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Holistic Value of Information Computation Methods for Informed Structural Integrity Management under Uncertainty

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Abstract: Information collecting by condition inspection or monitoring is important means to reduce uncertainty and improve the quality of maintenance decisions in structural integrity management. However, information collecting inevitably involves some costs. When information collecting brings added value and to what extent uncertainty reduction suffices are questions that often have not been fully accounted for before information collecting activities are carried out. Value of information (VoI) computation helps justifying investments and informing efficient strategies for information collecting. This paper develops a holistic approach to quantify the VoI from multiple inspections in the lifetime of an engineering structure, taking into account combined effects of maintenance interventions and dependencies in the intervention decisions. The approach can be used for holistic planning and optimization of lifetime inspections at an early stage. Also, a simplified VoI computation approach is developed for certain maintenance decision cases based on an alignment decision strategy (ADS). The approaches are exemplified on a typical marine structure, and sensitivities of VoI to the number of planned interventions, cost ratio, inspection time(s) and method(s) are studied. It is shown that the ADS and the simplified method are well applicable when the number of planned interventions is large. The optimal maintenance decisions and inspection times obtained by VoI-based and cost-based optimization methods are compared.

Key words: Structural integrity management; Uncertainty; Risk analysis; Bayesian inference; Decision analysis; Life cycle cost

1. Introduction

Structures and Infrastructures, such as ship structures, offshore installations, bridge decks, and aeroplane structures, are important assets that contribute to the economic growth and society development. Failures of these structures can cause significant economic losses, fatalities and environmental consequences (Frangopol and Soliman 2016). The performances of these structures normally degrade over time due to over-loading, extension of service life, accidental damages, natural hazards, deteriorating factors, etc., and it's of paramount importance to identify these threats timely, assess and mitigate the failure risk by inspection and maintenance activities. Fatigue crack initiation and propagation is one of the most common deteriorating factors compromising integrity and leading to failures in welded structural systems (Fisher, Kulak, and Smith

1998). Planning of maintenance activities for structural systems subject to fatigue deterioration is often complex due to a large number of hot-spot areas, high degree of uncertainty associated with both fatigue loading and resistance, and uncertainty relating to inspection performance and maintenance effect. Developing an effective maintenance strategy under uncertainty that balances maintenance costs and failure risk is challenging, yet of great significance to realize the economic and safety benefits of maintenance.

Optimal maintenance planning relies on availability of data, information, and models for accurate structural damage states. Maintenance planning optimization typically requires utilization of the data in the design plan, fabrication and as-built data, operational records as well as additional information collecting, e.g. by condition inspections, monitoring, surveys, etc. On one hand, additional information collecting is essential to collect up-to-date structural condition information and thus help to reduce uncertainty and make improved maintenance decisions. On the other hand, information comes at certain costs and is often imperfect. To what extent the collected information reveals true damage conditions depend on methods and times used for information collecting, which are influential to the costs of information, to optimal maintenance decision-making, and ultimately to lifetime safety assurance and cost reduction.

Value of information (VoI) computation presents a strong tool for rational decision-making on information collecting systems, techniques and activities. The rationale of VoI is that information is an asset that is of value to its owner (Moody and Walsh 1999). Uncertainty reduction is one of essential attributes of information. Information adds knowledge to the uncertain nature of interest, e.g. an inspection result adds knowledge on crack sizes. Due to the availability of additional information, an improved decision may be made which acts on the reduced uncertainty more appropriately and is associated with a higher expected utility. VoI is defined as the difference between the max utility with and without additional information, which can be calculated by Bayesian decision analysis and utility theory (Raiffa and Schlaifer 1961), and pre-posterior analysis (Goulet, Der Kiureghian, and Li 2015, Thöns 2018). VoI computation has been applied in a wide range of engineering fields, e.g. civil and structural engineering (Straub and Faber 2005, Straub 2014, Memarzadeh and Pozzi 2016a), transport engineering (Memarzadeh and Pozzi 2016b), geotechnical engineering (Karandikar et al. 2014), oil and gas industry (Bratvold, Bickel, and Lohne 2009), material technology (Bates et al. 2016), environmental engineering (Bates et al. 2014, Rehr et al. 2014, Von Winterfeldt et al. 2012, Cooke et al. 2014), etc. Typical applications include quantifying the expected benefits of future testing or research project (Thons and Faber 2013, Thöns, Schneider, and Faber 2015, Thöns 2018, Pozzi and Der Kiureghian 2011, Straub 2014, Memarzadeh and Pozzi 2016b), VoI-based maintenance optimization (Zitrou, Bedford, and Daneshkhah 2013, Goulet, Der Kiureghian, and Li 2015), inspection planning (Straub and Faber 2005, Straub 2004, Memarzadeh and Pozzi 2016a), sensor placement (Malings and Pozzi 2018, 2016, Malings and Pozzi 2019), etc.

VoI calculation becomes prohibitive with the complexity of a decision problem, e.g. system characteristics, uncertain parameters, time length of interest (e.g. the required service life of a system), available decision alternatives and possible signals (or observations, or results) from information collecting (Malings and Pozzi 2016). Rational decision-making is even more complex when multiple decisions are involved, e.g. planning of multiple maintenance interventions to the service life of an engineering system. As the signals from future inspections are unknown at the time of VoI computation, utilities associated with all possible combinations of decisions conditional on each possible combination of signals and the expectation of the max utility with respect to the signals must be calculated, in order to obtain the max utility with additional information. Such sophisticated calculations must be done within a probabilistic framework involving Bayesian updating, which is computationally demanding and hinders VoI application to complex decision problems. Approximate VoI algorithms for special types of systems have been developed by (Malings and Pozzi 2016, Malings and Pozzi 2019, Memarzadeh and Pozzi 2016a). These methods are typically based on Partially Observable Markov Decision Processes (POMDPs) and compute the VoI in sequential maintenance decision-making. However, it is worth considering combined effects of maintenance interventions and computing the VoI in holistic maintenance decision-making.

This paper develops methods to compute the VoI from multiple inspections in holistic planning of lifetime maintenance interventions, taking into account combined effects of maintenance interventions and dependencies in maintenance decisions, especially the effects of later interventions on the decision optimality of earlier interventions. Hence, the term 'holistic' refers to holistic maintenance decision-making on multi-interventions, and the holistic VoI is the information value to holistic decision-making. A simplified method for holistic VoI computation is developed for certain cases based on an alignment decision strategy (ADS). The methods are exemplified on a numerical example which reveals the combined effects of multiple maintenance interventions and advantages of the proposed methods. Sensitivity studies are carried out to explore the determinants of holistic VoI. In Section 2, a common maintenance problem in structural management is outlined and probabilistic aspects of crack growth are addressed. In Section 3, a generalised modelling framework is developed for holistic maintenance decision-making and VoI computation. In Section 4, a simplified VoI computation method is developed for the cases when the numbers of possible inspection results and available maintenance methods are equal. In Section 5, the methods are exemplified on fatigue crack management of a marine structure and sensitivities of holistic VoI to its determinants are shown.

2. Probabilistic crack growth

Maintenance planning is a typical decision-making problem under uncertainty. Structural damage states are uncertain at the time of decision-making. Structural failure probability and risk can be calculated based on a probabilistic model considering uncertainties associated with initial damage state, deterioration rate, modelling, etc. (Zou, Banisoleiman, et al. 2019, Zou, González, et al. 2019, Konakli, Sudret, and Faber 2015). Some maintenance alternative methods may be available, which are associated with different costs and benefits to risk mitigation. An optimal maintenance decision can be obtained by prior decision optimization based on prior knowledge and uncertainty. If additional inspection results are available, uncertainty on structural damage states is reduced and failure probability can be updated by Bayesian Theorem. The expected costs and benefits of the maintenance alternatives can be sorted again by posterior analysis, based on which posterior optimal maintenance decision can be obtained. The posterior optimal maintenance decision may be different from the prior optimal, as they are obtained subjected to different degree of uncertainty. Prior decision optimization and posterior decision optimization are the same in principle but differ in the available information and thus the degree of uncertainty, the distribution of damage state, and the projected failure probability, risk and costs.

2.1 Probabilistic crack growth

Herein, the initial flaw/crack size is labelled as a_0, and the critical crack size as a_c, which defines fracture failure of a structural detail. Under a stress range $\Delta\sigma$, the initial crack grows to $a(t)$ after time t. The required service life is T_{SL}, and the limit state function $L(t)$ is given by Equation (1).

$$L(t) = a_c - a(t) \tag{1}$$

Crack growth is governed by several factors, such as the initial crack size (a_0), the stress range ($\Delta\sigma$), material property parameters (C and m), geometry function (Y), threshold of the stress intensity factor (ΔK_{th}), etc. The relationship between these factors can be expressed by Equation (2).

$$a(t) = f(a_0, C, m, Y, \Delta K, \Delta K_{th}, t\,) \tag{2}$$

Explicit or implicit models for such a relationship are available, e.g. the well-known Paris' law (Paris and Erdogan 1963), or can be established by experimental, modelling and/or statistical methods for specific applications (Ayala-Uraga and Moan 2007, Chryssanthopoulos and Righiniotis 2006, Lotsberg et al. 2016). Most often, both fatigue loading and fatigue resistance are subjected to a high degree of uncertainty, so most of these crack growth models are integrated with probabilistic modelling and structural reliability methods. For example, the parameters associated with large variability and uncertainty are treated as random variables and their distributions are established by statistical methods based on experimental or in-service data. The failure probability (without any maintenance), P_f^0, and reliability index, β, are expressed by Equation (3) and (4) respectively. Equations (3) and (4) can be calculated via reliability methods, such as the well-known FORM, SORM, or sampling methods

(Ditlevsen and Madsen 1996, Faber 2012).

$$P_f^0(t) = P(L(t) < 0) \tag{3}$$

$$\beta(t) = -\Phi^{-1}\left(P_f(t)\right) \tag{4}$$

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

3. Holistic maintenance optimization and VoI computation

3.1 Holistic decision problem formulation

Fatigue and fracture reliability decreases with time due to crack growth, and maintenance interventions need to be assigned to ensure that structural reliability is above a target level and failure risk is well controlled. It is of great significance that at the beginning of service, maintenance interventions are well planned in terms of the number of interventions, maintenance areas, times and methods, as these determine the benefits and costs, and thus the efficiency of maintenance interventions. A maintenance strategy is beneficial only when expected maintenance costs are less than risk reductions.

