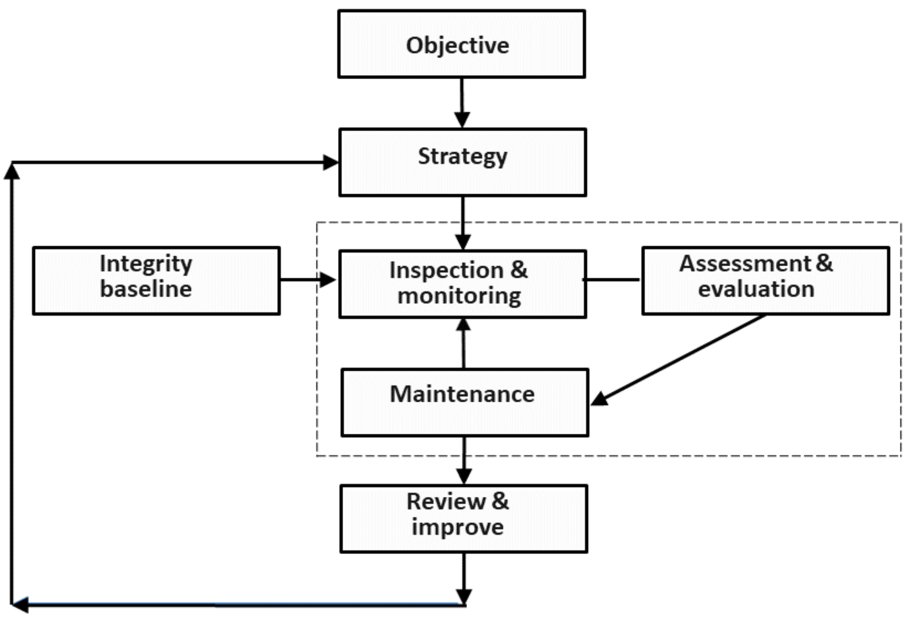

Figure 2 A flowchart of structural integrity management process

Figure 1 is schematic representation of stiffened plate structure that are common in ship and floating production storage and offloading (FPSO) structures. The figure shows that, a crack develops at the weld of a web frame to the main plate, under longitudinal fatigue loading imposed by waves. Crack propagation under fatigue loading can lead to fracture of structural components (i.e. structural integrity loss) and eventual structural system failures. The failure risks are controlled by developing and implementing structural integrity management (SIM) schemes. Figure 2 gives a flowchart of a typical SIM process, in which condition inspections (or monitoring) are employed to validate structural integrity or to identify potential cracks. The core of a SIM scheme is a maintenance strategy and plan.

The methods in Section 3 are developed to support maintenance decision process and improve the quality of maintenance decisions.

Rational maintenance decision-making relies on deterioration process information and data (i.e. crack initiation time and growth rate), capacity of the adopted inspection method, maintenance effects of the adopted repair method, required service life, cost and utility functions, etc. Prediction of deterioration process is usually subjected to sources of uncertainties. For example, crack growth is very sensitive to parameters such as, initial crack size, stress range, material fracture properties, the exact values of which are often hard to obtain (Lotsberg et al. 2016, Soliman, Frangopol, and Mondoro 2016). Moreover, there is modelling uncertainty associated using a physical model for the deterioration process, as a model can only represent reality to some extent. In addition, the capacity of an inspection method (i.e. the smallest crack size that can be reliably detected) is difficult to quantify and thus subjected to uncertainty (Beaurepaire et al. 2012, Cronvall et al. 2012). The result of an inspection can be affected by crack characteristics, instrumentation, the environments where an inspection performed, competence of inspector, etc. Difficulties in controlling these circumstances often hinder accurate quantification of the capacity of an inspection method. These uncertainties need to be taken into account while developing an optimal maintenance plan.

This paper addresses optimal maintenance decision-making on 1) inspection strategy, and; 2) maintenance criterion (i.e. the criterion or threshold to carry out maintenance). Impacts of uncertainty on maintenance decision-making and benefits of uncertainty reduction (via condition inspections) are studied. The maintenance optimization problem is solved by reliability, LCC and VoI based approaches respectively and the obtained maintenance plans are compared with each other. Advantages of explicit VoI computation and systematic decision optimization are highlighted, in comparison with reliability and LCC based approaches.

3 Methodology

The methodology of this paper is illustrated by Figure 3, and the rationale of the methodology is explained by below points.

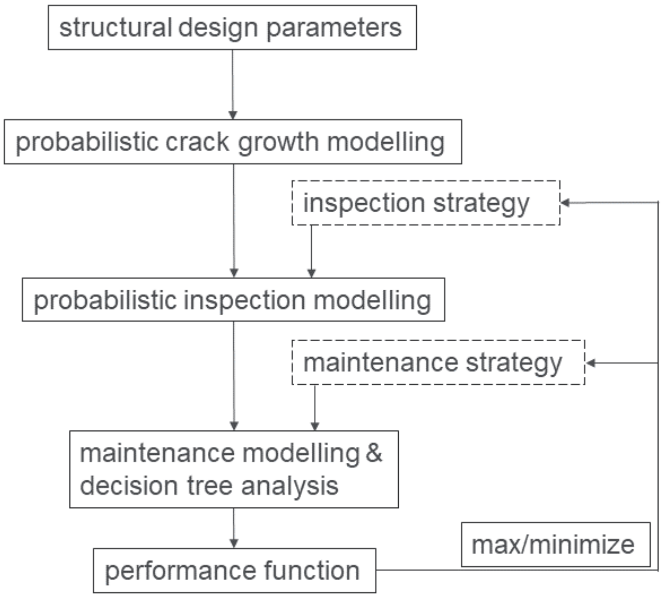

Figure 3 Optimization of lifetime maintenance intervention decisions

- At the structural design stage, fatigue reliability is checked by S-N fatigue analysis method while detailing structural design parameters. However, the as-built structural conditions may not be the same as that assumed at the design stage, e.g. existence of initial flaws or cracks, and the fatigue reliability at beginning of service can be lower than design fatigue reliability (Lassen and Recho 2015). Operational fatigue reliability of the structural system is decreasing with service life due to fatigue loading and operational hazards that are unforeseen or not considered at the design stage.
- Repairs and maintenance are reliability growth and risk mitigation measures at the operation stage, at the expense of some costs, which can account for a significant part of LCC of large ship and offshore structures. Optimal maintenance planning helps to improve maintenance efficiency and reduce LCC, but is challenged by sources of uncertainty.
- Condition inspections are employed to collect operational damage information and reduce uncertainty. Inspections often contribute to improved maintenance decisions but also incur additional costs, so the VoI is computed in support of inspection optimization.
- Optimal inspection and maintenance strategies are derived by maximization/minimization of performance functions, which are formulated via integrating probabilistic crack growth modelling, inspection reliability modelling, maintenance effect modelling, decision tree analysis (Faber 2012, Kim, Soliman, and Frangopol 2013), reliability, risk and VoI computations and Bayesian decision optimization (Straub 2014, Vereecken et al. 2020). In these modelling and computations, all possibilities of crack damage states, inspection results and maintenance actions are considered, which are uncertainty at the time of maintenance decision-making.

Sources of uncertainty, maintenance strategies, decision variables and performance functions that are considered in the study are discussed below.

- Uncertainty in material fracture property, stress range calculation, initial crack size and inspection capacity (i.e. the detectable crack size) are explicitly modelled.
- Condition based maintenance (CBM) is the focus of this paper, in comparison with detection based and time based maintenance (DBM, TBM). Under CBM, inspections are carried out first and following crack detection, crack size is measured. Maintenance would be performed if crack size is larger than a maintenance criterion (threshold for maintenance). Under DBM, inspections are carried out and maintenance performed following crack detection. Under TBM, maintenance is carried out periodically.
- Three performance functions are applied to evaluation of inspection & maintenance strategies: lifetime fatigue reliability, LCC and VoI.