Let the time of maintenance decision-making be at the beginning of service ($t = 0$), the number of planned maintenance interventions be n, the interventions be scheduled to times $t_1, t_2 \cdots t_n$ and the available maintenance methods (action alternatives) be $m_1, m_1 \cdots m_n$. The future crack size $a(t)$ is uncertain at the decision time $t = 0$. However, based on available statistical information on the variables, the distribution of $a(t)$ can be predicted by sampling methods based on a probabilistic model formulated by Equation (2). Herein, the crack size $a(t)$ is the uncertain nature of interest, which makes the outcomes and costs associated with a maintenance decision uncertain, and thus makes decision-making process obscure. Structured decision analysis formulated below helps to make the process clearer.

Table 1. Action alternatives in a two-action maintenance decision problem

Action alternative	Maintenance method	Crack size after repair
y_1	No action (N)	N/A
y_2	Welding (W)	a_0

Table 2. Action alternatives in a three-action maintenance decision problem

Action alternative	Maintenance method	Crack size after repair
y_1	No action (N)	N/A
y_2	Grinding (G)	a_G
y_3	Welding (W)	a_0

The action alternatives are the maintenance methods that can be chosen for an intervention. As listed in Table 1, in a two-action maintenance decision problem, the action alternatives are 'No action' (denoted by 'N') and 'Welding' (denoted by 'W'). The performance of repaired components by welding are usually good and maintenance effect of welding can be represented by a 'as good as new' model. The model assumes that the crack size after repair returns to the initial size, i.e. a_0 (Madsen, Torhaug, and Cramer 1991, Zitrou, Bedford, and Daneshkhah 2013, Huynh, Grall, and Bérenguer 2017, Garbatov and Soares 2001). The model allows for modelling of behaviours of repaired structural components. In engineering practice, cracks are also repaired by grinding (denoted by 'G'), which is a less effective and less expensive approach. Action alternatives in a three-action maintenance decision problem are listed in Table 2. The maintenance effect by grinding is modelled as imperfect, e.g. the crack size after repair returns to an equivalent size a_G, the mean value of which is larger than a_0 (Madsen, Torhaug, and Cramer 1991). By these maintenance models, the failure probability of repaired components by welding or grinding can also be calculated using Equations (1) - (3). It is worth noting that this paper addresses holistic maintenance decision for n interventions in the lifetime, so the number of action alternatives is the number of possible combinations, i.e. 2^n or 3^n. Also, as 'No action' is an alternative, the optimised number of actual interventions may be less than$n$, which is thus understood as the maximum allowable number of interventions in the lifetime.

The outcomes of a holistic decision are uncertain at the time of decision-making, as the crack sizes at the maintenance intervention times $a(t_1), a(t_2) \cdots a(t_n)$ are uncertain. To make a right decision, the relationship between present decisions, uncertainties and future outcomes must be formulated explicitly. These outcomes are integrated into life cycle costs $C_L(x, y)$, given by Equation (5).

$$C_L(x, y) = C_M(x, y) + C_F(x, y) \tag{5}$$

where $C_M(x, y)$ is expected maintenance costs, including expected costs of inspections and repairs; $C_F(x, y)$ is failure risk in terms of monetary loss; y signifies a decision on a sequence of n maintenance interventions; x is a representation of all variables, e.g. initial crack size a_0, material property parameter C, stress range $\Delta\sigma$.

A value function is defined based on the life cycle costs $C_L(x, y)$ as per Equation (6), and a utility function based on value function, as per Equation (7). These functions are assigned by a decision maker (DM) according to his/her engineering experience, risk attitude, subjective judgement, etc. on a specific decision problem (Howard 1988, Mehrez 1985, Sun and Abbas 2014, Abbas et al. 2013). Note that these functions are used to provide a consistent utility metric for the action alternatives. To make the right decision, the DM may only care about the sort order of the action alternatives according to the adopted the utility metric, not specific values and utilities. The aim of decision analysis is to rationalise the decision-making process by sorting the action alternatives, so that the DM is certain at the decision time that he/she is making the right decision in face of uncertain outcomes.

$$v(x,y) = v\big(C_L(x,y)\big) \tag{6}$$

$$u(x,y) = u\big(v(x,y)\big) \tag{7}$$

3.2 Prior maintenance decision optimization

Prior decision optimization is based on existing information. For a given structural model, existing information include the required service life T_{SL}, the critical crack size a_c, a deterioration model (Equation (2)), and associated parameters and random variables. The distributions of variables represent prior degree of belief on their uncertainties. Based on prior information, a prior lifetime failure probability P_f^0 can be calculated by Equations (1) - (3).

Prior maintenance action alternatives are: 'N' and 'W') or 'N', 'G' and 'W'. In a holistic decision problem involving n maintenance interventions, and the number of combinations of action alternatives is 2^n or 3^n. For given intervention times $t_1, t_2 \cdots t_n$, the life cycle costs C_L adopting each combination of actions (CA) is calculated based on decision tree analysis. For example, Figure 1 shows decision tree analysis for $n = 3$, and the CA is (W, W, W), where F, $\bar{F}$ mean failure, survival respectively. At the time an action is carried out, the crack size is reduced physically and new simulations for crack growth must be run. More discussions on life cycle costs analysis C_L are given in Section 4.4.

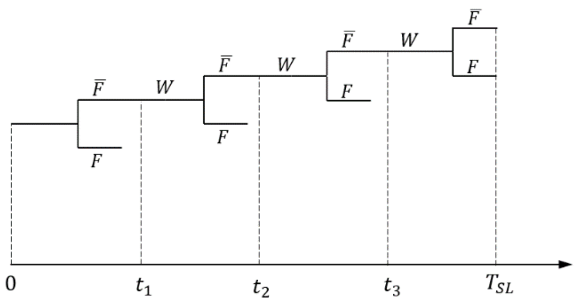

Figure 1. Decision tree analysis for a sequence of maintenance actions (W, W, W)

The value and utility of each CA is calculated based on Equations (6) and (7) respectively. Equation (8) provides the optimal CA and Equation (9) gives the max utility $u_{\max}$.

$$y_{opt} = \arg\max_y E\big(u(\,x,y)\big) \tag{8}$$

$$u_{\max} = E\left(u(\,x,y_{opt})\right) \tag{9}$$

3.3 Posterior maintenance optimization with additional information

When additional information on the crack size becomes available, the information could be integrated as a likelihood function and used to update the prior failure probability P_f^0. The updated failure probability P_f^1 is appreciated as posterior failure probability. For example, if an inspection is carried out (using an inspection method with a detectable crack size a_d) at time t_1 and the obtained inspection signal showing no detection ($\overline{D}$), then the additional information can be formulated by Equation (10). Utilizing the additional information by Bayesian Theorem (Ditlevsen and Madsen 1996), the failure probability after time t_1 can be updated by Equation (11), in which F signifies the event of failure, formulated by Equation (12).

$$\overline{D}: a(t_1) < a_d \tag{10}$$

$$P_f^1(t) = P(F|\overline{D}) = \frac{P(F \cap \overline{D})}{P(\overline{D})} = \frac{P\{[a_c - a(t)] < 0 \cap [a(t_1) - a_d] < 0\}}{P\{[a(t_1) - a_d] < 0\}}, \ t > t_1 \tag{11}$$

$$F: a_c - a(t) < 0 \tag{12}$$

By substituting the prior failure probability P_f^0 with posterior failure probability $P_f^1(t)$, posterior decision optimization can be done based on the same procedure as Section 3.2. The posterior optimal decision y_{opt}^z conditional on signal z, can be the same or different from the prior optimal decision y_{opt}, depending on the implication of the additional information z on failure probability (i.e. the changes in failure probability) and on specific utility function.

3.4 Holistic VoI computation

The aim of VoI computation is to evaluate whether there is added value in carrying out inspections with given methods. If the VoI is larger than zero, then there is added value and maintenance decision can be improved. At the time of decision analysis and VoI computation, inspections have not been implemented, and the signals (or results) are unknown. Thus, all possible signals must be considered in VoI computation.

Table 3. Two types of inspection activities under investigation

Number	Inspection activity	The number of possible results	Formulations for all possible results from an inspection
IA1	Detecting	2 ($\overline{D}$; D)	$\overline{D}: a(t_1) < a_d$ $D: a(t_1) \geq a_d$
IA2	Step 1: Detecting Step 2: Sizing, following crack detection	3 ($\overline{D}$; $D\&\overline{E}$; $D\&E$)	$\overline{D}: a(t_1) < a_d$ $D\&\overline{E}: a(t_1) \geq a_d \cap a(t_1) < a_r$ $D\&E: a(t_1) \geq a_d \cap a(t_1) \geq a_r$

Herein the VoI provided by two kinds of inspection activities are discussed comparatively. The features of the inspection activities (IA) are summarized in Table 3. Activity 1 (IA1) involves only crack detecting, while activity 2 (IA2) involves crack sizing following crack detection. As more in-depth information collection is pursued by IA2, it is obvious that the costs of IA2 would be higher than IA1.

In IA1, the number of possible inspection results is 2 and the results are: detection (D) and no detection ($\bar{D}$). In IA2, following detection, an in-depth inspection is assigned to measure the size of the crack to see if the size exceeds a limiting size a_r. The number of possible results is 3 and the results are: no detection ($\bar{D}$), detection but within the limiting size ($D\&\bar{E}$), detection and exceedance of the limiting size ($D\&E$). Formulae for these inspection results are listed in Table 3.

To quantify the VoI from n inspections, all possible combinations of n inspection signals must be taken into account. The number of combinations of signals is 2^n (IA1) or 3^n (IA2). For example, when $n = 3$ and IA2 is considered, a combination of signals (CS) could be ($D\&\bar{E}$, $\bar{D}$, $D\&E$), which can be formulated by Equation (16).

$$[a(t_1) \geq a_d \cap a(t_1) < a_r] \cap [a(t_1) < a_d] \cap [a(t_1) \geq a_d \cap a(t_1) \geq a_r] \quad (16)$$

Given a combination of actions (CA) and a combination of signals (CS), an updated failure probability P_f^1 can be obtained by Bayesian Theorem. The life cycle costs, value and utility associated with the CA and conditional on the specific CS can also be obtained based on Section 3.2 using the updated failure probability P_f^1. The maximum utility $u'_{\max}(h)$ with the availability of a combination of inspection signals Z is equal to the expectation value of posterior maximum utility $u_{\max}^Z(h)$ with respect to Z, given by Equation (17). Note that Z is a combination of signals which are unknown at the time of VoI computation. The holistic VoI from n inspection is equal to the value of h that solves the Equation (18).

$$u'_{\max}(h) = E_Z\left(u_{\max}^Z(h)\right) = \int u_{\max}^z \cdot p(z)dz \quad (17)$$

$$u'_{max}(h) = u_{max} \quad (18)$$

Where h denotes the costs of obtaining a sequence of inspection signals; $u_{\max}^z$ is the max utility conditional on a specific combination of signals z; $p(z)$ is the probability of that a specific combination of signals z would occur.

The probability $p(z)$ can be obtained based on the probability of detection (PoD) functions of adopted inspection methods (Dong and Frangopol 2016, Madsen, Torhaug, and Cramer 1991, Meyer et al. 2014). By a PoD function, the detectable crack size (a_d) of an inspection method is modelled as a random variable with a distribution. The probabilities of signals such as detection and no detection can be calculated based on the distributions of $a(t_i)$ and a_d. The $p(z)$ is obtained by considering that a sequence of inspections are independent on each other and the same method is used.

4 A simplified VoI computation method

4.1 Alignment decision strategy

The proposed holistic computation method for VoI from a sequence of future inspections in Section 3 involves the following steps:

(a) Calculate the prior max utility (by sorting the prior utilities of all combinations of action alternatives)
(b) Calculate the likelihoods of all possible combinations of signals (based on prior distribution of crack size and PoD functions of adopted inspection methods)
(c) Calculate the posterior max utility conditional on each combination of signals (by sorting the posterior utilities of all combinations of actions conditional on each combination of signals)
(d) Calculate the expectation of posterior max utility with respect to a sequence of unknown signals
(e) The VoI is equal to the expectation value of posterior max utility minus the prior max utility

To calculate the VoI, all possible combinations of signals must be considered. What's more, posterior decision optimization must be performed conditional on each combination. Finally, the expectation of posterior max utility needs to be calculated. These calculations can be rather cumbersome, especially when the number of action alternatives and the number of all possible signals are large.

In this section, a method is proposed to simplify the calculation steps (b) - (d) based on a new perspective on an unknown inspection signal, and an alignment decision strategy (ADS) reacting to an unknown signal. Let the number of action alternatives and the number of possible signals be denoted by s. Let all possible signals from an inspection be defined by a set Z, and actions mapped to the signals be a set Y, then a specific set of actions mapped to all possible signals is defined as a decision strategy (DS). For example, Figure 2 shows a random DS which assigns method y_i if an unknown signal is z_1, method y_s if the unknown signal is z_2, $\cdots$ method y_1 if the unknown signal is z_i, $\cdots$ method y_2 if the unknown signal is z_s.

If: $d(z_1) > d(z_2) > \cdots > d(z_i) > \cdots > d(z_s)$ (20)
and $e(y_1) > e(y_2) > \cdots > e(y_i) > \cdots > e(y_s)$ (21)
then ADS: $(z_1, z_2, \cdots, z_i, \cdots, z_s) \rightarrow (y_1, y_2, \cdots, y_i, \cdots, y_s)$ (22)

Although the number of possible DS is s^n, the one that is most relevant to VoI computation is ADS. The definition of alignment decision strategy is illustrated by Figure 3. Let $d(z_i)$ be the damage severity (e.g. the mean value of crack size) indicated by a realization of signal z_i and $e(y_k)$ be the effect of an action alternative y_k (e.g. the extent of crack mitigation by a maintenance method). Sort all possible realizations of an unknown signal according to damage severity, shown by Equation (20). Also, sort the available action alternatives according to their effects, shown by Equation (21). Then adopting the ADS (shown by Equation (22)), a DM would align his/her decision to the extent of damage severity indicated by a realization of an unknown inspection signal (based on the sort order of action alternatives and the sort order of possible realizations).

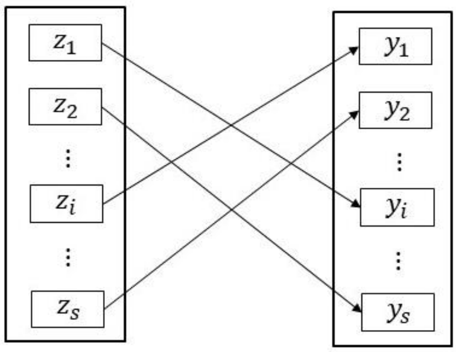

Figure 2. Signal set and decision strategy

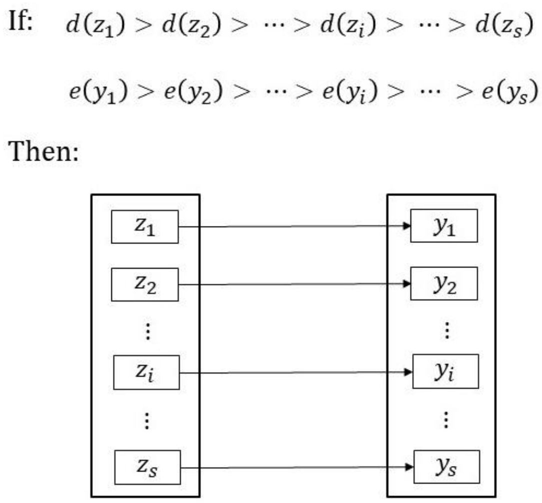

Figure 3. Alignment decision strategy (ADS)

4.2 VoI computation based on ADS

To justify VoI computation based on ADS, two essential questions need to be addressed:

- What is the additional information to present decision-making when future signals are unknown?
- How maintenance decision-making can be improved by unknown information?

Herein, although the specific signal that would be provided by a future inspection is unknown at the time of VoI computation and decision analysis, the likelihoods of possible signals can be predicated based on prior belief on the uncertain parameters and on the reliability of the adopted inspection method. Thus, the future signal from an inspection is a random variable, but with a predictable distribution. The information provided by a future inspection to the present decision-making lies in:

- A future inspection provides a categorization of the uncertain crack size;
- Each possible signal indicates a category of crack size, and;
- The likelihoods of the categories (the probabilities that the uncertain crack size would fall into the categories) can be calculated at the time of VoI computation.

Hence, a future information collection activity does not remove the uncertainty affecting the present decision-making but reduces uncertainty by providing a categorization. Due to the availability of such categorization, an ADS can be taken. The ADS is superior to the prior optimal decision which assigns a single action method.

The VoI is attributed to improved decision due to the availability of additional information. If the additional information provided by the categorization is of value, the optimal decision should be different from the prior optimal decision without the information (i.e. a single action method). The biggest value is created when the categorization is best utilized and acted upon, i.e. deciding different action methods according to different categories (which are signified by different inspection signals). Specifically, the action methods for two different signals should not the same; otherwise, there would be no value in providing two different signals, i.e. distinguishing between two categories of crack size. Upon availability of the categorization, the ADS is optimal, as it well tunes available action alternatives to the order of crack size indicated by the signal set.

4.3 Efficient information utilization by ADS

The VoI from a given information collecting system (characterized by its capacity, reliability, costs, the number of possible signals, etc.) to given decision contexts (characterized by uncertainties, available action alternatives, and the utility function, etc.) can be zero. The VoI = 0 indicates that the degree of uncertainty reduction by additional information can not lead to change in decision and thus the information collecting system is not fit for given decision contexts. If VoI = 0, the optimal decision is the same with or without the additional information. Irrespective of the future signal (i.e. an inspection result), the posterior optimal decision is the same as the prior optimal decision (i.e. a single action method). In such cases, it is not optimal to adopt the ADS, i.e. assign action methods in alignment to the realizations of future signal. Conversely, if the ADS is not optimal, VoI = 0, or at least part of information collection does not provide any value to decision-making. The ADS is not optimal means that the optimal decisions are the same upon at least two realizations of future signal. Thus, there is no added value to the decision problem in distinguishing between these two realizations.

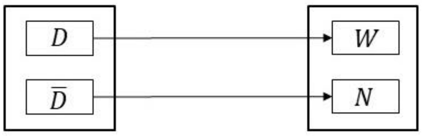

Figure 4. ADS and valuable information collecting by inspection activity 1 (IA1)

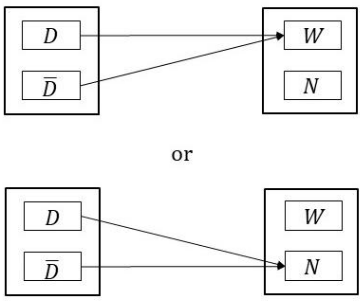

Figure 5. Valueless information collecting by inspection activity 1 (IA1)

When the IA1 (Table 3) is adopted to provide additional information for the two-action decision problem summarised in Table 1,

- The ADS (Figure 4) is to take 'welding' (W) when the inspection result (or signal) indicates crack detection (D) and take 'no action' (N) when the result indicates no detection ($\overline{D}$).

- If the optimal decision is to take the same action method (e.g. W or N), irrespective of inspection result (Figure 5), then the information provided by the IA1 cannot contribute to an improved decision and is thus completely of no value to maintenance decision-making, i.e. VoI = 0.