3.1 Crack propagation modelling

The probabilistic maintenance optimization approaches thereafter developed are based on a FM model for crack propagation. Specifically, Paris' law is used for modelling of crack propagation. The FM approach is able to provide detailed crack propagation information with time, based on which inspections and maintenance activities are scheduled. Figure 4 shows three stages of crack development. The crack initiation stage is long for high quality components, such as mechanical components fabricated with high quality control standard. But for structural components, the initiation stage is typically negligible compared with crack propagation stage, due to presence of initial cracks (Lassen and Recho 2013). The final fracture stage is usually short and thus crack propagation stage account for a large part of fatigue life for structural components. The one-dimensional Paris' law given by Equations (1) describes the relationship between crack growth rate da/dN and stress intensity factor range ΔK (Paris and Erdogan 1963). The model represents a good balance of sufficient accuracy and acceptable computational time, which is important when the model is integrated into a probabilistic framework.

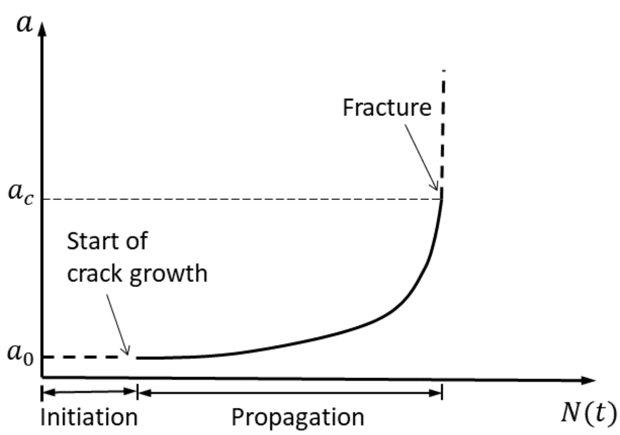

Figure 4 Schematic illustration of three stages of crack development

$$\frac{da}{dN} = C\Delta K^m, \quad \Delta K_{th} \leq \Delta K \leq K_{mat} \tag{1}$$

Where a is crack size; N is the number of cycles; C and m are material parameters; K_{mat} is material fracture toughness, and; ΔK_{th} is threshold value for the stress intensity factor range

The stress intensity factor range ΔK is given by Equation (2).

$$\Delta K = \Delta\sigma Y(a)\sqrt{\pi a} \tag{2}$$

Where $Y(a)$ is geometry function and $\Delta\sigma$ is stress range.

Based on Equations (1) and (2), it is able to obtain the crack size (under constant amplitude loading)_as a function of time $a(t)$ by numerical integration using Equation (3). If a critical crack size a_c (signifying fracture) is defined, the fatigue life can be obtained by Equation (4).

$$da(t) = \pi^{m/2} C\Delta\sigma^m a^{m/2}(t) Y(a)^m [a(t)] dN(t) \tag{3}$$

$$N_P = \frac{1}{\pi^{m/2} C\Delta\sigma^m} \int_{a_0}^{a_c} \frac{da}{a^{m/2} Y(a)^m} \tag{4}$$

Probabilistic aspects of using FM method for crack growth analysis have been extensively studied (Lotsberg et al. 2016, Dong and Frangopol 2016, Soliman, Frangopol, and Mondoro 2016, Maljaars and Vrouwenvelder 2014). The parameters C and m are often seen as material properties, although influenced by environment and loading conditions as well. The parameter uncertainty associated with C and m is believed to originate from material inhomogeneity, measurement method, statistical parameter estimation method, etc. (Lassen and Recho 2013). In probabilistic analysis, C is normally treated as a variable with a distribution and m is deterministic. Stress range $\Delta\sigma$ and the geometry function $Y(a)$ are critical parameters in using Equation (1) for crack growth prediction, as it enters into the equation with the power of m. Detailed calculations of $\Delta\sigma$ and $Y(a)$ can be carried out by finite element modelling. The geometry functions for common welded structural details are available in (BS 2000). The value of ΔK_{th} depends on factors such as stress ratio, loading sequence, residual stresses, mean stress, etc. The recommended value for welded joints is 63 $\mathrm{N \cdot mm^{-3/2}}$ in (BS 2000). However it is reported that the effect of ΔK_{th} on crack growth prediction is very small when a value less than 63 $\mathrm{N \cdot mm^{-3/2}}$ is used (Lotsberg and Salama 2010). The initial crack size a_0 depends on materials, welding techniques, non-destructive testing methods, quality control procedure, etc. As these factors are often only partly controllable during fabrication, there are usually uncertainty in a_0. Also, there is uncertainty associated with measuring the a_0. The a_c is usually set to be equal to the component thickness T, as the consequence of crack growth is usually not serious until through-thickness crack occurs. However, fatigue life and reliability are not very sensitive to small change in a_c, because crack typically develops very quickly at the final fracture stage.

3.2 Probabilistic inspection modelling

The information inferred from an inspection is highly affected by the capacity and reliability of the adopted inspection method. In order to quantify the VoI and risk reductions from adopting inspections, it is important to integrate probabilistic inspection modelling into maintenance optimization. There are limitations in any inspection method, whether visual inspection or non-destructive testing (NDT), and inspection results usually cannot reflect true crack states. Sometimes existing cracks cannot be identified (false negative), and a positive indication is found to be false due to absence of a crack (false positive). It is also found that an existing crack is detected by one inspector but missed by other inspectors. Generally, the result by a NDT depends on the reliability of a specific instrument-human system under given environments. The probability of crack detection can be affected by factors such as crack damage characteristics (sizes, shape, location, etc.), reliability of instrumentation, the environments in which an inspection is carried out, inspection procedure, human factors associated with an inspector, etc. (Carvalho et al. 2008, Wall, Burch, and Lilley 2009).

The probabilistic aspects of a NDT are illustrated conceptually by Figure 5. When the output signal strength from a NDT is larger than a detection threshold, the inspection result is an indication of a crack. However, the indication may be due to noise signal, i.e. false alarm. When the output signal strength is smaller than the detection threshold, the inspection result is no detection. Similarly, the result of no detection could be due to noise signal, i.e. miss detection. Figure 5 shows that both the probability of false alarm and the probability of miss detection are affected by detection threshold.
The probability of detection (PoD) is an important indicator of inspection reliability. PoD is defined as the probability that a given crack of a fixed size can be detected by a given inspection method (Georgiou 2007, Keprate and Ratnayake 2015). PoD functions are often expressed as a function of its main affecting factor, i.e. the crack size(s), although it is affected by factors such as material, geometry, crack shape, inspector, inspection procedure, instrumentation, etc. (Carboni and Cantini 2016). PoD functions can be obtained by statistical analysis of inspection experiments or in-service observations (Moan et al. 2000), or by simulation approaches (Li, Meeker, and Thompson 2011, Cobb, Fisher, and Michaels 2009, Carvalho et al. 2011).

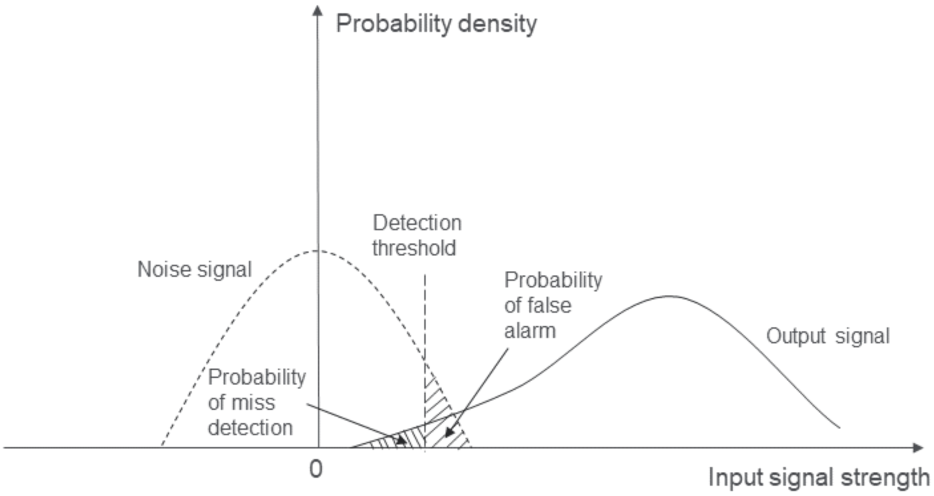

Figure 5 A conceptual illustration of probability of miss detection and probability of false alarm

Herein, an exponential PoD function, as given by Equation (9) is adopted. The PoD function is based on inspection data and widely adopted in probabilistic maintenance optimization (Chen, Wang, and Guedes Soares 2011, Lassen and Recho 2015, Moan and Song 2000, Dong and Frangopol 2016, Moan et al. 1997, Moan and Ayala-Uraga 2008, Beaurepaire et al. 2012, Valdebenito and Schuëller 2010). By using the function, the detectable crack size a_d is modelled as an exponentially distributed variable, and the PoD function is equal to the cumulative density function of a_d, i.e. $f(a_d)$.

$$PoD(a) = F(a) = 1 - \exp(-\, a/E(a_d)) \tag{5}$$

Where $E(a_d)$ is the mean detectable crack size, which is given in Section 4.

Herein, the information provided two inspection activities are examined: inspection activity 1 (IA1) involves only crack detection while inspection activity 2 (IA2) involves both crack detection and measurement. In IA2, the crack size would be measured accurately following crack detection.

3.3. Maintenance effect modelling

Inspections are means to provide additional information while maintenance actions (e.g. repair of cracks which exceed a threshold) ultimately improves structural reliability. The effect of a maintenance method must be quantified so that the effects of scheduled maintenance can be integrated into calculation of performance functions, based on which maintenance strategies are optimized.
Herein detailed crack evolution is of concern and maintenance effect in terms of crack size mitigation is quantified via a ‘as good as new’ maintenance model (Zitrou, Bedford, and Daneshkhah 2013, Sheils et al. 2010, Eltaief et al. 2015). It is adopted that a structural component is renewed after maintenance, and thus the distributions of initial crack size of repaired and original components are

identical. This effect corresponds to a maintenance action that is similar to replacement, or high-quality welding plus post-weld treatment. By using the model, the failure probability of repaired components can be taken into account, although the probability is low.

3.4 Maintenance strategies

A maintenance strategy defines rules for maintenance. This paper examines probabilistic optimization approaches for condition based maintenance (CBM). In CBM, a maintenance action would be carried out after IA2, i.e. following crack detection and exceedance of a maintenance criterion (or threshold). Probabilistic approaches for reliability, LCC and VoI computation are developed and then maintenance criteria are optimized using the approaches. Computational methods for the VoI from both IA1 and IA2 are developed, and inspection strategies are optimized based on their VoIs. IA1 is often carried out in detection based maintenance (DBM), in which a maintenance action would be carried out following crack detection. In prior analysis, inspections are not involved and maintenance decisions are made based on prior or existing information. In prior analysis, two strategies are available: no action and time based maintenance (TBM). The TBM can be understood as periodic maintenance or replacement in order to mitigate high failure risk.

3.5 Reliability based maintenance optimization

Lifetime fatigue reliability taking into account scheduled maintenance is formulated by integrating decision tree analysis, probabilistic crack growth modelling, probabilistic inspection modelling, and maintenance effect model. The number of maintenance interventions n is prescribed. Figure 6 shows the decision tree analysis when the number of planned maintenance interventions n = 2, and CBM is adopted. In the figure, 'F', 'D', 'E', 'M', 'N' mean 'failure', 'detection', 'crack size exceeds a threshold value', 'maintenance', 'no action' respectively. The maintenance interventions are scheduled to t_1 and t_2. The limit state is given by Equation (6). The probabilities of maintenance during the 1st and 2nd intervention ($pr^1(t_1)$, $pr^2(t_2)$) are calculated according to Equations (7) and (8). When n = 0, 1 and 2, the probabilities of failure ($pf^0(t)$, $pf^1(t)$ and $pf^2(t)$) are given by Equations (9) – (11), the probabilities of inspection ($pi^1(t_1)$, $pi^2(t_2)$) are given by Equations (12), and the reliability indexes ($\beta^0(t)$, $\beta^1(t)$ and $\beta^2(t)$) are given by Equations (13). In the equations, the required service life is denoted by T_{SL}. Lifetime failure probabilities and reliability indexes are obtained by using $t = T_{SL}$ in Equations (9) – (11), and (13).

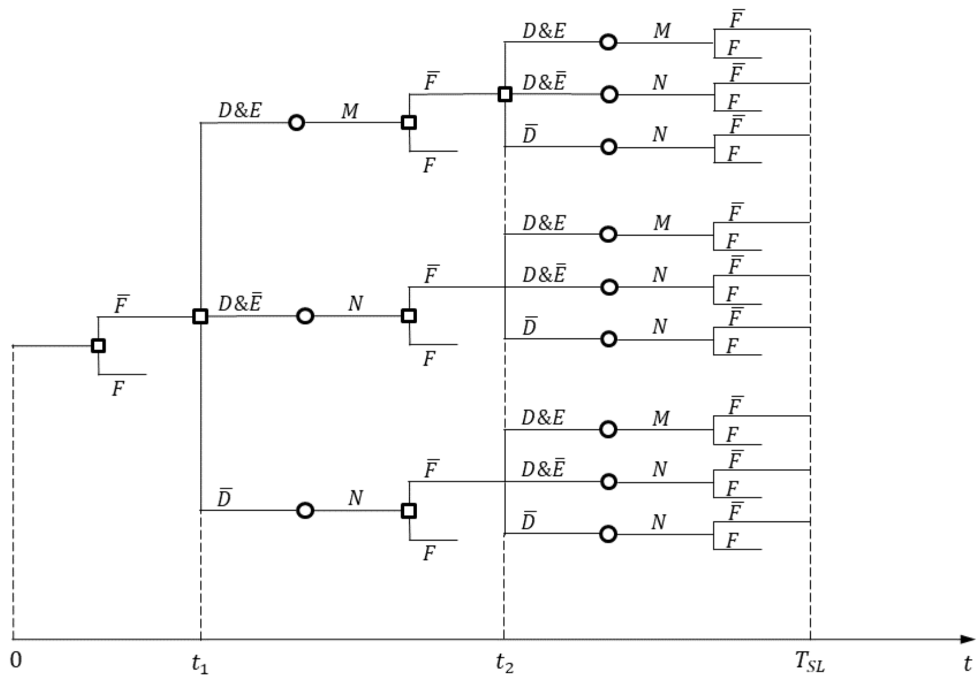

Figure 6 Decision tree analysis for planning of two maintenance interventions adopting CBM

$$h_1(t) = a_c - a(t) \tag{6}$$

$$pr^1(t_1) = P(a(t_1) \geq a_d, a_{r1} \leq a(t_1) < a_c) \tag{7}$$

$$pr^2(t_2) = pr^1(t_1) \cdot pr^1(t_2 - t_1) + P(a(t_1) < a_{r1}, a(t_2) \geq a_d, a_{r2} \leq a(t_2) < a_c) \tag{8}$$

where a_{r1} and a_{r2} are maintenance thresholds at the 1st and 2nd intervention respectively.

For 0< $t \leq t_1$,

$$pf^0(t) = P(a(t) \geq a_c) \tag{9}$$

For $t_1 < t \leq t_2$,

$$pf^1(t) = pf^0(t_1) + pr^1(t_1) \cdot pf^0(t - t_1) + P(a(t_1) < a_{r1}, a(t) \geq a_c) \tag{10}$$

For $t_2 < t \leq T_{SL}$,

$$pf^2(t) = pf^1(t_2) + pr^2(t_2) \cdot pf^0(t - t_2) + P(a(t_2) < a_{r2}, a(t) \geq a_c)$$
$$+ pr^1(t_1) \cdot P(a(t_2 - t_1) < a_{r2}, a(t - t_1) \geq a_c) \tag{11}$$

$$pi^i(t_1) = 1 - pf^{i-1}(t_1) \quad (i = 1, 2) \tag{12}$$

For $t_i < t \leq t_{i+1}$ $(i = 0, 1, 2;\ t_0 = 0;\ t_3 = T_{SL})$,

$$\beta^i(t) = -\Phi^{-1}\left[pf^i(t)\right] \tag{13}$$

where $\Phi^{-1}[\cdot]$ is the inverse function of standard normal cumulative density function.