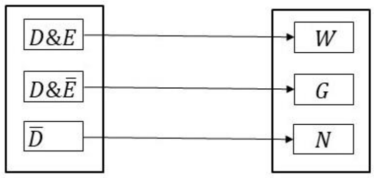

Figure 6. ADS and valuable information collecting by inspection activity 2 (IA2)

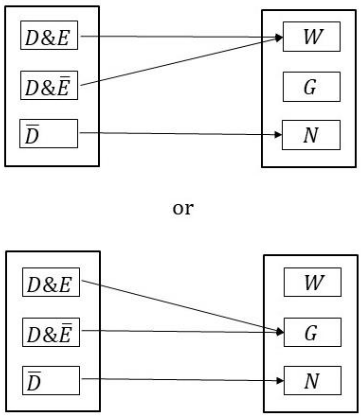

Figure 8. Partly valuable information collecting by inspection activity 2 (IA2)

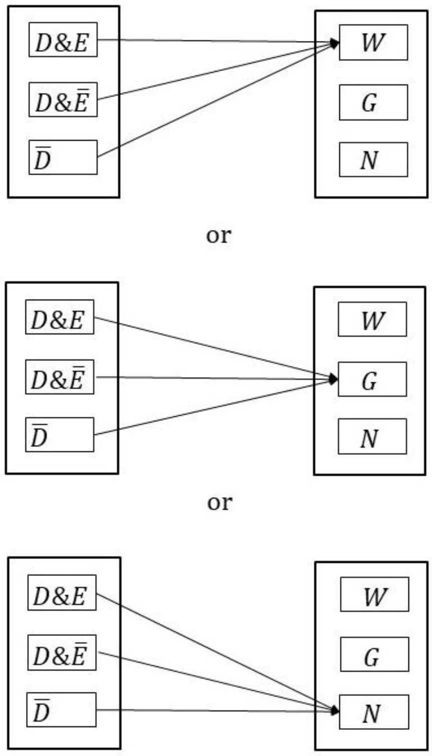

Figure 7. Valueless information collecting by inspection activity 2 (IA2)

When the IA2 (Table 3) is adopted to provide additional information for the three-action decision problem summarised in Table 2,

- The ADS (Figure 6) is to take 'welding' (W) when the inspection result is detection and exceedance of a limiting size ($D\&E$), take 'grinding' (G) when the result is detection but within the limiting size ($D\&\bar{E}$), and take 'no action' (N) when the result is no detection ($\bar{D}$).
- If the optimal decision is to take the same action method (e.g. W, G or N), whether the inspection result is $D\&E$ or $D\&\bar{E}$ or $\bar{D}$ (Figure 7), then the information provided by the IA2 would not contribute to an improved decision and is thus completely of no value to maintenance decision-making, i.e. VoI = 0.
- If the optimal decision is to take the same action method (e.g. W or G), whether the inspection result is $D\&E$ or $D\&\bar{E}$ (Figure 8), and take 'no action' (N) when the result is no detection ($\bar{D}$), then only part of the information provided by IA2 (i.e. detection or not, by step1) is of value to the decision problem, and part of the information (i.e. exceed a limiting size or not, by step 2) is of no value. In such a case, there is no need to take the step 2, which may be costly yet of little help to the decision problem.

Note that the step 2 does provide information and contribute to reduced uncertainty, because it provides another categorization of crack size. However, before taking the step 2, by decision analysis it can be evaluated weather the information and uncertainty reduction contribute to an improved decision. If not, then there is no need to perform such information collecting, or the information collecting system is not fit for the specific decision contexts and thus needs to be changed.

In summary, for a given decision problem,

- If an information collecting system is well designed (in terms of its capacity and reliability, etc.) based on the decision contexts (e.g. degree of uncertainty, available action alternatives, utility function, etc.), the ADS (e.g. see Figures 3, 4 and 6) is the optimal decision strategy considering additional information, and the VoI brought by the system is the maximum;
- If an information collecting system is not fit for decision contexts, additional information can not lead to change in decision and the optimal decisions upon all realizations of signal are the same as the prior optimal decision (e.g. see Figures 5 and 7). In such case, VoI = 0 and additional information collection using the system is completely unnecessary.
- If the information collecting system is average, the ADS is generally the optimal decision strategy considering additional information. But the optimal decisions upon some realizations of signal may be the same (e.g. see Figure 8), which means that part of the information could not be appropriately acted upon based on given action alternatives and thus could not be utilized. In such case, there is no need to distinguish between the realizations upon which the decisions are same. Thus, part of the information is valueless to decision-making, and the information collecting system is not fit for the decision contexts and needs to be optimized.

Hence, it is strongly recommended to frame an information collecting system based on given decision contexts and on the results of decision analysis and VoI computation.

4.4 Life cycle costs adopting ADS

After the optimal decision strategy (i.e. ADS) is identified, the expected life cycle costs C_L associated with the strategy can be calculated based on decision tree analysis. Figures 9 provides the decision tree for IA1. Herein the inspection result is probabilistic, but the maintenance method upon each possible inspection result is identified according to the ADS. Let the monetary consequences of failure be c_{f0}, the costs of a repair activity c_{r0}, and the costs of an inspection activity c_{i0}, then the life cycle costs C_L are given be Equations (23) – (25).

$$C_L = C_M + C_F \tag{23}$$

$$C_F = P_f^n(T_{SL}) \cdot c_{f0} \tag{24}$$

$$C_M = \sum_{i=1}^{n} P_{ins}^{i} \cdot c_{i0} \cdot \frac{1}{(1+r)^{t_{ins}^{i}}} + \sum_{i=1}^{n} P_{rep}^{i} \cdot c_{r0} \cdot \frac{1}{(1+r)^{t_{ins}^{i}}} \tag{25}$$

Where C_M is expected maintenance costs; C_F is failure risk in terms of monetary loss; $P_f^n(T_{SL})$ is lifetime failure probability considering n planned maintenance interventions; P_{ins}^i and P_{rep}^i are the probabilities of the *i*th inspection and repair would be carried out; t_{ins}^i is scheduled time for the *i*th inspection, and; r is average annual discount rate.

Equations (24) and (25) can be obtained easily by life cycle cost analysis methods, adopting some reasonable assumptions for simplification (Kim, Soliman, and Frangopol 2013, Soliman, Frangopol, and Mondoro 2016, Valdebenito and Schuëller 2010, Straub and Faber 2005). The posterior maximum value and utility can be defined based on life cycle costs C_L, i.e. by Equations (6) and (7).

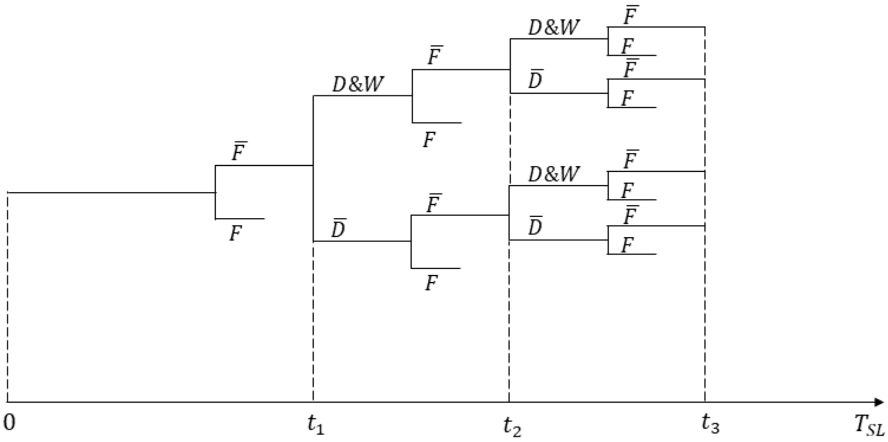

Figure 9. Decision tree analysis when adopting IA1 and ADS

5. An illustrative example

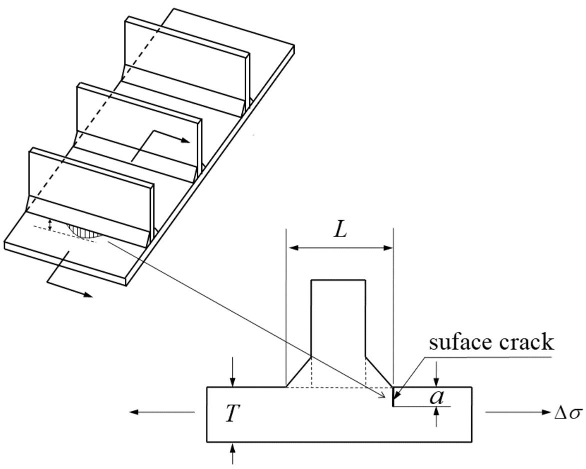

Figure 10. Fatigue-sensitive structural detail under investigation

Table 4. Design Parameters for the structural detail

Parameter	Unit	Value
T_{SL}	Year	20
N_0	Cycle	5×10^6
$\log_{10} \bar{f_1}$	[N, mm]	11.855
$\log_{10} \bar{f_2}$	[N, mm]	15.091
T	mm	25
$\Delta\sigma_e$	MPa	21.03
m_1	-	3
m_2	-	5

The objective of this case study is to apply the proposed methods to quantifying the value of inspections for a stiffened plate in a ship structure subjected to wave loading, which causes fatigue cracks. The welding toes of stiffeners are very prone to cracks and periodical inspections are needed to support maintenance decisions. The geometry of fatigue-critical detail is shown in Figure 10.

5.1 Probabilistic fatigue modelling

Herein crack growth in the depth direction perpendicular to the plate plane is examined, and the critical crack size a_c is defined to be equal to the plate thickness $T = 25$ mm. The one-dimensional Paris' law (Paris and Erdogan 1963), given by Equations (26) and (27) is adopted for crack growth prediction.

$$\frac{da}{dN} = C\Delta K^m, \quad \Delta K_{th} \leq \Delta K \leq K_{mat} \tag{26}$$

$$\Delta K = \Delta\sigma Y(a)\sqrt{\pi a} \tag{27}$$

where da/dN is crack growth rate; ΔK is stress intensity factor range; ΔK_{th} is a threshold of ΔK and, K_{mat} is material fracture toughness.

The required service life is $T_{SL} = 20$ years, and the frequency of wave loading is 0.16 Hz, which corresponding to $N_0 = 5 \times 10^6$ cycles per year (Lotsberg et al. 2016, DNVGL 2015). The structural detail has been designed by a S-N method, with a fatigue design factor $FDF = 3$. Fatigue strength of the structural detail is given by the two-segment S-N curve given by Equation (28).

$$\begin{cases} N_F \Delta\sigma^{m_1} = \overline{f_1} & N_F \leq 10^7 \\ N_F \Delta\sigma^{m_2} = \overline{f_2} & N_F \geq 10^7 \end{cases} \tag{28}$$

where N_F is fatigue life, m_1 and m_2 are the fatigue strength exponents, and $\overline{f_1}$and $\overline{f_2}$ are fatigue strength coefficients. The fatigue strength exponents and coefficients for the structural detail are adopted from a ship classification society (DNV 2014). Input parameters are summarized in Table 4.