The optimization problem is formulated as follows:

Given: crack growth parameters $(C, m, Y, \Delta K_{th})$, critical crack size a_c, the number of interventions n, intervention interval Δt, detectable crack size a_d, required service life T_{SL}, loading frequency ν, fatigue design factor (FDF)
Find: maintenance strategies (No action, TBM, DBM or CBM) and thresholds a_{ri} $(i = 1, 2, \cdots n)$
So that: lifetime fatigue reliability index $\beta^n(T_{SL})$ is maximum
Subjected to: $2\ \mathrm{mm} \le a_{ri} \le 20\ \mathrm{mm}$ and assume integral values

3.6 LCC based maintenance optimization

LCC based methods take into account failure consequences, in addition to uncertainties in fatigue loading and resistance and failure probability. Failure risk C_F in terms of monetary loss is calculated by the product of failure probability $pf^n(t)$ and failure consequences c_{f0}, as per Equation (14).

$$C_F(t) = pf^n(t) \cdot c_{f0} \tag{14}$$

where $pf^n(t)$ is failure probability taking into account n maintenance interventions (the number n is prescribed), and c_{f0} is costs of failure consequences.

While failure risk based methods drive maintenance priority to structural components associated with high failure risks, the "as low as reasonably practicable" (ALARP) principle (Jones-Lee and Aven 2011) should be applied to maintenance activities. More specifically, the efforts of risk reduction activities, i.e. the costs incurred by maintenance herein, should never be out of proportion to what would be obtained from the measures (i.e. reductions in failure risks). To support consistent evaluation and optimization of maintenance strategies, a life cycle cost (C_L) analysis framework is developed by integrating risk assessment with maintenance (& inspection if any) cost models.

$$C_L = C_M + C_F \tag{15}$$

$$C_M = C_I + C_R \tag{16}$$

$$C_I = \sum_{k=1}^{n} pi^k \cdot c_{i0} \cdot \frac{1}{(1+r)^{t_k}} \tag{17}$$

$$C_R = \sum_{k=1}^{n} pr^k \cdot c_{r0} \cdot \frac{1}{(1+r)^{t_k}} \tag{18}$$

where C_M, C_I, C_R are maintenance costs, inspection costs and repair costs; n is the number of interventions (inspection or repair); c_{i0} and c_{r0} are the costs associated with an inspection and repair activity, and; r is average annual discount rate of money.

The optimization problem is formulated as follows:

Given: crack growth parameters $(C, m, Y, \Delta K_{th})$, critical crack size a_c, the number of interventions n, intervention interval Δt, detectable crack size a_d, required service life T_{SL}, loading frequency ν, fatigue design factor (FDF), costs of failure, inspection and maintenance (c_{f0}, c_{i0}, c_{r0}), annual discount rate r

Find: maintenance strategies (No action, TBM, DBM or CBM) and thresholds a_{ri} $(i = 1, 2, \cdots n)$

So that: expected life cycle costs C_L is minimum

Subjected to: $2\ \mathrm{mm} \leq a_{ri} \leq 20\ \mathrm{mm}$ and assume integral values

3.7 VoI based maintenance optimization

VoI computation methods are developed for optimization of both inspection and maintenance strategies. The maintenance strategies that can best utilize VoI are regarded as optimal. The VoI is defined as added values brought to a decision problem due to availability of additional information (uncertainty reduction), and quantified via utility increments (Faber 2012). Herein it is considered that a decision maker is risk neutral and the utility increments are computed via cost savings, i.e. reductions in LCC formulated in Section 3.6. The VoI is given by Equation (19).

$$VoI = C_{Lmin} - C'_{Lmin}(\boldsymbol{I}(c_{i0}; a_d)) \tag{19}$$

where C_{Lmin} and $C'_{Lmin}(\boldsymbol{I}(c_{i0}; a_d))$ are the minimum LCC without and with adopting an inspection strategy $\boldsymbol{I}$. The inspection strategy $\boldsymbol{I}$ is characterized by the detectable crack size a_d and the costs of an inspection c_{i0}.

1) Prior decision optimization

The optimal maintenance decision $(\boldsymbol{d}_{opt})$ and minimum LCC (C_{Lmin}) without inspection are obtained by prior decision optimization, given by Equations (20) and (21).

$$\boldsymbol{d}_{opt} = \arg\min_{\boldsymbol{d}} C_L(\boldsymbol{d}; \boldsymbol{p}) \tag{20}$$

$$C_{Lmin} = C_L\left(\boldsymbol{d}_{opt}; \boldsymbol{p}\right) \tag{21}$$

Where $\boldsymbol{d}$ denotes a maintenance decision or strategy, and $\boldsymbol{p}$ denotes a vector containing probabilities of failure, inspection and maintenance formulated in Section 3.5, i.e. $\boldsymbol{p} = (\boldsymbol{pf}, \boldsymbol{pi}, \boldsymbol{pr})^{\boldsymbol{T}}$.

At the time of maintenance planning, crack damage is forecasted. The distribution of crack size $a(t_1)$ at the planned intervention time t_1 is obtained by the probabilistic FM approach established in Section 3.1 taking uncertainty into account. Figure 7 illustrates decision tree and decision tree analysis for an intervention scheduled to t_1. Decision analysis is performed conditional on every survival events (i.e.$B_{1,}B_2 \cdots B_n$).

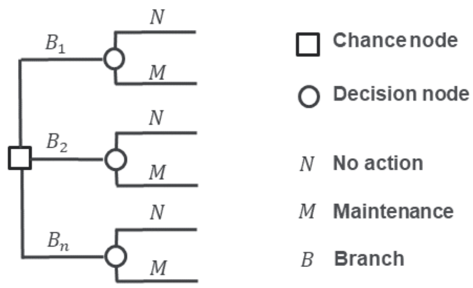

Figure 7 Schematic illustration of a decision tree

Prior decision optimization is based on prior information, without adopting an inspection strategy. At time t_1, the structural component would either have failed or survived (Table 1). Decision tree analysis is performed conditional on survival event (i.e. B_1), and decision alternatives are: no action ('N') and maintenance ('M'), i.e. time based maintenance ('TBM'). Conditional on the survival event, the LCC associated with each decision alternative is calculated based on the method established in Section 3.6.

Table 1 Event branches without inspection

Symbol	Event	Formulation
B_0	Failure	$a(t_1) \geq a_c$
B_1	Survival	$a(t_1) < a_c$

2) Posterior decision optimization

The minimum LCC with inspection ($C'_{Lmin}(\boldsymbol{I}(c_{i0};\ a_d))$) is obtained by posterior decision optimization, via Equations (22) - (24). Note that the inspection results (denoted by $\boldsymbol{S}$) are uncertain at the time of maintenance decision-making and optimization, so all possible combinations of inspection results (when $n \geq 2$), should be taken into account in VoI calculation.

$$C'_{Lmin}(\boldsymbol{I}(c_{i0};\ a_d)) = E_{\boldsymbol{S}}\left(C^{\boldsymbol{s}}_{Lmin}(\boldsymbol{I}(c_{i0};\ a_d))\right) \tag{22}$$

$$\boldsymbol{d}^{\boldsymbol{s}}_{opt}(\boldsymbol{a}_{ropt}) = \arg\min_{\boldsymbol{d}} C_L(\boldsymbol{d}^{\boldsymbol{s}}(\boldsymbol{a}_r); \boldsymbol{p}^{\boldsymbol{s}};\ \boldsymbol{I}(c_{i0};\ a_d)) \tag{23}$$

$$C^{\boldsymbol{s}}_{Lmin}(\boldsymbol{I}(c_{i0};\ a_d)) = C_L\left(\boldsymbol{d}^{\boldsymbol{s}}_{opt}(\boldsymbol{a}_{ropt}); \boldsymbol{p}^{\boldsymbol{s}};\ \boldsymbol{I}(c_{i0};\ a_d)\right) \tag{24}$$

where $C^{\boldsymbol{s}}_{Lmin}(\boldsymbol{I}(c_{i0};\ a_d))$ denotes the minimum LCC conditional on specific inspection results $\boldsymbol{s}$; $E_{\boldsymbol{S}}\left(C^{\boldsymbol{s}}_{Lmin}(\boldsymbol{I}(c_{i0};\ a_d))\right)$ is the expectation of $C^{\boldsymbol{s}}_{Lmin}(\boldsymbol{I}(c_{i0};\ a_d))$ with respect to uncertain inspection results $\boldsymbol{S}$; $\boldsymbol{d}^{\boldsymbol{s}}(\boldsymbol{a}_r)$ is a maintenance decision (when the decision is CBM, $\boldsymbol{a}_r$ is optimized so that the VoI is best utilized); $\boldsymbol{p}^{\boldsymbol{s}}$ is a vector containing probabilities of failure, inspection and maintenance conditional on specific inspection results $\boldsymbol{s}$, and; $\boldsymbol{d}_{opt}^{s}(\boldsymbol{a}_{ropt})$ is the optimal maintenance decision conditional on specific inspection results $\boldsymbol{s}$.

The VoI depends on: 1) the information received, and, 2) decision contexts. The information received is affected by the adopted inspection method, e.g. its capacity, reliability, etc. Herein, both the information from IA1 and IA2 are examined: IA1 involves only crack detection while IA2 involves both crack detection and measurement. Maintenance decision contexts include uncertainties, action alternatives (i.e. maintenance methods), utility function (i.e. cost structure c_{i0}, c_{r0}, c_{f0}), etc. In this paper, the influences of these factors on VoI are investigated in depth.

Decision tree analysis for IA1: An inspection is scheduled to t_1 to gather additional information. At t_1, if the structural component doesn't fail (Table 2), an inspection would be carried out. The inspection result would be either detection (B_1) or no detection (B_2). Decision analysis is performed conditional on every survival event, i.e. every inspection results (i.e. B_1 and B_2).

Table 2 Event branches when adopting IA1

Symbol	Event	Inspection results	Formulation
B_0	Failure	N/A	$a(t_1) \geq a_c$
B_1	Survival	Detection	$a(t_1) \geq a_d$
B_2	Survival	No detection	$a(t_1) < a_d$

Decision tree analysis for IA2: An inspection is scheduled to t_1 to gather additional information. At t_1, if the structural component doesn't fail (Table 3), an inspection would be carried out. If the inspection result is crack detection, crack size would be measured. Also possible inspection results are: detection & beyond a threshold (B_1), detection but within a threshold (B_2) or no detection (B_3). Decision analysis is performed conditional on every survival event, i.e. every inspection results (i.e. B_1, B_2 and B_3).

Table 3 Event branches when adopting IA2

Symbol	Event	Inspection results	Formulation
B_0	Failure	N/A	$a(t_1) \geq a_c$
B_1	Survival	Detection & beyond threshold	$a_r \leq a(t_1) < a_c$
B_2	Survival	Detection & within threshold	$a_d \leq a(t_1) < a_r$
B_3	Survival	No detection	$a(t_1) < a_d$

The optimization problem is formulated as follows:

Given: crack growth parameters $(C, m, Y, \Delta K_{th})$, critical crack size a_c, the number of interventions n, intervention interval Δt, detectable crack size a_d, required service life T_{SL}, loading frequency ν, fatigue design factor (FDF), costs of failure, inspection and maintenance (c_{f0}, c_{i0}, c_{r0}), annual discount rate r

Find: inspection strategies (IA1 or IA2), maintenance strategies (No action, TBM, DBM or CBM) and thresholds a_{ri} $(i = 1, 2, \cdots n)$

So that: the value of information VoI is maximum

Subjected to: $2 \text{ mm} \leq a_{ri} \leq 20 \text{ mm}$ and assume integral values

4 A numerical example

The probabilistic maintenance optimization approaches are exemplified on the fatigue-sensitive details (Figure 1) in a marine structure. The marine vessel routinely operates in the sea environment in which the frequency of wave loading is about 0.16 Hz (Lotsberg et al. 2016, DNVGL 2015), and thus annual fatigue loading is approximately $N_0 = 5 \times 10^6$ cycles. The required service life of the marine structure is 20 years, i.e. T_{SL} =20. The plate thickness is T=25 mm. The geometry function $Y(a)$ follows (Lassen and Sørensen 2002). The fatigue-sensitive details have been designed against fatigue by S-N method based on the 'F' class S-N curve in (DNV 2014), which is expressed by Equation (25) and associated parameters are listed in Table 4. A fatigue design factor (FDF) of 3 has been adopted in the fatigue design.

$$\begin{cases} N_F \Delta\sigma^{m_1} = \overline{q_1} & N_F \leq 10^7 \\ N_F \Delta\sigma^{m_2} = \overline{q_2} & N_F \geq 10^7 \end{cases} \tag{25}$$

Where N_F is fatigue life, m_1 and m_2 are the fatigue strength exponents, and $\overline{q_1}$and $\overline{q_2}$ are the fatigue strength coefficients.

Table 4 Input deterministic parameters

Parameter	Unit	Value
$\log_{10} \overline{q_1}$	[N, mm]	11.855
$\log_{10} \overline{q_2}$	[N, mm]	15.091
m_1	-	3
m_2	-	5
FDF	-	3
T_{SL}	Year	20
N_0	Cycle	5×10^6
T	mm	25
m	-	3
ΔK_{th}	[N, mm]	0
a_c	mm	25
t_1	Year	10

Uncertainties in the FM model have been discussed in Section 3.1. In this numerical example, the probabilistic models in Table 5 are adopted to explicitly consider the uncertainties in initial crack size a_0, crack growth rate C and stress range $\Delta\sigma$. The initial crack size a_0 follows an exponential distribution with mean value $E(a_0)$=0.04 mm (Lotsberg et al. 2016, DNVGL 2015). Uncertainties associated with stress range $\Delta\sigma$ are taken into account via a normally distributed multiplier B. The statistical descriptors for B are: mean value $E(B)$=1 and standard deviation (SD) $\mu(B)$=0.15 (Lassen and Recho 2015). The crack propagation rate parameter C follows a lognormal distribution (Lotsberg et al. 2016, DNVGL 2015). When inspections are considered, e.g. in CBM and DBM, magnetic particle inspection (MPI) is used. Uncertainty in crack detection by the method is considered via the exponential PoD function discussed in Section 3.2 and the mean value $E(a_d)$=0.89 mm (Dong and Frangopol 2016, Madsen, Torhaug, and Cramer 1991). Probabilistic models for variables are listed in Table 5.

Table 5 Probabilistic models for variables

Variable	Distribution	Unit	Mean	SD
a_0	Exponential	mm	0.04	0.04
$\log_{10} C$	Normal	[N, mm]	-12.74	0.11
B	Normal	-	1.00	0.15
a_d	Exponential	mm	0.89	0.89

The reliability, LCC and VoI based approaches developed in Sections 3.5, 3.6 and 3.7 are applied to maintenance optimization of the fatigue-sensitive details. When LCC and VoI based approaches are used, it is clear the input costs of an inspection, a repair and a failure (c_{i0}, c_{r0} and c_{f0}) have large effect on the final decision making process. Herein, for inputs of this study, only cost ratios are needed. Based on some references (Straub and Faber 2006, Breysse et al. 2009, Kulkarni and Achenbach 2007), three cost structures listed in Table 6 are tested to investigate sensitivity of obtained optimal maintenance strategies by the approaches. CS2 is a baseline scenario. CS1 is a scenario of high repair costs while CS3 is a scenario of high failure costs. The optimization results for a maintenance intervention (the intervention time t_1=10 years) are discussed in Sections 4.1 – 4.4.

Table 6 The cost structures (CS) under investigation

Parameter	CS1	CS2	CS3
c_{i0}	1	1	1
c_{r0}	40	10	10
c_{f0}	100	100	10000
c_{i0}/c_{ro}	0.025	0.1	0.1
c_{r0}/c_{f0}	0.4	0.1	0.001

In this paper, the decision 'CBM or C' means IA2 is adopted and maintenance would be carried out if crack size is larger than a maintenance criterion a_r, while the decision 'DBM or D' means that IA1 is adopted and maintenance would be carried out upon crack detection. Decision alternatives in prior decision optimization are: No action ('N') and time based maintenance ('TBM' or 'T').

Figure 8 gives lifetime fatigue reliability against maintenance criterion. Figures 9, 11 & 13 show LCC against maintenance criterion (CS1, CS2 and CS3 respectively). Figures 10, 12 & 14 illustrate VoI against maintenance criterion (CS1, CS2 and CS3 respectively), where VoI (CBM) means the VoI from IA2 in CBM, and VoI (DBM) means the VoI from IA1 in DBM. In the figures, for comparison purpose, equivalent maintenance (crack size) criteria $a_{r,e}$ for 'No action', 'TBM' and 'DBM' strategies are marked, which are obtained based on definitions of the strategies: under 'No action', the maintenance criterion is so large that it cannot be met, $a_{r,e}$= a_c=25 mm; under 'TBM', maintenance performed periodically and the criterion is very easy to meet, $a_{r,e}$= $E(a_0)$=0.04 mm; under 'DBM', maintenance depends on the detectable crack size, $a_{r,e}$= $E(a_d)$=0.89 mm.