Table 5. Variables and statistical descriptors used in reliability analysis

Variable	Distribution	Unit	Mean Value (E)	Standard Deviation
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	0.89/2.00/4.35	0.89/2.00/4.35

Uncertainties associated with initial crack size a_0, material property C, and equivalent stress range $\Delta\sigma_e$ are considered to be the main sources of uncertainty in using the one-dimensional model for prediction of crack growth $a(t)$. It is assumed that a_0 follows an exponential distribution (Lotsberg et al. 2016, DNVGL 2015). Uncertainties associated $\Delta\sigma_e$ are modelled as an additional variable B, which follows a normal distribution (Lassen and Recho 2015). Following common practice, C is assumed to be lognormally distributed while m is fixed (Lotsberg et al. 2016, DNVGL 2015). Table 5 provides the statistical descriptors adopted for all variables.

Monte Carlo simulations are carried out to calculate probabilities, reliability indexes and expected values of life cycle costs and VoI, with 5×10^6 samples for each variable. It is checked that a larger number of samples do not lead to much change in results. The initial lifetime fatigue reliability with no maintenance is 1.11, which is low, e.g. lower than the typical target reliability (β_t = 2) for structural details with not serious failure consequences (Chen, Wang, and Guedes Soares 2011, Mansour 1996). So, maintenance interventions need to be scheduled to increase operational reliability. The reliability index becomes higher with more maintenance interventions.

5.2 VoI quantification and decision analysis

Table 6. Decision parameters defining maintenance decision contexts

Parameter	Symbol	Value
The number of interventions	n	1/ 2/ 3
Action alternatives (in prior analysis)	y	'-'/ 'r'
Action alternatives (in posterior analysis)	y'	'-'/ 'r'/ 'a'
Inspection method	m_{ins}	MPI/ CVI/ VI
Cost ratio	c_{r0}/c_{f0}	1:25/ 1:10/ 1:4
Intervention times	t_{ins}	5 years/10 years/15 years

At the beginning of service ($t = 0$), it is decided to schedule some maintenance interventions. Decision optimization and VoI computation is employed at $t = 0$ to develop efficient inspection and maintenance strategies. The number of planned interventions n is given. The cases when n=1, 2 and 3 are investigated, i.e. the VoIs from one inspection, a sequence of two inspections and a sequence of three inspections. When n=3, three inspections are scheduled to t_1=5 years, t_2=10 years, t_3=15 years (i.e. time interval Δt=5 years). When n=2, two inspections are scheduled to any two of the times t_1, t_2 and t_3. When n=1, one inspection is scheduled to any one of the times t_1, t_2 and t_3. The decision alternatives in prior decision optimization (without any inspection) are: '-' (No action) and 'r' (time-based repair, repair to the as-good-as-new condition). Herein, IA1 is considered, i.e. an inspection providing information of detection or no detection. The decision alternatives in posterior decision optimization (with inspections) are: '-', 'r' and 'a' (alignment decision strategy). As discussed in Section 4.3, 'a' means to repair to as-good-as-new condition (i.e. take 'r') when the inspection result indicates detection and take no action ('-') when the result indicates no detection. Three inspection methods are studied: magnetic particle inspection (MPI, with good detection capacity and reliability), close visual inspection (CVI, with average detection capacity and reliability) and visual inspection (VI, with pool detection capacity and reliability). Important factor affecting optimal decisions and VoIs are the input costs, e.g. monetary costs of failure c_{f0}, and costs of one repair activity c_{r0}. Three values of the cost ratio c_{r0}/c_{f0} are tested: 1:25, 1:10 and 1:4. It is assumed that the costs of an inspection are negligible, compared with the costs of repair (Huynh, Barros, and Bérenguer 2012, Breysse et al. 2009, Kulkarni and Achenbach 2007). All decision parameters are summarized in Table 6. In order to compare the VoI based and cost based approaches to inspection optimization, in this numerical example simple value and utility functions are applied: the value associated with a decision is equal to minus life cycle costs, and the utility of decision is equal to its value.

Tables 7 - 13 give prior and posterior optimal decisions (y_{opt} and y'_{opt}), expected life cycle costs associated with the prior and posterior optimal decisions (C_L and C'_L), VoIs and posterior failure probability (P_f^n), under different inspection methods (m_{ins}) and times (t_{ins}). Tables 7 - 9 provide results when $n = 1$ and c_{r0}/c_{f0}=1:25, 1:10 and 1:4 respectively; Tables 10 - 12 give results when $n = 2$ and c_{r0}/c_{f0}=1:25, 1:10 and 1:4 respectively, and; Table 13 gives results when $n = 3$. In the tables, the unit of inspection time is 'year'. Life cycle costs and VoI are given as ratios to the costs of an inspection.

Table 7. Optimal decisions, life cycle costs and VoI ($n = 1, c_{r0}/c_{f0} = 1:25$)

m_{ins}	MPI			CVI			VI		
t_{ins}	5	10	15	5	10	15	5	10	15
y_{opt}	r	r	r	r	r	r	r	r	r
C_L	818.2	480.2	801.5	817.8	481.2	801.1	818.4	480.7	801.6
y'_{opt}	r	a	a	r	a	a	r	r	a
C'_L	818.2	208.0	665.3	817.8	144.6	579.8	818.4	480.7	505.9
VoL	0	272.2	136.2	0	336.6	221.3	0	0	295.7
P_f^n	0.0394	0.0057	0.0418	0.0394	0.0073	0.0419	0.0394	0.0083	0.0418

Table 8. Optimal decisions, life cycle costs and VoI ($n = 1, c_{r0}/c_{f0} = 1:10$)

m_{ins}	MPI			CVI			VI		
t_{ins}	5	10	15	5	10	15	5	10	15
y_{opt}	-	r	-	-	r	-	-	r	-
C_L	1327.2	1077.8	1327.2	1327.2	1077.8	1327.2	1327.2	1077.8	1327.2
y'_{opt}	a	a	a	a	a	a	a	a	a
C'_L	864.3	435.2	1036.0	1239.9	251.1	823.1	1314.7	725.1	636.6
VoL	462.9	642.6	291.2	87.3	826.7	504.1	12.5	352.7	690.6
P_f^n	0.0806	0.0057	0.0418	0.1233	0.0073	0.0419	0.1313	0.0658	0.0418

Table 9. Optimal decisions, life cycle costs and VoI ($n = 1$, $c_{r0}/c_{f0} = 1:4$)

m_{ins}	MPI			CVI			VI		
t_{ins}	5	10	15	5	10	15	5	10	15
y_{opt}	-	-	-	-	-	-	-	-	-
C_L	1327.2	1327.2	1327.2	1327.2	1327.2	1327.2	1327.2	1327.2	1327.2
y'_{opt}	a	a	-	a	a	-	a	a	a
C'_L	950.5	1003.1	1327.2	1255.1	518.5	1327.2	1316.9	825.9	965.0
VoL	376.7	324.1	0	72.1	808.7	0	10.3	501.3	362.2
P_f^n	0.0806	0.0057	0.1328	0.1233	0.0073	0.1328	0.1313	0.0658	0.0418

Table 10. Optimal decisions, life cycle costs and VoI ($n = 2$, $c_{r0}/c_{f0} = 1:25$)

m_{ins}	MPI			CVI			VI		
t_{ins}	(5, 10)	(5, 15)	(10, 15)	(5, 10)	(5, 15)	(10, 15)	(5, 10)	(5, 15)	(10, 15)
y_{opt}	(-, r)	(-, r)	(r, -)	(-, r)	(-, r)	(r, -)	(-, r)	(-, r)	(r, -)
C_L	480.7	802.4	480.7	480.7	802.4	480.7	480.7	802.4	480.7
y'_{opt}	(a, a)	(a, a)	(a, -)	(a, a)	(a, a)	(a, -)	(a, r)	(r, a)	(a, a)
C'_L	171.9	332.8	208.0	108.2	483.2	144.6	467.5	468.2	147.4
VoL	308.8	469.6	272.7	372.5	319.2	336.1	13.2	334.2	333.3
P_f^n	0.0035	0.0071	0.0057	0.0036	0.0316	0.0073	0.0068	0.0036	0.0043

Table 11. Optimal decisions, life cycle costs and VoI ($n = 2$, $c_{r0}/c_{f0} = 1:10$)

m_{ins}	MPI			CVI			VI		
t_{ins}	(5, 10)	(5, 15)	(10, 15)	(5, 10)	(5, 15)	(10, 15)	(5, 10)	(5, 15)	(10, 15)
y_{opt}	(-, r)	(-, -)	(r, -)	(-, r)	(-, -)	(r, -)	(-, r)	(-, -)	(r, -)
C_L	1077.8	1327.2	1077.8	1077.8	1327.2	1077.8	1077.8	1327.2	1077.8
y'_{opt}	(a, a)	(a, a)	(a, -)	(a, a)	(a, a)	(a, -)	(a, a)	(a, a)	(a, a)
C'_L	403.7	726.4	435.2	217.2	732.1	251.1	711.6	624.9	304.2
VoL	674.1	600.8	642.6	860.6	595.1	826.7	366.2	702.3	773.6
P_f^n	0.0035	0.0071	0.0057	0.0036	0.0316	0.0073	0.0644	0.0403	0.0043

Table 12. Optimal decisions, life cycle costs and VoI ($n = 2$, $c_{r0}/c_{f0} = 1:4$)

m_{ins}	MPI			CVI			VI		
t_{ins}	(5, 10)	(5, 15)	(10, 15)	(5, 10)	(5, 15)	(10, 15)	(5, 10)	(5, 15)	(10, 15)
y_{opt}	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)
C_L	1327.2	1327.2	1327.2	1327.2	1327.2	1327.2	1327.2	1327.2	1327.2
y'_{opt}	(a, -)	(a, -)	(a, -)	(a, a)	(a, -)	(a, -)	(a, a)	(a, a)	(a, a)
C'_L	950.5	950.5	1003.7	491.5	1255.1	518.5	814.7	955.4	696.1
VoL	376.7	376.7	323.5	835.7	72.1	808.7	512.5	371.8	631.1
P_f^n	0.0806	0.0806	0.0057	0.0036	0.1233	0.0073	0.0644	0.0403	0.0043