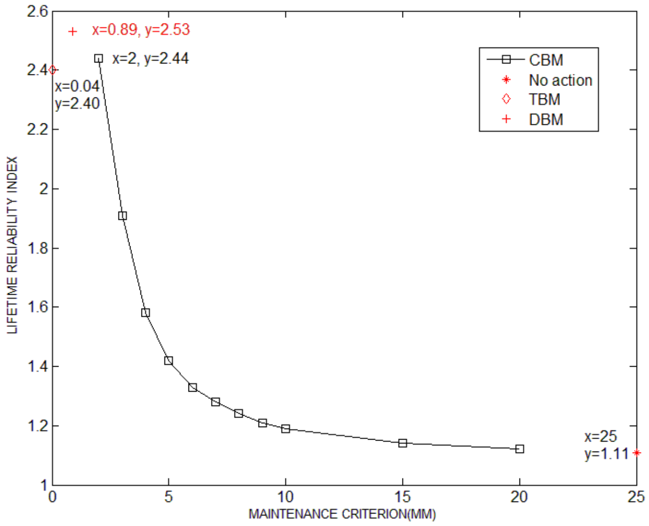

Figure 8 Liftime fatigue reliablity (n = 1)

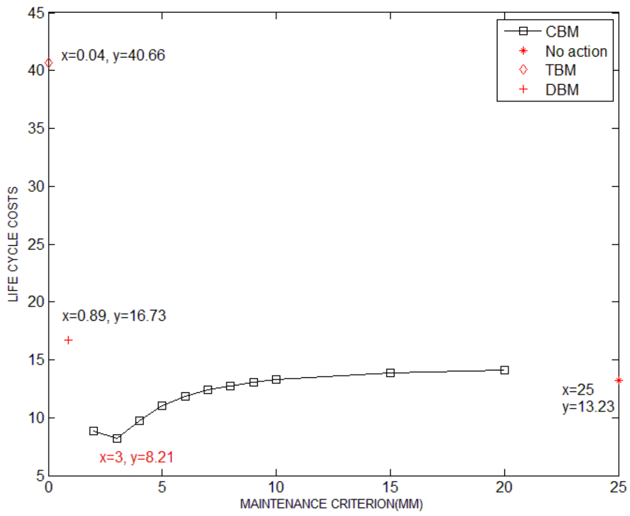

Figure 9 Life cycle costs (n = 1, CS1)

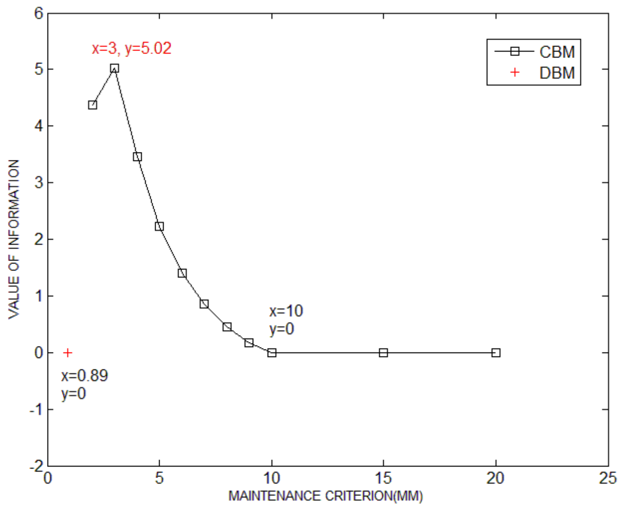

Figure 10 VoI (n = 1, CS1)

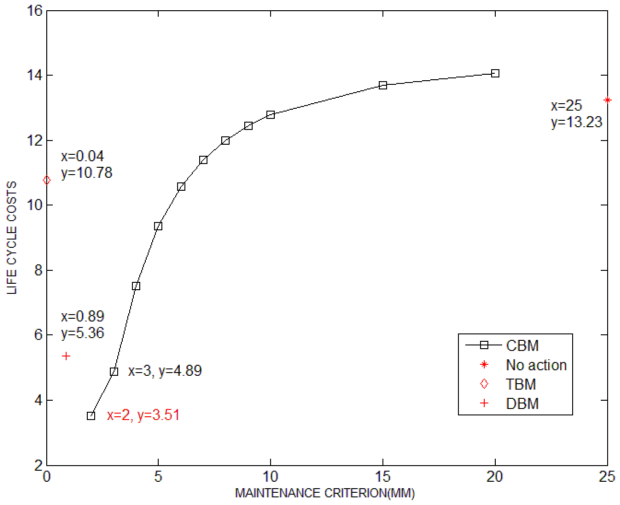

Figure 11 Life cycle costs (n = 1, CS2)

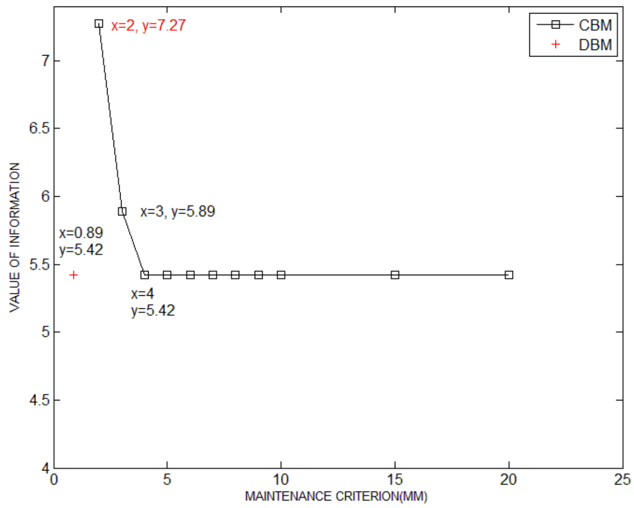

Figure 12 VoI (n = 1, CS2)

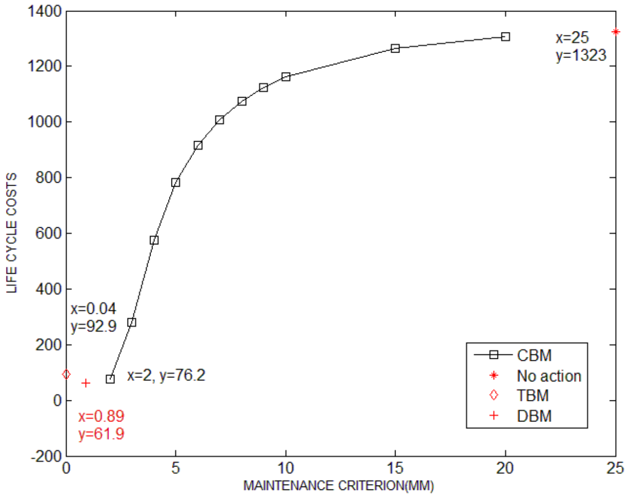

Figure 13 Life cycle costs (n = 1, CS3)

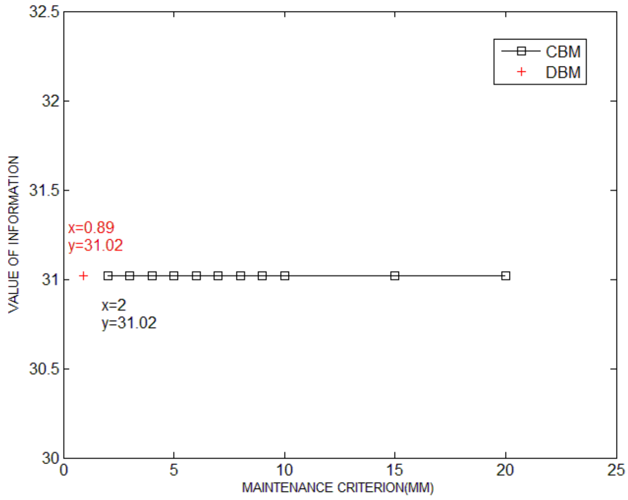

Figure 14 VoI (n = 1, CS3)

4.1 Differences in the VoI, LCC and reliability based approaches

As shown by Table 7, the optimal inspection strategies obtained by the VoI based approach are IA2, IA2, and IA1 for CS1, 2, 3 respectively. The optimal maintenance strategies & criterion depend on the adopted optimization approach.

Table 7 Optimal maintenance strategies & criteria by different approaches

Cost structure (CS)	Reliability based	LCC based	VoI based
CS1	DBM (0.89 mm)	CBM (3 mm)	CBM (3 mm)
CS2		CBM (2 mm)	CBM (2 mm)
CS3		DBM (0.89 mm)	DBM (0.89 mm)

Table 7 also shows that under CS1 and 2 the optimal maintenance strategies & criteria by LCC and VoI based approaches are the same, and different from those obtained by reliability based approach. The maintenance criteria obtained by LCC and VoI based approaches are larger than those by reliability based approach, which means that the reliability based approach requires more intense maintenance. The difference in the optimal maintenance criteria by cost (or value) based approach and reliability based approach depends on the cost ratio c_{r0}/c_{f0}. It is shown that the difference becomes larger (specifically the optimal maintenance criterion by LCC and VoI based approach becomes larger) with larger cost ratio c_{r0}/c_{f0}. When the ratio c_{r0}/c_{f0} is large, cost (or value) based approach results in a balanced maintenance strategy which realizes a trade-off between maintenance costs and failure risks. When the ratio c_{r0}/c_{f0} is very small (e.g. CS3), cost (or value) based approach yields the same maintenance strategy as the reliability based approach.

4.2 Sources of VoI

In most cases, reducing maintenance costs would lead to a compromise in structural reliability. However, reducing maintenance costs and increasing structural reliability are not always contradictive. For example, Figure 8 and Table 8 show that the lifetime fatigue reliability under DBM is 2.53, which is higher than the reliability under TBM, i.e. 2.40, while maintenance costs under DBM are 4.79 (Table 8), which are much lower than the maintenance costs under TBM, i.e. 9.95 (Table 8). Compared with adopting TBM, by adoption of inspections and DBM (or CBM), unnecessary maintenance is avoided and maintenance costs are reduced (when inspection results are 'no detection'). The failure probability and risks may also be reduced, because 'no detection' inspection results imply a slower crack growth rate and a lower failure probability than without the inspection information. The low failure probability inferred from 'no detection' inspection results may be lower than the failure probability if the structure was repaired, especially when the effect of repair is not good.

Table 8 Lifetime reliability index, maintenance costs, failure risks and life cycle costs (CS2)

	Reliability	Maintenance costs	Failure risks	Life cycle costs
No action	1.11	0	13.23	13.23
TBM	2.40	9.95	0.83	10.78
DBM	2.53	4.79	0.57	5.36
CBM (a_r=2 mm)	2.44	2.78	0.73	3.51

Table 9 Sources of VoI (CS1, initial optimal decision 'No action')

Maintenance criterion	Reduced maintenance costs	Reduced failure risks
2 - 9	No	Yes

Table 10 Sources of VoI (CS2, initial optimal decision 'TBM')

Maintenance criterion	Reduced maintenance costs	Reduced failure risks
0.89	Yes	Yes
2	Yes	Yes
3	Yes	No

Table 11 Sources of VoI (CS3, initial optimal decision 'TBM')

Maintenance criterion	Reduced maintenance costs	Reduced failure risks
0.89	Yes	Yes

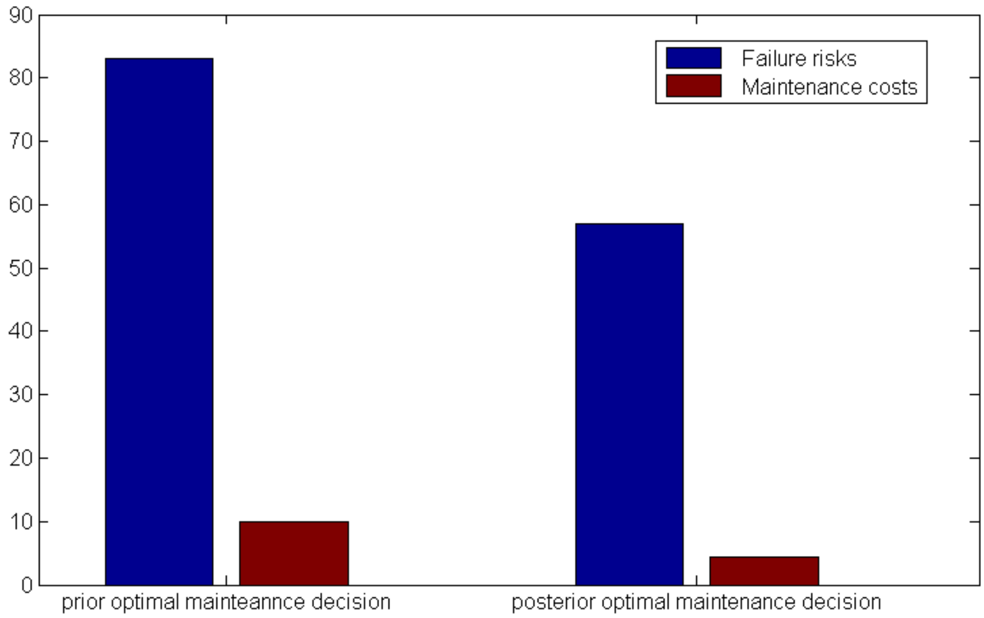

Figure 15 Failure risks and maintenance costs associated with prior and posterior optimal maintenance decisions (CS3)

The VoI is essentially attributed to reduced failure risks or reduced maintenance costs, compared with prior optimal decision without inspection. But it is also found that the VoI can be attributed to both. The sources of VoI have been analysed in depth and listed in Tables 9 - 11. Under CS2 (Table 10), the VoI from IA1 (a_r = 0.89 mm) and VoI from IA2 (a_r = 2 mm) are attributed to reduced maintenance costs as well as reduced failure risks. Under CS3 (Table 11), the VoI from IA1 (a_r = 0.89 mm) is attributed to reduced maintenance costs as well as reduced failure risks. Figure 15 clearly illustrates that under CS3, prior optimal decision is 'TBM' and associated failure risks and maintenance costs would be 83 and 9.93 respectively. Adopting IA1 and DBM (posterior optimal decision), failure risks and maintenance costs would be reduced to 57 and 4.91 respectively. The VoI from IA1 (31.02, Figure 14) is comprised of two parts, i.e. reductions of maintenance costs (83-57) and reductions of failure risks (9.93-4.91).

4.3 Strengths of the VoI based approach

By VoI calculation and decision analysis, all decision alternatives are considered, while by adopting CBM, the decision is prescribed. As can be seen from the formulations of VoI (Section 3.7), VoI calculation need to consider the LCC associated with the posterior optimal decision, which may not be the CBM.

- When VoI (IA2) > VoI (IA1), the posterior optimal decision obtained by VoI based approach is CBM. The optimal maintenance strategy and criterion obtained by VoI based approach then is the same as those obtained by VoI based approach, e.g. when 2 mm ≤ a_r ≤ 3 mm (Figure 12, CS2) and 2 mm ≤ a_r ≤ 9 mm (Figure 10, CS1).
- When VoI (IA2) = VoI (IA1) or VoI (IA2) =0, the posterior optimal decision obtained by VoI based approach is not CBM, i.e. the prior decision without inspection or DBM is optimal. The optimal maintenance strategy obtained by VoI based approach then is not the same as that obtained by LCC based approach. Below some examples are discussed in details.

Figure 14 shows that under CS3, the VoI from IA2 is equal to the VoI from IA1 (i.e. the added value by crack measuring is 0) under all maintenance criteria ($a_r \geq 2$ mm) and thus there is no need to adopt IA2. In this case, according to results of posterior decision optimization, it is not optimal to adopt CBM, which leads to higher LCC than adopting DBM. This highlights the importance of VoI computation before adopting IA2 (crack measuring) and CBM. Also, it shows that it is not always reliable to make a maintenance decision based on an inspection result and a maintenance criterion, i.e. adopting CBM strategy directly.

Under CS1, the VoI from IA1 is equal to 0 (Figure 10). According to results of posterior decision optimization, the DBM if adopted, would lead to higher LCC than the prior optimal decision, i.e. 'No action'. This also shows that it is more reliable to make rational maintenance decisions based on VoI calculation and decision analysis, and VoI > 0 is a prerequisite to adopt DBM or CBM.