Table 13. Optimal decisions, life cycle costs and VoI ($n = 3$)

m_{ins}	1:25			1:10			1:4		
t_{ins}	MPI	CVI	VI	MPI	CVI	VI	MPI	CVI	VI
y_{opt}	(-, r, -)	(-, r, -)	(-, r, -)	(-, r, -)	(-, r, -)	(-, r, -)	(-, -, -)	(-, -, -)	(-, -, -)
C_L	480.7	480.7	480.7	1077.8	1077.8	1077.8	1327.2	1327.2	1327.2
y'_{opt}	(a, a, -)	(a, a, -)	(a, a, a)	(a, a, -)	(a, a, -)	(a, a, a)	(a, -, -)	(a, a, -)	(a, a, a)
C'_L	171.9	108.2	132.2	403.7	217.2	287.0	950.5	491.5	674.3
VoL	308.8	372.5	348.5	674.1	860.6	790.8	376.7	835.7	652.9
P_f^n	0.0035	0.0036	0.0029	0.0035	0.0036	0.0029	0.0806	0.0036	0.0029

5.3 Advantages of holistic decision-making and VoI computation

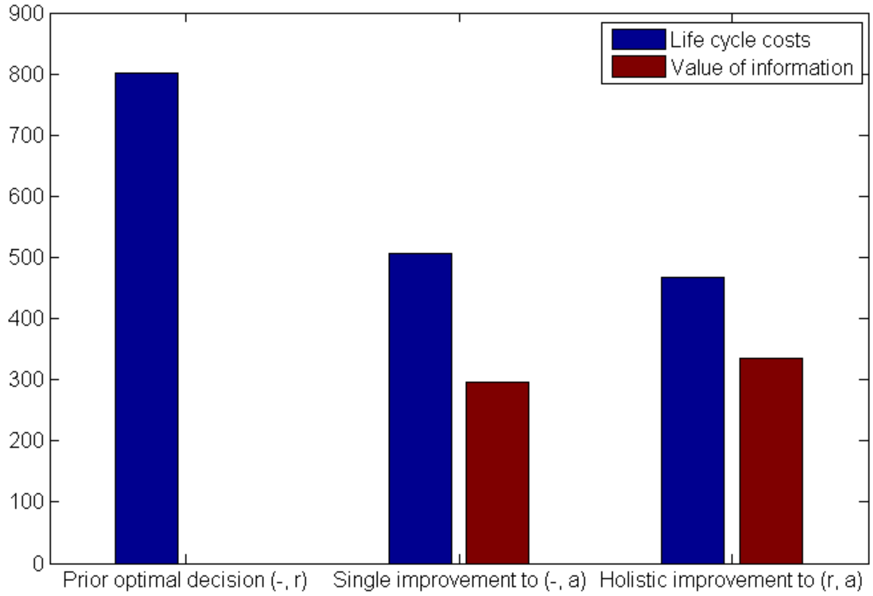

Figure 11. The benefit of holistic decision optimization and VoI computation

It is important to quantify the VoI and optimize a sequence of inspections holistically, rather than to quantify the VoI and optimize each inspection separately and sequentially, because combined effects of interventions can only be captured by a holistic approach. For example, when c_{r0}/c_{f0}=1:25 (Table 10), and adopting VI, the prior and posterior optimal decisions are (-, r) and (r, a) respectively for interventions at t_1=5 years and t_3=15 years ($n = 2$). The posterior optimal decision (r, a) indicates that only one inspection needs to be scheduled to t_3=15 years, although the number of planned interventions is $n = 2$. Due to this planned inspection, the optimal decisions for both interventions change. The posterior optimal decisions capture combined effects of two interventions. The following discussions are made on this case.

- By a holistic approach, when an inspection is scheduled to an intervention, the optimal decision for another intervention (even a prior intervention) can change. In this case, when an inspection is scheduled to t_3=15 years (the 2nd intervention), the optimal decision for the intervention at t_1=5 years (the 1st intervention) has changed from ‘-’ to ‘r’. This result captures combined effects of a sequence of interventions and exemplifies dependencies in decisions, i.e. a decision on one intervention can improve the decision optimality of other interventions, even prior interventions. This dependency and related decision improvement can only be captured by a holistic approach.

- By a holistic approach, the VoI (whether from one inspection or multiple inspections) is the value to the holistic decision problem involving multi-decisions, not only the value to the decisions that adopt inspections. In other words, the VoI comes from improvement of a holistic decision on multi-interventions, due to the availability of additional information. As shown by Figure 11, when an inspection is scheduled to the 2nd intervention, the optimal decision for this intervention changes from ‘r’ to ‘a’. If we only consider the decision improvement for this intervention, the life cycle costs reduce to 505.9 and VoI=296.5, while by a holistic decision optimization approach, the life cycle costs reduce to 468.2 and the holistic VoI=334.2.
- The posterior optimal decision for the intervention scheduled to t_1=5 years is ‘-’ (Table 10) rather than ‘a’, which means that an inspection, if scheduled to t_1=5 years, cannot add value to decision-making.

5.4 Influences of the number of planned interventions and decision flexibility on VoI and optimal decisions

As ‘-’ (No action) is a decision alternative, the optimal number of interventions (i.e. the decisions ‘a’ and ‘r’) N_{inv} can be less than the number of planned interventions n, i.e. $N_{int} \leq n$. Also, as ‘r’ (Repair) is a decision alternative, the optimal number of inspections (i.e. the decision ‘a’) N_{inp} can be less than the optimal number of interventions, i.e. $N_{ins} \leq N_{int} \leq n$.

Tables 7 - 13 show that the optimal number of interventions N_{inv} by posterior analysis is generally larger than by prior analysis. This is due to the fact that when inspections are considered, ‘a’ (i.e. ADS) is the optimal posterior decision in most cases. Further, the N_{inv} by posterior analysis decreases with an increase in c_{r0}/c_{f0} or in the detection capacity of the adopted inspection method. This is because ‘r’ becomes a less cost-effective decision with an increase in c_{r0}/c_{f0}. Also, with an increase in the detection capacity, the probability of repair increases, and ‘a’ becomes less cost-effective either.

5.4.1 The number of planned interventions $n = 1$

Tables 7 - 9 show that ‘a’ is not always the optimal decision. When ‘a’ is not the optimal decision, VoI = 0, which indicates there is no need to plan an inspection or the given inspection method is not appropriate. When ‘a’ is the optimal decision, then VoI > 0.

5.4.2 The number of planned interventions $n = 2$

Tables 10 - 12 show that in most cases, the posterior optimal decision is 'a' for both interventions. There are however cases with the optimal decision being 'a' and '-' for the 1st and 2nd interventions respectively. The optimal decision for the second intervention are more likely to be '-' with a larger c_{r0}/c_{f0} and MPI is used. Besides, there are two cases with the optimal decision for one of the interventions being 'r' (Table 10).

The VoI = 0, if an inspection was scheduled to an intervention for which the optimal decision is '-' or 'r'. For example, when c_{r0}/c_{f0}=1:25 (Table 10), and adopting MPI, the posterior optimal decision is 'a' and '-' for interventions scheduled to t_2=10 years and t_3=15 years (C_L'=208.0, and VoI=272.7). If two inspections were scheduled and 'a' was adopted for both interventions, C_L'=360.4, which is higher than 208.0, and thus the information provided by the inspection scheduled to t_3=15 years would not be utilized by the DM and thus valueless.

5.4.3 The number of planned interventions $n = 3$

Tables 7-13 show that 'a' is more likely to be the posterior optimal decision when $n = 3$ than when $n = 1$ or 2. The reason for this interesting finding has been explored. It is believed that the finding shows the VoI depends also on the number of available action alternatives, i.e. depends on decision flexibility, which has been studied in management science and operational research (Merkhofer 1977, Ketzenberg et al. 2007), but herein discussed for the first time in civil and structural engineering. In the maintenance decision-making problem herein discussed, the number of combinations of maintenance action alternatives is 3^n, which increases exponentially with n. When $n = 3$, there are more combinations of action alternative available (than when $n = 1$ or 2), and thus it is more likely that the additional information provided by inspections can be acted upon and utilized. Therefore when $n = 3$, it is more likely that VoI>0, and the 'a' is the posterior optimal decision.

5.5 Optimal decisions by VoI based and cost based methods

The obtained posterior optimal decisions by VoI method are fully validated by the cost-optimal repair (crack size) criterion method established in (Zou, González, et al. 2019), in which the following points are presented.

- The cost-optimal repair criterion $a_{r,opt}$ defines a bound for optimal repair. Repairing of cracks larger or equal to $a_{r,opt}$ (i.e. $a \geq a_{r,opt}$) would be cost-beneficial and smaller than $a_{r,opt}$ (i.e. $a < a_{r,opt}$) would not be beneficial.
- The value of $a_{r,opt}$ depends on both the intervention time t_{ins} (t_{ins} =t_1 or t_2 or t_3) and cost ratio c_{r0}/c_{f0}. It becomes larger with a later intervention time, i.e. the cost-optimal repair

criterion $a_{r,opt}$ for maintenance scheduled to t_3=15 years should be larger than to t_1=5 years. Also, it becomes larger with a larger cost ratio c_{r0}/c_{f0}, i.e. the cost-optimal repair criterion $a_{r,opt}$ should be larger when $c_{r0}/c_{f0} = 1:4$ than when $c_{r0}/c_{f0} = 1:25$.

- The crack size a is updated with inspection results and thus depends on the adopted inspection method m_{ins}. The inferred crack sizes are different using different inspection methods (associated with different values of $E(a_d)$).

Employing the cost-optimal repair criterion method, the optimal decisions by the VoI method can be analysed. For example, when the ratio c_{r0}/c_f is small (Table 7), the prior optimal decision is ‘r’, and thus the VoI, if larger than 0, can only be attributed to choosing the decision ‘-’ when the inspection result is ‘no detection’. Based on the above points, whether ‘-’ is the optimal decision when the additional information is ‘no detection’ (and whether VoI > 0) depends on the intervention time t_{ins} and the adopted inspection method m_{ins}.

- The VoI from an inspection scheduled to t_1=5 years is 0 and the optimal decision is ‘r’, whether using MPI or CVI or VI (Tables 7 - 9). These results are explained by that the optimal $a_{r,opt}$ for a repair scheduled to t_1=5 years is smaller than the smallest $E(a_d)$ of MPI, CVI and VI (i.e. $a_{r,opt} < E(a_d)$=0.89 mm), so ‘’r is the optimal decision even when the inspection results by MPI, CVI and VI are no detection (i.e. when a <0.89 mm).
- An inspection scheduled to t_3=15 years brings added value (i.e. VoI > 0) and the optimal decision is ‘a’, whether using MPI or CVI or VI. These results are explained by that the optimal $a_{r,opt}$ for a repair scheduled to t_3=15 years is larger than the largest $E(a_d)$ of MPI, CVI and VI (i.e. $a_{r,opt} > E(a_d)$=4.35 mm), so ‘’r is not the optimal decision (i.e. ‘-’ is the optimal decision) when the inspection results by MPI, CVI and VI are no detection (i.e. when a <4.35 mm).
- For t_2=10 years, the VoI > 0 by MPI or CVI, and VoI = 0 by VI, which indicates the VoI from an inspection scheduled to t_2=10 years depends on the adopted inspection method. These results are explained by that the optimal $a_{r,opt}$ for a repair scheduled to t_2=10 years is larger than the detectable crack size $E(a_d)$ of CVI but smaller than the $E(a_d)$ of VI (i.e. $2\text{ mm} < a_{r,opt}$ <4.35 mm), so ‘r’ is not the optimal decision (i.e. ‘-’ is the optimal decision) when the ‘no detection’ result is obtained by MPI and CVI (i.e. when a <0.89 or 2 mm), but ‘r’ is the optimal decision when is ‘no detection’ result is obtained by VI (i.e. when a <4.35 mm).

In summary, the posterior optimal decision and VoI are dependent not only on the adopted inspection method, but also on the prior optimal decision, which is further dependent on the given intervention time and cost ratio. The influences of inspection the method, intervention time and cost ratio shown in this paper are in agreement with the discussions in (Zou, González, et al. 2019).

5.6 Optimal inspection methods

The detection capacity of the adopted inspection method (characterized by $E(a_d)$) affects posterior life cycle costs C_L', the optimal decision a_{opt}', the optimal number of inspections N_{ins} and VoI. For example, when $n = 3$ (Table 13) and c_{r0}/c_{f0}=1:4, the posterior optimal decisions are (a, -, -), (a, a, -), and (a, a, a) when MPI, CVI and VI are adopted respectively, with the optimal number of inspections being N_{ins} =1 (MPI), 2 (CVI), 3 (VI), and the VoI=376.7 (MPI), 835.7 (CVI), 652.9 (VI) respectively. The influences of the parameter $E(a_d)$ on posterior life cycle costs C_L' are twofold: on one hand, the parameter determines probability of detection (& repair) and thus expected maintenance costs C_M; on the other hand, the parameter $E(a_d)$ affects the lifetime failure risk C_F inferred from the inspection result of no detection. In total, the parameter $E(a_d)$ affects the expected life cycle costs C_L' associated with the decision 'a', and thus affects the posterior optimal decision.

Tables 7-13 however show that VoI from an inspection method with a higher detection capacity (i.e. a smaller $E(a_d)$) can be less. For example, when $n = 3$ (Table 13), under all cost ratios, the VoI is the largest when using CVI ($E(a_d)$=2 mm), and smallest when using MPI ($E(a_d)$=0.89 mm). When $n = 3$, c_{r0}/c_{f0}=1:10 and adopting MPI and CVI respectively, the posterior optimal decisions are the same: (a, a, -). The C_L' is higher when using MPI than CVI (403.7 versus 217.2) and the VoI is smaller when using MPI than CVI (674.1 versus 860.6). This can be explained reasonably. When the optimal decisions using MPI and CVI are both 'a', it means that repair to as-good-as-new condition is the optimal decision, when the inspection results (by both MPI and CVI) are crack detection. Since the $E(a_d)$ of MPI is smaller than CVI, using MPI can lead to a larger probability of repair and higher maintenance costs (386.4 versus 182.3), higher posterior life cycle costs C_L' (403.7 versus 217.2) and thus smaller VoI (674.1 versus 860.6). As per the discussions in Section 4, the VoI depends on information utilization in given maintenance decision contexts (given action alternatives). Although a crack is more likely to be detected by MPI, this information may not be acted upon appropriately. In a two-action decision problem, if (by decision analysis) repair is the optimal decision upon crack detection, a higher detection probability (using MPI) leads to higher maintenance costs and smaller VoI. Hence, the VoI brought by an inspection method with a high detection capacity can be less, depending on specific decision contexts.

Also, it is shown that more inspections can add more or the same value. Table 13 clearly shows that when the given max number of interventions is n=3, the optimal number of inspections is N_{ins}=2 in most cases, and an inspection scheduled to $t_3 = 15$ years is unnecessary. When c_{r0}/c_{f0}=1:4 and MPI is adopted, only one inspection scheduled to $t_1 = 5$ years adds value to decision-making.

In addition, it is sensible to adopt better inspection methods (with a higher detection capacity) for earlier interventions. Tables 4 - 6 show that when $n = 1$, the inspection methods that bring the largest VoI for t_1=5, 10 or 15 years are MPI, CVI and VI respectively. When $n = 2$ (Tables 10 - 12), for early maintenance interventions, e.g. the intervention times are (5, 10) years, the VoI by MPI or CVI is the largest, while for late interventions, e.g. the intervention times are (10, 15) years, the VoI by VI or CVI is the largest. This is because the maintenance strategy 'a' is most effective when the detectable crack size $E(a_d)$ of the adopted inspection method is close to the cost-optimal repair criterion $a_{r,opt}$, and the $a_{r,opt}$ becomes smaller with an earlier intervention time (Zou, González, et al. 2019).

5.7 VoI-based and cost-based optimal inspection times

Table 14. Optimal inspection times by VoI-based and cost-based optimization methods ($n = 1, c_{r0}/c_{f0} = 1:25$, VI)

	VoI-based optimization	Cost-based optimization
y_{opt}	(-, -, r)	(-, r, -)
C_L	801.6	480.7
y'_{opt}	(-, -, a)	(-, r, -)
t_{ins}	15	10
C'_L	505.9	480.7
VoL	295.7	0

Table 15. Optimal inspection times by VoI-based and cost-based optimization methods ($n = 2, c_{r0}/c_{f0} = 1:25$, MPI)

	VoI-based optimization	Cost-based optimization
y_{opt}	(-, -, r)	(-, r, -)
C_L	802.4	480.7
y'_{opt}	(a, -, a)	(a, a, -)
t_{ins}	(5, 15)	(5, 10)
C'_L	332.8	171.9
VoL	469.6	308.8

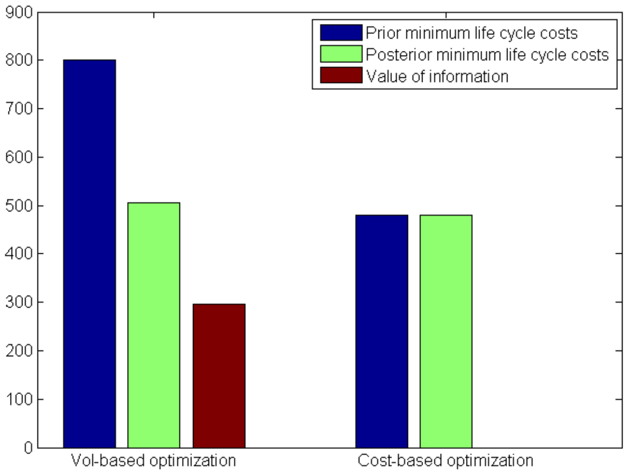

Figure 12. A comparison of VoI-based and cost-based inspection timing optimization ($n = 1, c_{r0}/c_{f0} = 1:25$, VI)

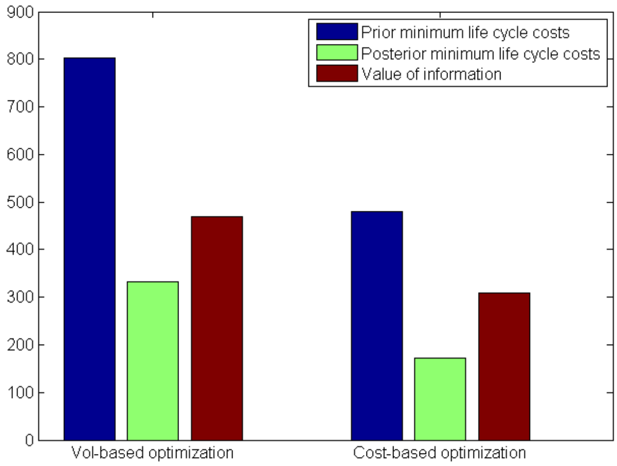

Figure 13. A comparison of VoI-based and cost-based inspection timing optimization ($n = 2, c_{r0}/c_{f0} = 1:25$, MPI)

The VoI is dependent not only on the posterior optimal decision, but also on the prior optimal decision, as per the formulae in Section 3 and discussions in Section 5.5. When inspection times are given, the prior optimal decision and associated life cycle costs C_L are specific, the VoI then only depends on the posterior optimal decision and associated life cycle costs C_L'. In such cases, the obtained optimal inspection methods by VoI maximization and (life cycle) cost minimization are the same (Section 5.6).