Under CS2, when the maintenance criterion $a_r \geqslant 4$ mm, the VoI from IA2 (CBM) is constant and is equal to IA1 (DBM) (see Figure 12), i.e. there is no added value in crack size measuring. This is because if the crack size was measured and a maintenance criterion a_r is set to be larger than 4 mm, the life cycle costs (LCC) associated with the CBM strategy would be higher than the DBM strategy (see Figure 11). Under the circumstances, a rational decision maker would adopt the DBM strategy (rather than CBM) and thus the crack size would not be utilized and valueless. Hence, the VoI is constant and equal to the VoI provided by IA1 and DBM. Under CS1, when a_r ≥ 10 mm, the VoI from IA2 is equal to IA1 (Figure 10). These can be explained by the fact that when the criterion a_r becomes larger (>10 mm), risk reductions by maintenance would become smaller than maintenance costs (Figure 16).

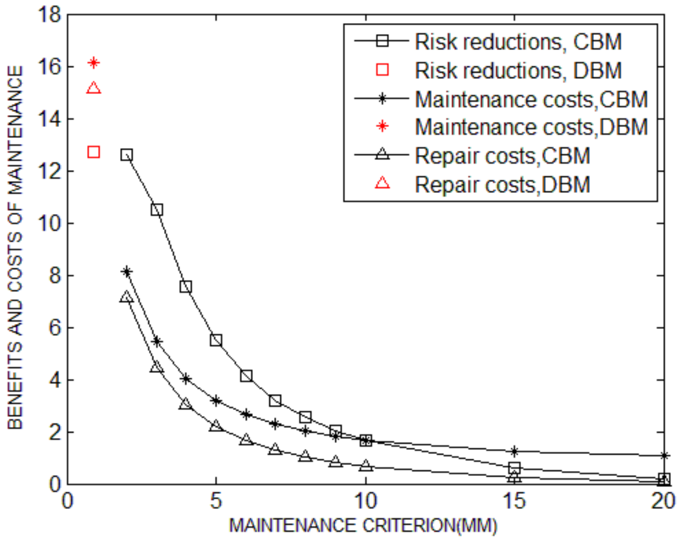

Figure 16 Maintenance costs and risk reductions, compared with prior optimal decision (CS1)

4.4 Influence of cost structure on VoI

Figure 10 shows that the VoI from IA1, i.e. VoI (IA1) = 0 under CS1 (the costs of a maintenance activity are very high) and Figure 14 indicates that the added value by crack measuring is 0 (i.e. VoI (IA2) > VoI (IA1)) under CS3 (i.e. the costs of failure are very high). These results show that when the cost ratio c_{r0}/c_{f0} is very large or very small, the VoI from detection or from measuring is likely to be equal to zero. This is reasonable, because a) the cost ratio c_{r0}/c_{f0} is very large or very small means that the costs of maintenance or failure are very high; b) given that context, the prior optimal decision is very stable and unlikely to be changed by small changes in failure risks inferred from an inspection result; c) especially given that the available decision alternatives are very limited when n = 1 (either 'No action' or 'TBM'). In other words, given a) and c), it is unlikely that a more optimal decision than the prior optimal is available even when additional information from an inspection is available, and thus the VoI from an inspection is more likely to be equal to zero.

Figures 11, 13 and 15 indicate that with a larger cost ratio c_{r0}/c_{f0}, a wider range of a_r values can make VoI (CBM) > VoI (DBM), i.e. can utilize the added values from crack measuring. For example, under CS3 (Figure 15), none of a_r value makes VoI (CBM) > VoI (DBM); under CS2 (Figure 13), when 2 mm ≤ a_r ≤ 3 mm, VoI (CBM) > VoI (DBM); under CS3 (Figure 11), when 2 mm ≤ a_r ≤ 9 mm, VoI (CBM) > VoI (DBM)

5 Conclusions

This paper presents a comparative study on reliability, LCC and VoI based approaches to fatigue inspection and maintenance optimization under uncertainty. While all approaches take uncertainty into account, the obtained optimal results show differences of the approaches. The LCC based approach evaluates cost consequences of failure and expected maintenance costs, which are not covered by the reliability based approach. Exploiting Bayesian decision optimization, the VoI based approach can always result in optimal maintenance decisions (or strategies), and quantify added values from condition inspections to maintenance decision making explicitly via cost savings.

Reliability and LCC based approaches are normally applied to optimization of a specific maintenance strategy, i.e. a decision rule needs to be pre-defined before performing optimization (e.g. the CBM strategy is widely adopted), while VoI based approach exhausts all available maintenance strategies without and with condition inspections in prior and posterior decision optimization. Thus, the VoI based approach is more reliable in yielding optimal maintenance strategies under a wider range of maintenance contexts (whether VoI > 0 or VoI=0). By VoI computation, it is confirmed that VoI can be zero in some maintenance contexts, and the prior maintenance strategy without inspection is the optimal strategy, rather than the CBM. However, by reliability and LCC based approaches, VoI is not quantified and inspections and CBM are usually adopted directly, which is not optimal when VoI = 0. Hence, computing the VoI to confirm that VoI > 0 is very important before adopting the CBM strategy. The VoI = 0 means that the added information cannot contribute to an improved decision and thus valueless to the decision making. It has been shown that when VoI is computed via cost savings and VoI > 0, then the VoI and LCC based approaches yield the same maintenance strategy.

It has been found that the differences in the derived maintenance strategies by the approaches depend largely on maintenance contexts, specifically the cost ratio of maintenance to failure (c_{r0}/c_{f0}). The results by the LCC based approach are very sensitive to the cost ratio while the results by the reliability based approach are independent on the cost ratio. It has been shown that when the cost ratio becomes larger, the optimal maintenance criterion obtained by the LCC based approach becomes lager than by the reliability based approach. When the cost ratio is very large or very small, the VoI from detection or from measuring is likely to be zero and the optimal maintenance strategies by LCC based and VoI based approaches are different.

The VoI (i.e. added value due to availability of additional information), if quantified via cost savings, can be attributed to reductions of failure risks or maintenance costs or reductions of both. It has been shown that in some maintenance contexts, due to adoption of inspections and improved maintenance decisions, maintenance costs and failure risks are reduced simultaneously. In other words, reducing maintenance costs and mitigating failure risks (or increasing structural reliability) are not always contradictive.

In this study, a simple probabilistic crack growth model is presented and provides crack growth predictions for maintenance planning. The model is adopted, because the objective of this study is to compare the advantages and limitations of three probabilistic maintenance optimization approaches, not to investigate in-depth physics of crack growth. Depending on the study objective, a more complex fracture mechanics model can be employed, e.g. the models taking loading characteristics and sequence into account (Mansor, Abdullah, and Ariffin 2019). However, when a complex fracture mechanics model is integrated with a probabilistic optimization framework, computational costs increases dramatically and it would be computationally difficult to derive an optimal inspection & maintenance strategy.

In terms of failure criteria, herein a one-component system is studied and a through-thickness crack is defined as failure. If multi-component system is studied, the impact of one component failure on the system depends on the location and criticality of the component, and system failure needs to be defined differently. Ship structures are complex and generally designed with much redundancy in strength. Crack growth would normally lead to stress re-distribution. Crack growth in offshore jacket platform structures, e.g. legs, k-joints, etc., may cause serious consequences.

In this study, a periodic intervention policy is adopted, i.e. inspections or repairs are scheduled with an equal time interval. The policy is widely adopted, because it facilitates practical implementation of a maintenance strategy from a management perspective (Huynh, Grall, and Bérenguer 2017). It is also noted that maintenance intervention times affect reliability, life cycle costs and value of information. The optimal maintenance intervention times normally can be obtained by the cost based approach (Zou et al. 2019). The information value based approach can be used to obtain optimal inspection times when the added value by future inspection are maximum (Zou, Banisoleiman, and González 2018).

For a multi-component system, the information collected from one component also can reduce uncertainties on other components due to dependencies among them. The optimal sensor placement can be obtained adopting the information value based approach, with the objective to reap the maximum information value using as less sensors as possible. To achieve this, the system configuration should be properly modelled. Also, when the number of components in the system are large, it may be needed to define some maintenance rules, which are formulated as constraints of the maintenance optimization problem.

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