However, when inspection times are optimization variables, the prior optimal decision and associated life cycle costs C_L are not specific, the obtained inspection times by VoI-based and cost-based (Zou, González, et al. 2019) optimization approaches may not be the same. In this section, optimization of inspection time(s) is performed by both VoI-based and cost-based approaches, i.e. inspection times are optimization variables, rather than given. To narrow the domain of optimization variables, inspection times are limited to three discrete values: a) when $n = 1$, possible times are 5, 10 and 15 years; b) when $n = 2$, possible times are (5, 10), (5, 15) and (10, 15) years.

Table 14 shows the optimal inspection times by VoI-based optimization when $n = 1$, c_{r0}/c_{f0}=1:25, and using VI, compared to the cost-based optimization method developed in (Zou, González, et al. 2019). The optimal inspection time is t_{ins}=15 years (VoI= 295.7, C_L'=505.9) by VoI-based method and t_{ins}=10 years (VoI= 0, C_L'=480.7) by cost-based method. Table 15 compares the optimal inspection times obtained by VoI-based and cost-based optimization methods when $n = 2$, c_{r0}/c_{f0}=1:25, and using MPI. The optimal inspection times are (5, 15) years (VoI= 469.6, C_L'=332.8) by VoI-based method and (5, 10) years (VoI= 308.8, C_L'=171.9) by cost-based method. Tables 14 & 15 show that the VoI-based inspection optimization method can result in inspection times at which the VoI is larger (mainly due to higher prior life cycle costs C_L, as can be seen from Figures 12 & 13), but the posterior life cycle costs C_L' are higher than the cost-based inspection optimization method. Such inspection times are optimal in terms of inspection efficiency but not optimal in terms of maintenance efficiency. Note that inspections are means to collect additional information in support of decision-making and thus focus should be placed upon maintenance efficiency, i.e. the life cycle costs C_L'. Hence, the cost-based method is more suitable for optimisation of inspection times.

Tables 16 and 17 provide optimal decisions and inspection times by cost-based method when $n = 1$ and $n = 2$ respectively under different cost ratios and using different inspection methods, i.e. the inspection times leading to the minimum life cycle costs C_L'. For example, in Table 17 ($n = 2$), when $c_{r0}/c_{f0} = 1{:}\,25$ and MPI is adopted, the optimum inspection times are (5, 10) years and the optimum decision is (a, a, -), which corresponds to the minimum life cycle costs, i.e. C_L'=171.9. Note that in Table 16, when $c_{r0}/c_{f0} = 1{:}\,10$ and different inspection methods are adopted, the prior life cycle costs C_L are different, due to different optimal inspection times, not due to different inspection methods. When intervention times are specific, the prior optimal decision y_{opt} and associated life cycle costs C_L should be independent on the inspection method (as evidence by Tables 7 - 13), because prior decision optimization is performed based on existing information without any inspection.

Table 16. Optimal inspection times, decisions, life cycle costs and VoIs under different cost ratios and inspection methods ($n = 1$)

c_{r0}/c_{f0}	1:25			1:10			1:4		
m_{ins}	MPI	CVI	VI	MPI	CVI	VI	MPI	CVI	VI
y_{opt}	(-, r, -)	(-, r, -)	(-, r, -)	(-, r, -)	(-, r, -)	(-, -, -)	(-, -, -)	(-, -, -)	(-, -, -)
C_L	480.7	480.7	480.7	1077.8	1077.8	1327.2	1327.2	1327.2	1327.2
y'_{opt}	(-, a, -)	(-, a, -)	(-, r, -)	(-, a, -)	(-, a, -)	(-, -, a)	(a, -, -)	(-, a, -)	(-, a, -)
t_{ins}	10	10	No insp.	10	10	15	5	10	10
C'_L	208.0	144.6	480.7	435.2	251.1	636.6	950.5	518.5	825.9
VoL	272.2	336.6	0	642.6	826.7	690.6	376.7	808.7	501.3

Table 17. Optimal inspection times, decisions, life cycle costs and VoIs under different cost ratios and inspection methods ($n = 2$)

c_{r0}/c_{f0}	1:25			1:10			1:4		
m_{ins}	MPI	CVI	VI	MPI	CVI	VI	MPI	CVI	VI
y_{opt}	(-, r, -)	(-, r, -)	(-, r, -)	(-, r, -)	(-, r, -)	(-, r, -)	(-, -, -)	(-, -, -)	(-, -, -)
C_L	480.7	480.7	480.7	1077.8	1077.8	1077.8	1327.2	1327.2	1327.2
y'_{opt}	(a, a, -)	(a, a, -)	(-, a, a)	(a, a, -)	(a, a, -)	(-, a, a)	(-, -, a)	(a, a, -)	(-, a, a)
t_{ins}	(5, 10)	(5, 10)	(10, 15)	(5, 10)	(5, 10)	(10, 15)	15	(5, 10)	(10, 15)
C'_L	171.9	108.2	147.4	403.7	217.2	304.2	950.5	491.5	696.1
VoL	308.8	372.5	333.3	674.1	860.6	773.6	376.7	835.7	631.1

When $n = 1$ (Table 16), the optimal inspection time is t_{ins}=10 years in most cases. The exceptions are: when c_{r0}/c_{f0}=1:10 and using VI, the optimal inspection time is t_{ins}=15 years; when c_{r0}/c_{f0}=1:4 and using MPI, the optimal inspection time is t_{ins}=5 years, and; when c_{r0}/c_{f0}=1:25 and using VI, there is no need to schedule an inspection. When $n = 2$ (Table 17), the optimal inspection times are 5 and 10 years in most cases. The exceptions are: when VI is used, the optimal inspection times are 10 and 15 years under all cost ratios, and; when c_{r0}/c_{f0}=1:4 and MPI are used, the optimal inspection time is 5 years (i.e. only one inspection adds value to maintenance decision-making).

6 Conclusions

Information contributes to a reduced level of uncertainty, based on which a decision maker (DM) may be able to make an improved decision and thus, mitigate the risk of making a wrong decision and incurring significant losses. This paper has addressed maintenance planning problem in life cycle management of structures against fatigue cracks by a holistic VoI computation method. Rather than considering one maintenance intervention, herein a holistic decision on multiple interventions has been sought for and a method has been developed to quantify the VoI from multiple inspections in holistic maintenance decision-making. It has been shown that the method is able to capture combined effects of a sequence of interventions and dependencies in decisions, i.e. a decision on one intervention can affect the decision optimality of other interventions, even prior interventions.

An efficient simplified method for holistic VoI computation has also been proposed based on an alignment decision strategy (ADS), which reduces computational costs The simplified method is applicable when each inspection adds value and when the number of possible results from one inspection is equal to the number of available action alternatives in one intervention. Although the results from future inspections are unknown at the time of decision-making, a future inspection can provide a categorization of the probabilistic crack size and the likelihood of each category can be calculated based on the reliability of the adopted inspection method. Such categorization reduces uncertainty on crack size and thus provides additional ‘known’ information to maintenance decision-making, based on which an improved decision can be derived. This is a new perspective on a future inspection and the information provided to present decision-making.

The relationship between VoI and ADS has been discussed, and the simplified VoI computation method validated via proof by contradiction. It has been shown that for a well-designed inspection system and activity, VoI > 0 and the ADS is the optimal strategy. When the ADS is not optimal, VoI = 0 or at least part of the inspection activity is of no value, which indicates that there is no need to schedule an inspection or that the planned inspection system and activity does not fit given maintenance decision contexts and need to be optimised. When VoI = 0, the optimal maintenance decision is the same as the prior optimal decision without inspection.

The holistic VoI computation method has been exemplified on a typical fatigue-sensitive structural detail in ships. Sensitivities of VoI and optimal decisions to the number of planned interventions, cost ratio, inspection time(s), and method(s) have been investigated. It has been shown that it is more likely that the ADS is the posterior optimal strategy and VoI > 0 when the number of planned interventions is larger. The cause for this finding has been attributed to a larger number of possible combinations of action alternatives and higher decision flexibility, when the number of planned interventions is larger. This is the first time that decision flexibility has been discussed in maintenance planning for engineering structures.

The optimal maintenance decisions obtained by VoI-based method have been checked against the cost-optimal repair (crack size) criterion method established in (Zou, González, et al. 2019), and good agreements have been found in the derived optimal decisions. The cost-optimal repair criterion can be derived based on a given cost ratio and inspection time, while the mean detectable crack size of an inspection method represents a repair criterion that can actually be utilized in practice. Whether ADS is the optimal decision and whether VoI > 0 depend on how close the mean detectable crack size to the cost-optimal repair criterion.

It has been found that the VoI from an inspection method with a higher detection capacity can be less. This is because that an inspection method with a higher detection capacity (e.g. MPI) leads to a higher probability of detection, which indicates higher maintenance costs. In addition, it has been found that more inspections can bring more or the same value, as some inspections may not add value if not well-designed. These findings highlight the importance of VoI computation (to confirm that VoI > 0) and VoI based inspection method optimisation. When the costs of an inspection are not negligible, the VoI would be slightly smaller than shown in the numerical example, it is likely that VoI = 0 in more cases and thus VoI computation is even more important.

The optimal inspection times obtained by VoI-based optimization have been compared with the cost-based optimization method (Zou, González, et al. 2019). It has been shown that there are cases in which the VoI-based method results in inspection times associated with a higher VoI and higher life cycle costs. Such inspection times are optimal in terms of inspection efficiency but not optimal in terms of maintenance efficiency.

This paper has proposed holistic VoI computation methods to take into account combined effects of maintenance interventions and dependencies in the decisions. The methods support holistic maintenance planning at an early stage by giving a decision which is optimal from the perspective of whole lifetime and ensures the quality of the decision for earlier interventions. The methods have been applied to life cycle management of engineering structures and provided some useful conclusions and insights in terms of inspection method and time optimization. It is acknowledged that when an inspection (or measurement) has been carried out and additional information available, the decision for remaining interventions can be updated holistically. The optimal decision for the first intervention is ‘a’ (as shown by Tables 10 – 13) in most cases. Thus, if an inspection result is detection and a repair is carried out during the first intervention, then the structural system is renewed to initial condition, and the remaining service life is shortened. If the structural reliability is high, a probable inspection result would be no detection, which indicates a slightly lower failure probability than prior prediction. A simplified method has been developed for VoI calculation for certain cases. In future work, the cases would be studied in which the numbers of possible inspection results and available maintenance methods are not equal.

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